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Time-Varying Impacts of Geopolitical Risk on Industrial Commodity Markets: A Comparative Study of China, the US and the EU

Xianghao Meng [1,*]

[1] Renmin University of China, Beijing, China

* Correspondence: Xianghao Meng, Renmin University of China, Beijing, China

Abstract: In recent years, major international economic frictions and regional security tensions have intensified, contributing to a sustained rise in global geopolitical risk (GPR) and exerting profound influences on commodity markets characterized by both physical and financial attributes. Natural gas, aluminum, and copper, as key commodities in the energy and industrial sectors, exhibit price fluctuations that are closely associated with industrial chain stability and macroeconomic performance. This study focuses on the natural gas, aluminum, and copper markets across three major economic regions-China, the United States, and the European Union-by constructing a time-varying parameter structural vector autoregression model with stochastic volatility (TVP-SVAR-SV) and employing Markov Chain Monte Carlo (MCMC) methods for parameter estimation. Combined with impulse response analysis and comparative examination of major events, this paper systematically investigates the time-varying transmission patterns of geopolitical risk across nine segmented commodity markets. The empirical results indicate that: first, the transmission of geopolitical risk to commodity markets demonstrates a clear unidirectional characteristic, with geopolitical risk functioning as the primary external driver of market volatility, while feedback effects from commodity market fluctuations to geopolitical risk remain limited; second, transmission effects exhibit pronounced horizon dependence and short-term persistence, as strong short-term shocks gradually converge over longer horizons; third, significant heterogeneity exists across commodity categories and regions, with energy commodities displaying higher overall sensitivity than metal commodities, the European market experiencing comparatively stronger impacts, and the Chinese market showing relatively greater resilience supported by policy coordination and well-integrated industrial systems; fourth, major global public health emergencies and large-scale international economic frictions amplify transmission mechanisms, with shock intensity increasing in line with the severity of external disturbances. This study not only enriches the theoretical understanding of the dynamic relationship between geopolitical risk and commodity markets but also provides valuable empirical evidence for policymakers designing differentiated regulatory frameworks and for enterprises seeking to manage exposure to commodity price volatility.

Keywords: Geopolitical Risk; Commodity Markets; TVP-SVAR-SV Model; Regional Heterogeneity

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1. Introduction

1.1. Research Background and Significance

1.1.1. Research Background

In recent years, international economic frictions, regional security tensions, and major global public health emergencies have occurred with increasing frequency. The intensity of external shocks has continued to rise, gradually becoming a core exogenous factor influencing global economic performance and market volatility. Industrial commodities, as fundamental raw materials supporting national economic systems, exhibit price fluctuations that are closely associated with industrial chain and supply chain stability, macroeconomic performance, and household consumption costs. Natural gas, aluminum, and copper, as representative products in the energy and industrial sectors, are influenced not only by supply-demand fundamentals but also by complex international economic linkages and policy coordination mechanisms. As a result, their price dynamics demonstrate pronounced complexity, uncertainty, and volatility.

1.1.2. Research Significance

From a practical perspective, since 2018, fluctuations in international economic and trade relations have led to periodic and significant volatility in global prices of aluminum, copper, and other industrial metals. In 2020, the global outbreak of a major public health emergency sharply increased policy uncertainty, exposing commodity markets to extreme conditions characterized by rapid declines followed by swift recoveries. In 2022, escalating regional tensions further intensified concerns over energy supply stability in certain markets, contributing to sharp increases in natural gas prices and transmitting pressures to energy-dependent industrial metals such as aluminum and copper. Against this backdrop, clarifying the transmission channels, time-varying characteristics, and regional heterogeneity of global geopolitical risk across segmented commodity markets, and accurately identifying differences in volatility resilience and risk exposure among various markets, is of substantial practical importance. Such analysis provides valuable references for government authorities in designing differentiated market regulation policies, for enterprises seeking to hedge against price fluctuation risks, and for maintaining the stability of industrial and supply chains.

From a theoretical perspective, existing studies largely concentrate on single-category commodities or aggregate commodity indices, with relatively limited attention to refined, cross-regional comparisons among natural gas, aluminum, and copper markets in China, the United States, and the European Union. Furthermore, the time-varying features of geopolitical risk transmission and the heterogeneity associated with major external disturbances warrant deeper and more systematic investigation. Based on a time-varying parameter structural vector autoregression framework, this paper conducts a comprehensive analysis of the dynamic relationships between major geopolitical risk factors in recent years and nine segmented commodity markets. This approach not only broadens the analytical perspective on the linkage between policy uncertainty and commodity markets but also enriches empirical evidence on time-varying transmission mechanisms, thereby providing additional empirical support for the development and refinement of related theoretical frameworks.

2. Literature Review

2.1. Measuring Geopolitical Risk

Accurate measurement of geopolitical risk constitutes the foundation for empirical analysis in this field. Existing studies generally classify measurement approaches into two categories: event-counting methods and text-based measurement methods. In recent years, the latter has gradually become the mainstream approach due to its advantages in timeliness, coverage, and replicability.

Early research primarily relied on event-counting methods, constructing risk indicators by quantifying the frequency and severity of specific geopolitical events. Although intuitive in design, such methods are often subject to selection bias and limited coverage, making it difficult to fully capture the complex and evolving nature of geopolitical risk within an increasingly interconnected global environment.

With the advancement of text analysis techniques, index construction methods based on large-scale media reports have developed rapidly. One strand of research incorporated geopolitically related vocabulary into broader economic policy uncertainty indices, providing an important reference framework for subsequent geopolitical risk measurement [1]. Building upon this approach, later studies developed the Geopolitical Risk Index (GPR), which has become one of the most widely adopted indicators in the field. This index identifies and counts the frequency of selected keyword groups related to geopolitical tensions and instability within major international newspaper articles, thereby covering a broad range of global events with relatively strong timeliness and cross-country comparability [2].

2.2. Research on the Impact of Geopolitical Risk on Commodity Prices

Commodity pricing mechanisms provide the theoretical foundation for analyzing the transmission channels through which geopolitical risk affects markets. The core analytical framework emphasizes the joint influence of "supply-demand fundamentals" and "non-fundamental factors," with geopolitical risk exerting time-varying effects on both components. Existing research can be broadly categorized into traditional pricing theory and financialization-oriented pricing theory.

The supply-demand channel is widely recognized as the primary pathway through which geopolitical risk influences commodity markets. Traditional pricing theory, grounded in supply-demand equilibrium analysis, holds that commodity prices are determined by the interaction between market supply and demand. Geopolitical risk affects the supply side through mechanisms such as disruptions to production facilities, increases in transportation costs due to trade frictions, and export restrictions imposed by resource-producing economies, all of which may result in short-term supply contractions and upward price pressure. On the demand side, rising uncertainty may weaken global growth expectations, thereby reducing industrial demand for energy and industrial metals and exerting downward pressure on prices. The three commodity categories examined in this paper-natural gas, aluminum, and copper-differ in demand elasticity and exposure to geopolitical disturbances, providing a theoretical basis for subsequent heterogeneity analysis.

With the rapid development of commodity futures and derivatives markets, the financialization channel has become increasingly important. Financialization-oriented pricing theory emphasizes that commodities, alongside equities and bonds, have evolved into a distinct asset class. Their prices are therefore influenced not only by fundamental supply-demand conditions but also by capital flows, portfolio allocation behavior, and changes in risk preferences [3]. As a typical external shock factor, geopolitical risk may trigger heightened risk aversion in financial markets, leading to capital reallocation across asset classes and causing commodity prices to deviate temporarily from fundamental values, thereby amplifying short-term volatility.

2.3. Segmented Categories and Regional Differences

Recent research has shifted from aggregate commodity market analysis toward a more refined examination of category-specific and region-specific heterogeneity. Empirical findings indicate that the impact of geopolitical risk varies significantly across commodity types and regional market structures.

From a category perspective, energy commodities tend to exhibit greater sensitivity to geopolitical disturbances. As foundational inputs for economic activity, energy production and trade often rely on geographically concentrated resources and infrastructure networks, making them more directly exposed to supply-side shocks. Existing studies have shown that large-scale international tensions have historically been associated with substantial increases in international energy prices, with relatively persistent volatility effects [4]. Further research suggests that energy markets, particularly natural gas markets characterized by infrastructure dependence and regional segmentation, display heightened sensitivity to external geopolitical disturbances, as potential supply disruptions can quickly translate into sharp price movements [5].

From a regional perspective, commodity markets in different economic areas demonstrate heterogeneous responses and transmission mechanisms. Under conditions of global economic integration, trade linkages and capital flows connect regional markets closely; however, differences in economic structure, resource endowment, and policy coordination capacity lead to divergent transmission effects when external shocks occur [6]. Empirical evidence focusing on the Chinese market also indicates that spillover effects of geopolitical risk differ across commodity categories, underscoring the necessity of conducting fine-grained analysis by both region and commodity type.

2.4. Time-Varying Characteristics and Methodological Evolution

Early empirical studies generally assumed that the effects of geopolitical risk on commodity markets were constant over time and thus relied on static econometric frameworks, such as traditional VAR and GARCH models. Research using GARCH-type models has demonstrated that major geopolitical events can significantly increase the volatility of commodity futures prices [7]. However, such static approaches have limitations in capturing the dynamic evolution of transmission effects and may fail to identify differences across distinct periods and varying levels of shock intensity.

With the advancement of time-varying econometric techniques, models incorporating evolving parameters have become increasingly prominent in analyzing dynamic shock transmission. Time-varying transmission theory provides the core conceptual foundation for the adoption of the TVP-SVAR framework in this study. The central premise is that the impact of external shocks on markets is not constant but instead exhibits stage-specific and time-dependent characteristics influenced by shock magnitude, market conditions, and policy responses. This perspective is supported by two theoretical strands.

First, time-varying parameter theory posits that structural relationships within economic systems evolve over time. The Time-Varying Parameter Vector Autoregression (TVP-VAR) framework relaxes the assumption of fixed coefficients in conventional VAR models, allowing structural parameters to change dynamically. Consequently, the transmission channels and intensities of external shocks vary with shifts in the economic environment, and the impact of geopolitical risk on commodity markets may differ depending on the type, duration, and scope of external disturbances [8].

Second, asymmetric shock transmission theory suggests that external shocks generate heterogeneous effects across regions and market types. Such asymmetry arises from differences in supply-demand structures, policy buffering capacity, financial market development, and industrial chain resilience. This theoretical perspective underpins the dual-dimension analytical framework adopted in this paper, which integrates segmented commodity markets with major external disturbance events in order to examine dynamic and heterogeneous transmission mechanisms in a systematic manner.

3. Research Design

3.1. Model Specification

3.1.1. TVP-SVAR-SV Model Specification

Consider a K-dimensional system containing the Geopolitical Risk Index (GPR) and N commodity market variables (in this paper, K=10, containing GPR and nine segmented market variables). The benchmark reduced-form Vector Autoregression (VAR) model can be expressed as:

$$Y_t = C_t + B_{1,t}Y_{t-1} + B_{2,t}Y_{t-2} + \cdots + B_{p,t}Y_{t-p} + u_t$$
$$u_t \sim N(0, \Omega_t)$$

Where Y_t is a $K \times 1$ dimensional vector of endogenous variables; C_t is a $K \times 1$ dimensional vector of time-varying intercepts; $B_{i,t}$ ($i = 1,2,\dots,p$) are $K \times K$ dimensional matrices of time-varying coefficients; p is the lag order (determined as $p =$

2 based on information criteria in this paper); u_t is the reduced-form disturbance term with covariance matrix allowed Ω_t to vary over time.

To further identify structural shocks, the reduced-form VAR is transformed into structural SVAR form. Assuming the existence of a time-varying structural matrix A_t such that structural shocks ε_t satisfy $A_t\varepsilon_t = u_t$, with $\varepsilon_t \sim N(0, I_K)$. This yields the TVP-SVAR-SV model:

$$Y_t = C_t + B_{1,t}Y_{t-1} + B_{2,t}Y_{t-2} + \cdots + B_{p,t}Y_{t-p} + A_t^{-1}\Sigma_t\varepsilon_t$$

Where Σ_t is a diagonal matrix with diagonal elements representing standard deviations, used to depict Stochastic Volatility. For estimation convenience, time-varying parameters C_t,$B_{i,t}$, A_t and are stacked into vector β_t, assumed to follow a random walk process:

$$\beta_t = \beta_{t-1} + v_t, v_t \sim N(0, \Omega_\beta)$$

Meanwhile, the lower triangular elements of the structural matrix A_t (stacked into vector a_t) are also assumed to follow a random walk:

$$a_t = a_{t-1} + \zeta_t, \zeta_t \sim N(0, \Omega_a)$$

The stochastic volatility component is modeled through log-volatility $h_{i,t} = \ln\left(\sigma_{i,t}^2\right)$, assumed to follow an AR(1) process:

$$h_{i,t} = \mu_i + \phi_i(h_{i,t-1} - \mu_i) + \eta_{i,t}, \eta_{i,t} \sim N(0, \sigma_{\eta,i}^2)$$

Where μ_i is the long-term mean, ϕ_i is the persistence parameter, $|\phi_i| < 1$, and $\eta_{i,t}$ is the volatility shock.

3.1.2. Prior Distribution and Estimation Methods

To enhance the robustness of model estimation and mitigate potential overfitting, it is necessary to impose appropriate prior distributions on the model parameters, following established specification principles in the time-varying parameter VAR framework.

Initial value priors for time-varying coefficients β_0 , time-varying structural parameters a_0, and log-volatility h_0 are all set to zero mean, with covariance matrices $4 \times I$,$4 \times I$ and I.

Priors for random walk process covariance matrices Ω_β,Ω_a, and volatility equation variances $\sigma_{\eta,i}^2$ are set to inverse Gamma distributions, with hyperparameters calibrated based on pre-sample information to balance the weight of prior information and data information.

Model parameter estimation employs Bayesian framework Markov Chain Monte Carlo (MCMC) methods, combining Gibbs sampling and Metropolis-Hastings algorithms for posterior sampling. Specific settings are as follows:

Total MCMC iterations: 20,000, with the first 10,000 as burn-in to ensure chain convergence, retaining the latter 10,000 for posterior inference.

To ensure reproducibility, the random number seed (Ranseed) is fixed at 123.

Model lag order is comprehensively determined as 2nd order based on LR, FPE, AIC, SC, and HQ information criteria.

3.1.3. Model Diagnostics and Robustness Checks

To ensure reliability of model estimation, systematic diagnostic tests are conducted after parameter estimation:

Convergence Diagnostics: Geweke statistics are employed to test MCMC sampling chain convergence. This statistic compares mean differences between front and back segments of the chain; values close to 0 and failing significance tests indicate chain convergence.

Sampling Efficiency Assessment: Measured through Inefficiency Factors, reflecting autocorrelation during the sampling process. Lower inefficiency factors indicate higher sampling efficiency, typically considered acceptable when below 100.

Path and Autocorrelation Plot Inspection: Observing whether parameter sampling paths are stable and trendless, and whether sample autocorrelation coefficients rapidly decay to 0, to verify chain mixing effects and independence.

3.1.4. Dynamic Correlation Analysis Tools

Based on the estimated TVP-SVAR model, the following tools are employed to reveal dynamic correlations between geopolitical risk and industrial commodity markets:

Time-Varying Impulse Response Functions (TVP-IRF): Calculating dynamic impacts of unit structural shocks over future horizons at different time points, thereby depicting time-varying characteristics and horizon-dependence of transmission effects.

$$IRF_t(h) = \frac{\partial Y_{t+h}}{\partial \varepsilon_t}$$

Time-Varying Structural Parameters and Transmission Coefficients: Identifying dynamic evolution of shock transmission direction and intensity through analysis of time-varying structural parameters and their derived time-varying transmission coefficients.

Stochastic Volatility Analysis: Comparing stochastic volatility paths of GPR and various commodity markets to reveal relative changes and correlations between external uncertainty shocks and market endogenous volatility.

Critical Event Analysis: Selecting critical event time points such as trade friction (March 2018), pandemic outbreak (March 2020), and Russia-Ukraine conflict (February 2022), comparing impulse response patterns and magnitudes across different periods to test asymmetry and event-dependence characteristics of transmission mechanisms.

3.2. Data Sources

3.2.1. Commodity Market Price Data

Categories and Regions: Natural gas, aluminum, and copper markets in China, the United States, and the European Union.

Indicator Selection: To maintain comparability and reflect overall market price levels, representative futures or spot benchmark prices are employed for each market.

Natural Gas: China uses the LNG ex-factory price index or import arrival price published by the Shanghai Petroleum and Natural Gas Exchange; the U.S. uses Henry Hub natural gas futures settlement prices; the EU uses Dutch Title Transfer Facility (TTF) natural gas futures prices.

Aluminum: China uses SHFE aluminum futures main contract settlement prices; the U.S. uses LME aluminum futures settlement prices (USD-denominated); the EU refers to LME aluminum prices.

Copper: China uses SHFE copper futures main contract settlement prices; the U.S. uses LME copper futures settlement prices; the EU refers to LME copper prices.

3.2.2. Data Processing

All price data are converted to USD-denominated to eliminate direct impacts of exchange rate fluctuations. Seasonal adjustments are applied to raw price series, and log returns are calculated as model input variables, i.e. $R_t = \ln(P_t/P_{t-1})$, where P_t is the price at t period. For few missing values, linear interpolation or estimation based on adjacent market information is used for filling.

3.2.3. Sample Period

Considering data availability and the objectives of this study, the sample period is set from January 2010 to June 2024. This interval encompasses major international economic frictions, large-scale global public health events, and significant regional security disturbances, thereby providing a sufficiently comprehensive time span to capture the time-varying characteristics of geopolitical risk transmission.

4. Empirical Analysis

Based on the TVP-SVAR-SV model, this chapter takes the Geopolitical Risk Index as the core explanatory variable and selects price variables from nine segmented markets-natural gas, aluminum, and copper markets in China, the United States, and the European Union-as dependent variables for empirical analysis.

4.1. Aluminum Market

4.1.1. Parameter Estimation

For the aluminum markets of China (AL_CN), the United States (AL_US), and the European Union (AL_EU), this section conducts empirical analysis using a TVP-SVAR model with lag order 2, MCMC iterations set to 20,000 (with first 10,000 as burn-in), and Ranseed fixed at 123 to ensure reproducibility. Core estimation results are shown in the table below (S_{b1},S_{b2},S_{a1},S_{h1},S_{h2},correspond to variances of time-varying coefficients β_t, structural parameters, and stochastic volatility) (As shown in Table 1).

Table 1. Parameter Estimation of aluminum markets.

Market	Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef.
AL_CN	S_{b1}	0.0022	0.0001	0.0024	0.0021	0.021	0.64
	S_{b2}	0.0022	0.0001	0.0024	0.0021	0.314	0.89
	S_{a1}	0.0037	0.0006	0.0053	0.0028	0.767	8.61
	S_{h1}	0.2921	0.1164	0.5505	0.1144	0.000	172.44
	S_{h2}	0.0052	0.0014	0.0085	0.0033	0.840	18.93
AL_US	S_{b1}	0.0022	0.0000	0.0023	0.0021	0.262	1.06
	S_{b2}	0.0022	0.0000	0.0023	0.0021	0.088	0.84
	S_{a1}	0.0041	0.0007	0.0057	0.0029	0.024	10.42
	S_{h1}	0.2568	0.1164	0.5318	0.0831	0.004	87.83
	S_{h2}	0.0053	0.0014	0.0087	0.0033	0.768	13.15
AL_EU	c	0.0022	0.0000	0.0023	0.0022	0.011	0.68
	S_{b2}	0.0022	0.0000	0.0023	0.0022	0.000	0.91
	S_{a1}	0.0043	0.0008	0.0062	0.0031	0.000	18.40
	S_{h1}	0.2690	0.0865	0.4787	0.1457	0.005	95.66
	S_{h2}	0.0054	0.0015	0.0091	0.0032	0.168	16.85

Estimation results show that Geweke statistics for all three aluminum markets are close to 0 and do not significantly deviate from reasonable intervals, indicating good MCMC sampling convergence. Inefficiency factors are generally at low levels except for in AL_CN (172.44), indicating overall adequate sampling efficiency. Core parameter means range between 0.25-0.29, with the Chinese aluminum market highest at 0.2921, but considering standard deviations, the EU market shows relatively greater volatility, reflecting differences in sensitivity to geopolitical risk across regional aluminum markets, consistent with subsequent impulse response analysis results.

4.1.2. MCMC Diagnostics

To verify the reliability of TVP-SVAR model parameter estimation and ensure validity of all subsequent analysis results, systematic MCMC diagnostics must first be conducted on core variance parameters. This paper sequentially conducts MCMC diagnostics for the Chinese, U.S., and EU aluminum markets (As shown in Figure 1).

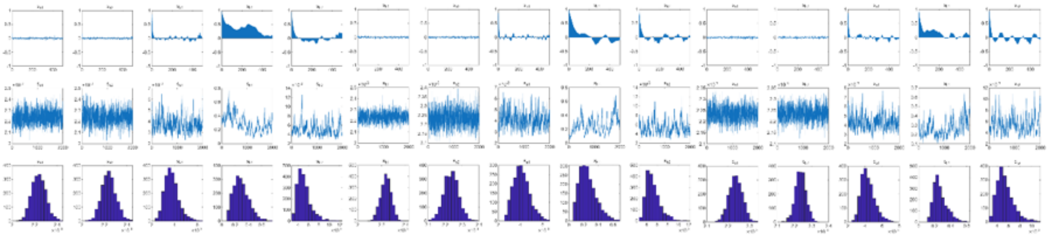

Figure 1. MCMC diagnostic plots of the aluminum market in China, the United States, and Europe Union.

MCMC diagnostic results confirm the sampling reliability of the core variance parameters in the TVP-SVAR model. In the sample autocorrelation plots, the autocorrelation coefficients of all parameters decline rapidly toward zero as the lag order increases. Most autocorrelation curves fluctuate closely around the zero line, and the remaining parameters approach zero within 200 lag periods, indicating strong mixing efficiency of the Markov chains and a high degree of sample independence.

The sampling path plots show that all parameter draws display stable fluctuation patterns without systematic drift. The sampled values remain within relatively narrow and bounded intervals, oscillating around stable means throughout the simulation process. No persistent upward or downward trends are observed, suggesting that the sampling chains have converged to their respective target stationary distributions.

The posterior density histograms further exhibit unimodal and approximately symmetric distributions, with parameter values concentrated around central regions. This pattern reflects clear central tendencies and a well-controlled range of estimation uncertainty, thereby supporting the overall stability and reliability of the model estimation results.

4.1.3. Raw Data and Stochastic Volatility

Upon confirming reliable parameter estimation, to reveal volatility patterns and differences between geopolitical shocks and aluminum markets themselves, and to lay groundwork for subsequent transmission mechanism analysis, analysis is conducted combining raw data and stochastic volatility. Raw data and stochastic volatility plots are drawn for the Chinese, U.S., and EU aluminum markets respectively (As shown in Figure 2).

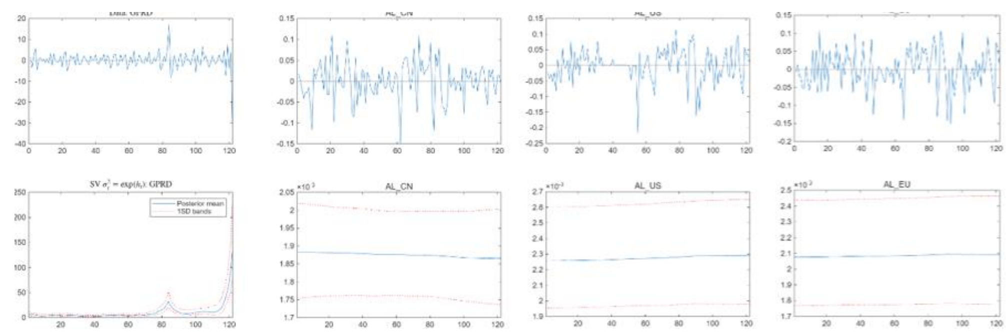

Figure 2. Volatility of raw data and stochastic volatility characteristics in the aluminum markets.

By comparing geopolitical shocks with raw data volatility and Stochastic Volatility (SV) characteristics across Chinese, U.S., and EU aluminum markets, volatility resilience and external shock response differences across regional aluminum markets can be revealed. From raw data perspective, GPR fluctuated moderately in the early sample period (periods 0-80), mainly oscillating between -10 and 10, while in later periods (80-120), volatility amplitude experienced mutational amplification due to extreme geopolitical events such as the Russia-Ukraine conflict. In contrast, the Chinese aluminum market maintained stable volatility ranges between -0.15 and 0.15, with frequent periodic fluctuations but no significant mutations. The U.S. aluminum market showed slightly wider ranges between -0.25 and 0.15, with short-term volatility more sensitive to external events. The EU aluminum market ranged between -0.2 and 0.15, with volatility amplitude between China and the U.S., indicating stronger direct impacts of regional geopolitical risk.

From stochastic volatility estimation results, GPR volatility approached 0 with extremely narrow confidence bands in early periods, then sharply climbed above 200 in later periods with synchronously widening confidence bands, reflecting significantly rising volatility risk of policy uncertainty. However, volatility across the three major aluminum markets remained stable long-term: Chinese aluminum market volatility maintained between 1.7-2.05×10^{-3}, U.S. aluminum market between 1.9-2.7×10^{-3}, and EU aluminum market between 1.7-2.5×10^{-3}. All three showed stable posterior means with narrow confidence bands, without significant volatility following GPR's later mutation, demonstrating the resilience of aluminum markets as commodity markets and reflecting that their price fluctuations are driven more by supply-demand fundamentals than direct transmission of short-term policy uncertainty.

4.1.4. Time-Varying Structural Parameters and Transmission Coefficients

To deeply explore dynamic evolution characteristics of transmission mechanisms between variables and clarify changes in transmission effect direction and intensity across different stages, analysis is conducted through time-varying structural parameters and transmission coefficients (As shown in Figure 3).

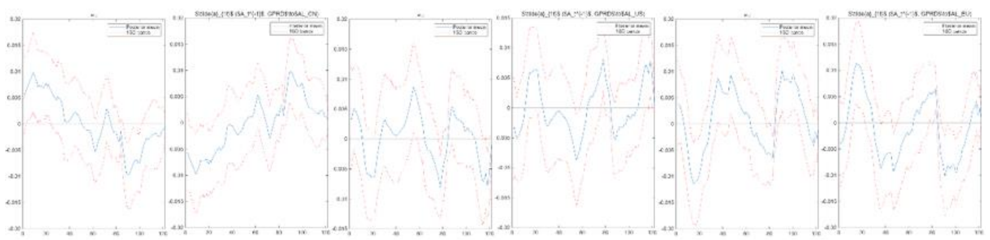

Figure 3. Time-Varying Structural Parameters and Transmission Coefficients in the aluminum markets.

The posterior means of time-varying structural parameter and transmission coefficient and their ±1 standard deviation confidence bands jointly reveal core common time-varying characteristics of geopolitical risk transmission mechanisms to global aluminum markets. The most prominent commonality is that both and exhibit significant phased dynamic adjustment characteristics, with the medium-term serving as a key turning point and enhancement stage for transmission effects, accompanied by rising estimation uncertainty. Specifically, for all regional markets, both show prominent positive effect characteristics in the medium-term-either transitioning from negative to positive or reaching positive effect peaks-with significantly widened confidence bands during corresponding stages. This indicates that while transmission effects of geopolitical risk on aluminum markets are strengthening, estimation uncertainty also rises synchronously, with uncertainty particularly prominent during positive-negative alternation or effect transition phases. Furthermore, all three demonstrate consistent dynamic trajectories of "early-period volatility → medium-term positive reinforcement → late-period convergence to zero or renewed adjustment," without long-term stable transmission directions, confirming that transmission effects of geopolitical risk on aluminum markets have universal and significant time-variability highly consistent with the rhythm of global geopolitical event shocks. Among them, the Chinese market shows a transition period from negative to positive in the medium-term, while U.S. and EU markets show positive effect peak periods in the medium-term, with specific time intervals varying slightly.

4.1.5. Impulse Response Analysis

Aluminum Market Impulse Responses to Geopolitical Risk Shocks

First, analyzing aluminum market impulse responses to geopolitical risk shocks, the following figures show impulse response pathways for Chinese, U.S., and EU aluminum markets to geopolitical risk shocks at 1-period, 3-period, and 6-period horizons, with horizontal axes representing monthly observation indices and vertical axes representing response magnitudes (As shown in Figure 4).

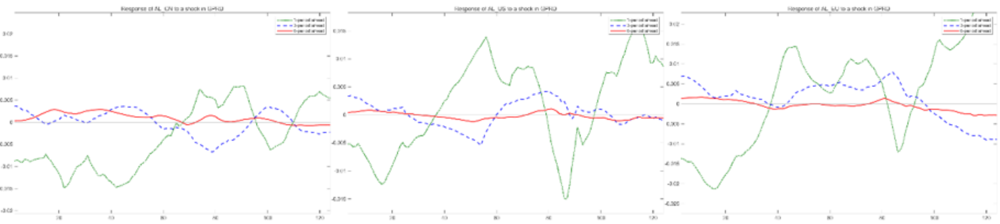

Figure 4. Aluminum Market Impulse Responses to Geopolitical Risk Shocks.

From common characteristics, all three aluminum markets exhibit "short-term negative fluctuation → medium-term adjustment rebound → long-term convergence to 0" response patterns to geopolitical risk shocks, with 1-period horizon showing the most significant volatility amplitude, 3-period horizon second, and 6-period horizon approaching the 0 line, demonstrating distinct horizon-dependence-policy uncertainty impacts on aluminum markets rapidly decay over time. From regional differences, the EU aluminum market shows the deepest short-term negative response (-0.02 to -0.025) and highest medium-term positive peak (0.015 to 0.02), reflecting strongest sensitivity to policy uncertainty. The U.S. aluminum market shows medium-term positive responses of 0.01 to 0.015 with slightly higher peaks and more distinct phased fluctuation characteristics. The Chinese aluminum market shows relatively moderate overall responses, with short-term negative fluctuations (-0.01 to -0.015) and medium-term rebound amplitudes smaller than EU and U.S. markets, demonstrating stronger market resilience. These regional differences relate not only to direct shock intensity of global geopolitical events but also reflect differences in supply-demand structures and policy buffering capacities across regional aluminum markets.

Geopolitical Risk Impulse Responses to Aluminum Market Shocks

In this group of figures, responses of geopolitical risk to aluminum market shocks are overall weak, nearly 0 at 6-period horizons, with only small negative fluctuations of -0.04 to -0.06 at 1-period horizons and responses nearly 0 at 3-period horizons. This indicates that geopolitical risk is a driving factor for aluminum market volatility, while reverse impacts of aluminum market volatility on geopolitical risk are almost negligible, with clear unidirectionality in transmission direction (As shown in Figure 5).

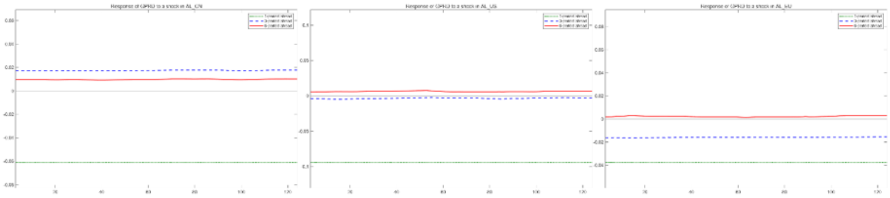

Figure 5. Geopolitical Risk Impulse Responses to Aluminum Market Shocks.

4.1.6. Impulse Responses at Critical Event Time Points

To examine the asymmetry of transmission mechanisms and the influence of major external disturbances on transmission effects, impulse response analysis is conducted with a focus on selected critical event time points. The three figures present the impulse response trajectories corresponding to these key periods. The horizontal axis represents the number of periods following the shock (1-12 periods, corresponding to 1-12 months after the shock), while the vertical axis indicates the magnitude of the response. The green dotted line, blue dashed line, and red solid line represent three distinct event phases: March 2018 (international trade friction), March 2020 (global public health emergency outbreak), and February 2022 (escalation of regional tensions), respectively (As shown in Figure 6).

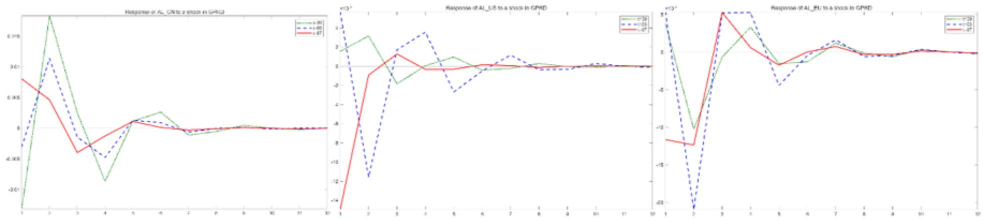

Figure 6. Impulse Responses at Critical Event Time Points.

These three figures show differences in impulse responses of Chinese, U.S., and EU aluminum markets to geopolitical risk shocks at different critical event time points, further revealing transmission patterns when combined with prior analysis. From the relationship between event intensity and response magnitude: the Chinese aluminum market shows positive initial responses of approximately 0.008 during the Russia-Ukraine conflict period, while initial responses are negative (-0.01 to -0.005) during trade friction and pandemic periods, with overall fluctuation ranges between -0.01 and 0.015-the most moderate among the three major markets. The U.S. aluminum market, in units of 10^{-3}, shows initial negative responses of approximately -14×10^{-3} during the Russia-Ukraine conflict and -12×10^{-3} during the pandemic, significantly higher than -2×10^{-3} during trade friction. The EU aluminum market shows the most violent fluctuations, with deepest initial negative shocks of approximately -20×10^{-3} during the pandemic, -12×10^{-3} during the Russia-Ukraine conflict, and -10×10^{-3} during trade friction, reflecting significantly enhanced shocks to aluminum markets as global event intensity increases.

From regional resilience differences, the Chinese aluminum market consistently shows the most moderate responses, demonstrating stronger policy buffering and industrial resilience. The EU aluminum market shows the largest fluctuations, related to its high dependence on external imports and stronger direct impact from geopolitical events. The U.S. aluminum market fluctuates between the two, reflecting its combination of global market linkage and certain domestic buffering capacity. Additionally, all responses converge to 0 after period 12, verifying that geopolitical risk shocks to aluminum markets are significant in the short term but converge over the long term.

4.2. Copper Market

4.2.1. Parameter Estimation

For the copper markets of China (CU_CN), the United States (CU_US), and the European Union (CU_EU), consistent TVP-SVAR model specifications are adopted with aluminum markets-lag order 2, 20,000 MCMC iterations, Ranseed=123-with identical critical event time points selected for impulse response analysis. Model estimation results are shown in the table below (As shown in Table 2).

Table 2. Parameter Estimation of copper markets.

Market	Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef.
CU_CN	S_{b1}	0.0022	0.0000	0.0023	0.0022	0.431	0.37
	S_{b2}	0.0022	0.0000	0.0023	0.0022	0.813	0.50
	S_{a1}	0.0039	0.0007	0.0055	0.0028	0.988	20.74
	$S_{\mathrm{h}1}$	0.2368	0.0758	0.4093	0.1145	0.447	49.78
	$S_{\mathrm{h}2}$	0.0055	0.0015	0.0093	0.0034	0.858	15.68
CU_US	S_{b1}	0.0022	0.0000	0.0023	0.0022	0.148	0.27
	S_{b2}	0.0022	0.0000	0.0023	0.0022	0.000	0.91
	S_{a1}	0.0040	0.0008	0.0059	0.0029	0.000	12.87
	$S_{\mathrm{h}1}$	0.2470	0.1028	0.4842	0.0963	0.362	60.91
	$S_{\mathrm{h}2}$	0.0052	0.0016	0.0094	0.0033	0.341	18.18
CU_EU	S_{b1}	0.0022	0.0000	0.0023	0.0022	0.918	0.46
	S_{b2}	0.0022	0.0000	0.0023	0.0022	0.000	0.43
	S_{a1}	0.0040	0.0008	0.0058	0.0028	0.065	9.95
	$S_{\mathrm{h}1}$	0.2128	0.1069	0.4590	0.0705	0.020	64.56
	$S_{\mathrm{h}2}$	0.0056	0.0014	0.0092	0.0037	0.000	25.26

Copper market estimation results show all parameters' Geweke statistics within reasonable ranges, indicating effective MCMC sampling convergence. Inefficiency factors are overall lower than aluminum markets, indicating superior sampling efficiency. Core shock parameter means show characteristics of China (0.2368) > U.S. (0.2470) > EU (0.2128), but the EU market shows the largest standard deviation of 0.1069, indicating greater volatility amplitude in its copper market from geopolitical risk shocks, consistent with the EU copper industry's high dependence on external sources. Additionally, and means are essentially consistent across the three copper markets at 0.0022, indicating consistent impacts of 2nd-lag policy uncertainty shocks on copper markets.

4.2.2. MCMC Diagnostics

MCMC diagnostic plots confirm the sampling reliability of core variance parameters, as autocorrelation decays rapidly, sampling paths exhibit stable fluctuations, and posterior densities show unimodal, concentrated distributions (As shown in Figure 7).

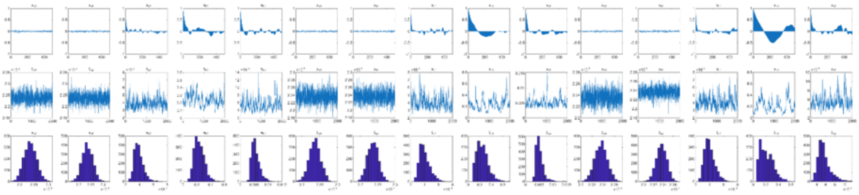

Figure 7. MCMC diagnostic plots of the copper market in China, the United States, and Europe Union.

4.2.3. Raw Data and Stochastic Volatility

Overall, the transmission of geopolitical risks to copper markets exhibits significant time-varying characteristics with distinct regional differences: the EU market, influenced by both geopolitical shocks and financial attributes, demonstrates the highest uncertainty; the U.S. market shows frequent fluctuations, reflecting the immediate impact of global capital flows; and the Chinese market transitions from negative effects initially to positive ones later, highlighting the phased effects of policy buffers and industrial resilience (As shown in Figure 8).

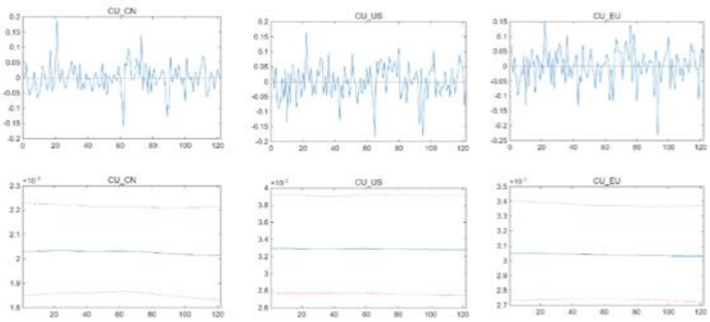

Figure 8. Volatility of raw data and stochastic volatility characteristics in the copper markets.

4.2.4. Time-Varying Structural Parameters and Transmission Coefficients

These figures reveal distinct regional patterns in both the dynamic correlations and geopolitical risk transmission across copper markets: China demonstrates stable, moderate fluctuations with a notable shift from negative to positive risk transmission, reflecting policy-driven resilience; the U.S. exhibits phased volatility and frequent transmission reversals, mirroring global capital flow dynamics; while the EU shows the widest fluctuations and highest uncertainty, indicating it is the most sensitive to geopolitical shocks. Overall, the time-varying nature of risk transmission highlights clear regional differences-greatest in the EU due to heightened sensitivity, intermediate in the U.S. driven by capital flows, and most stabilized in China through policy and industrial buffers (As shown in Figure 9).

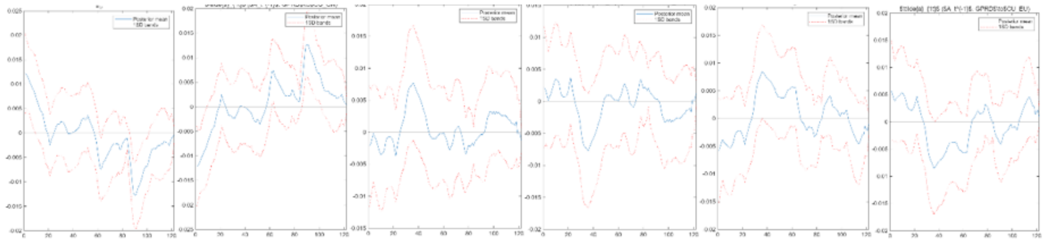

Figure 9. Time-Varying Structural Parameters and Transmission Coefficients in the copper markets.

4.2.5. Impulse Response Analysis

Copper Market Impulse Responses to Geopolitical Risk Shocks

The impulse responses of Chinese, U.S., and EU copper markets to geopolitical risk shocks exhibit clear horizon dependence and regional divergence. While all three markets follow a pattern of initial decline, medium term rebound, and long term convergence-with the strongest impact at 1 period and fading by period 6, indicating rapid shock decay-the regional differences are pronounced: the EU shows the greatest volatility and strongest rebound, reflecting high import reliance and geopolitical sensitivity; the U.S. displays the deepest initial drop and ongoing fluctuations, driven by volatile global capital flows; and China demonstrates the most stable response with quick stabilization, underscoring its policy buffers and supply chain resilience (As shown in Figure 10).

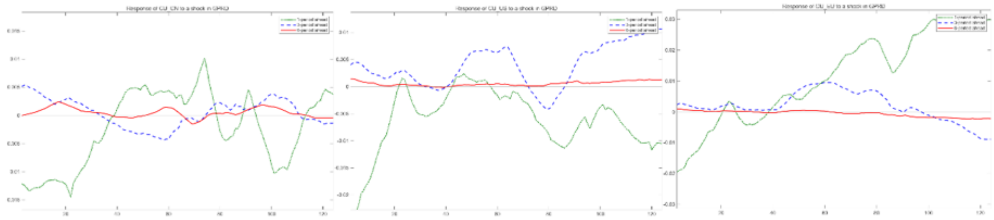

Figure 10. Copper Market Impulse Responses to Geopolitical Risk Shocks.

Geopolitical Risk Impulse Responses to Copper Market Shocks

The impulse responses of geopolitical risk to shocks from the three copper markets are weak overall-small negative at 1 period, negligible at 3 periods, and zero at 6 periods-in sharp contrast to the strong responses of copper markets to geopolitical risk shocks, confirming the unidirectional transmission of risk as a driver of market volatility (As shown in Figure 11).

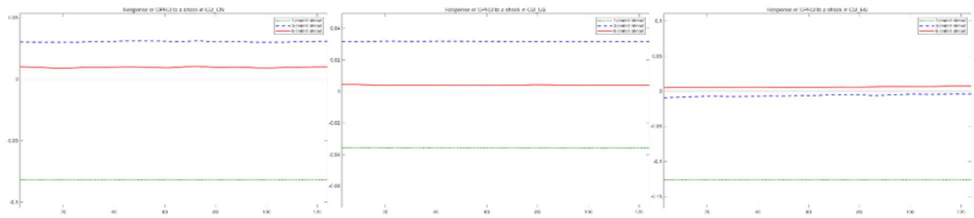

Figure 11. Geopolitical Risk Impulse Responses to Copper Market Shocks.

Regional response intensities are consistent across both directions: the EU shows the deepest initial drop, followed by the U.S., and China the mildest, reflecting stable differences in sensitivity tied to geopolitical exposure, financial attributes, and industrial structure.

4.2.6. Impulse Responses at Critical Event Time Points

These three figures combined show differences in impulse responses of Chinese, U.S., and EU copper markets to geopolitical risk shocks across critical event time points and different horizons. Overall, all three markets exhibit patterns of higher event intensity corresponding to larger shock magnitudes and short-term significant but long-term converging responses, with obvious regional resilience differences: the Chinese market shows weakening later shocks reflecting policy buffering capacity; the EU market shows the most violent fluctuations reflecting higher geopolitical sensitivity; the U.S. market fluctuates between the two, possessing both global linkage and domestic buffering capacity (As shown in Figure 12).

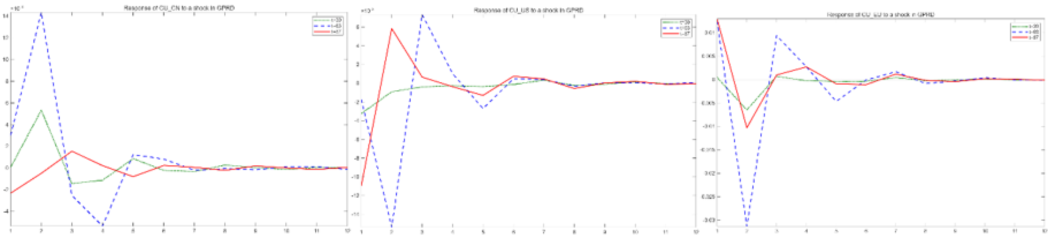

Figure 12. Impulse Responses at Critical Event Time Points.

4.3. Natural Gas Market

4.3.1. Parameter Estimation

For the natural gas markets, three core markets are selected: China (NG_CN), the United States (NG_US), and the European Union (NG_EU). Identical TVP-SVAR model specifications are adopted with aluminum and copper markets-lag order 2, 20,000 MCMC iterations, Ranseed=123-with critical event time points consistent with aluminum and copper markets. Model estimation results are shown in the table below (As shown in Table 3).

Table 3. Parameter Estimation of natural gas markets.

Market	Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef.
	S_{b1}	0.0023	0.0003	0.0029	0.0018	0.577	3.20
	S_{b2}	0.0023	0.0003	0.0029	0.0018	0.351	1.26
NG_CN	S_{a1}	0.0064	0.0019	0.0112	0.0038	0.011	49.02
	$S_{\mathrm{h}1}$	0.2802	0.0959	0.4768	0.1168	0.061	48.81
	$S_{\mathrm{h}2}$	0.0057	0.0019	0.0114	0.0032	0.033	70.31
	S_{b1}	0.0023	0.0002	0.0027	0.0019	0.002	4.23
	S_{b2}	0.0023	0.0002	0.0026	0.0019	0.739	6.17
NG_US	S_{a1}	0.0046	0.0010	0.0068	0.0030	0.009	10.93
	$S_{\mathrm{h}1}$	0.2844	0.0968	0.5116	0.1395	0.000	101.79
	$S_{\mathrm{h}2}$	0.0054	0.0014	0.0086	0.0034	0.257	15.28
NG_EU	S_{b1}	0.0022	0.0001	0.0025	0.0020	0.000	1.33

Market	Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef.
	S_{b2}	0.0022	0.0001	0.0025	0.0020	0.833	1.04
	S_{a1}	0.0041	0.0008	0.0062	0.0028	0.473	7.81
	S_{h1}	0.2364	0.0981	0.4519	0.0953	0.000	92.61
	S_{h2}	0.1181	0.0461	0.2301	0.0482	0.426	93.78

Natural gas market estimation results show that the EU natural gas market's mean of 0.1181 is far higher than other markets' 0.005-0.006, indicating that 2nd-lag geopolitical risk shocks still significantly affect the EU natural gas market, closely related to the EU natural gas supply's high dependence on imports and weaker industrial chain resilience. Additionally, all Geweke statistics for natural gas markets pass convergence tests, indicating reliable model estimation results.

4.3.2. MCMC Diagnostics

MCMC diagnostics for all three natural gas markets indicate reliable sampling, evidenced by rapidly decaying autocorrelation, stable sampling paths, and concentrated posterior densities (As shown in Figure 13).

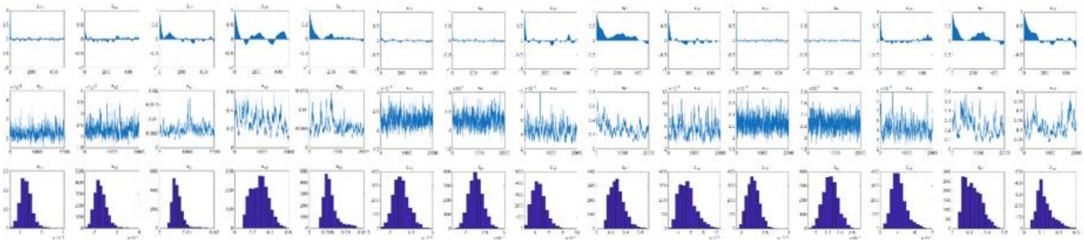

Figure 13. MCMC diagnostic plots of the natural gas market in China, the United States, and Europe Union.

4.3.3. Raw Data and Stochastic Volatility

Geopolitical risk shows significant volatility jump in later periods, while the Chinese natural gas market's volatility remains stable long-term, demonstrating strong market resilience; the U.S. natural gas market's volatility rises slowly, remaining relatively stable overall; the EU natural gas market's volatility surges in later periods, reflecting significantly higher sensitivity to geopolitical or policy shocks than China and U.S. markets (As shown in Figure 14).

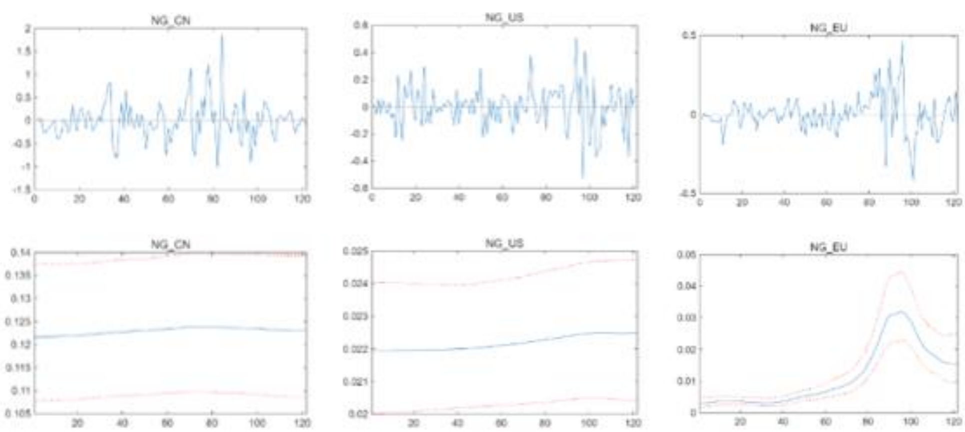

Figure 14. Volatility of raw data and stochastic volatility characteristics in the natural gas markets.

4.3.4. Time-Varying Structural Parameters and Transmission Coefficients

The figures reveal that the dynamic correlations and transmission patterns between the three major natural gas markets and geopolitical risk are markedly time-varying and regionally distinct: China exhibits a mid-term correlation peak and a negative-to-positive transmission shift under policy buffers; the U.S. shows a suppressed-then-enhanced pattern reflecting lagged global policy impacts; while the EU maintains moderate correlation with persistently high uncertainty, underscoring its sustained exposure to geopolitical disturbances (As shown in Figure 15).

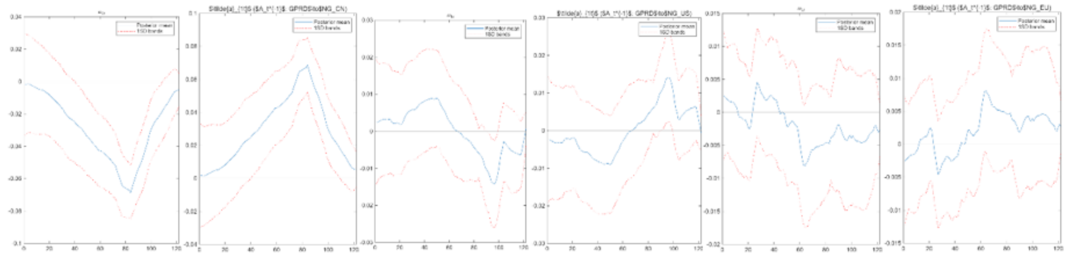

Figure 15. Time-Varying Structural Parameters and Transmission Coefficients in the natural gas markets.

4.3.5. Impulse Response Analysis

Natural Gas Market Impulse Responses to Geopolitical Risk Shocks

These figures reveal the dynamic correlations and transmission patterns between geopolitical risks and the three major natural gas markets: China's correlation peaks mid-term with a shift from negative to positive transmission, reflecting policy-buffered adaptation; the U.S. shows a suppressed-then-enhanced pattern, indicating lagged effects of global policy and capital flows; while the EU maintains moderate but persistently uncertain correlation, highlighting sustained geopolitical disturbance. Overall, the time-varying dynamics and regional differences in correlation and transmission are closely tied to each market's policy resilience and geopolitical exposure (As shown in Figure 16).

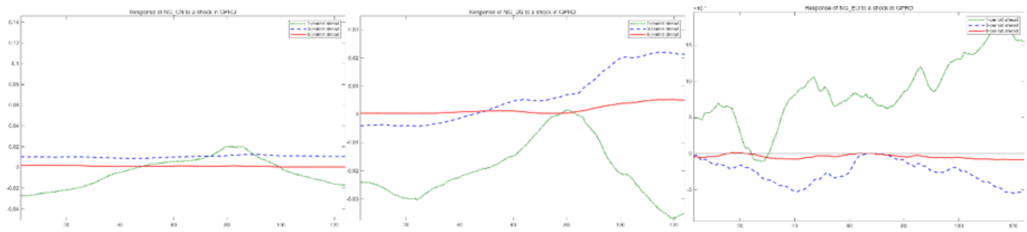

Figure 16. Natural Gas Market Impulse Responses to Geopolitical Risk Shocks.

Geopolitical Risk Impulse Responses to Natural Gas Market Shocks

Combined with earlier findings, these figures confirm the unidirectional transmission between geopolitical risk and the three natural gas markets: while the markets-especially the EU-react strongly to geopolitical shocks, geopolitical risk itself shows only marginal and short-lived responses to market shocks, fully fading within six periods. This demonstrates that geopolitical risk is the primary driver of natural gas market volatility, with negligible feedback effects from the markets (As shown in Figure 17).

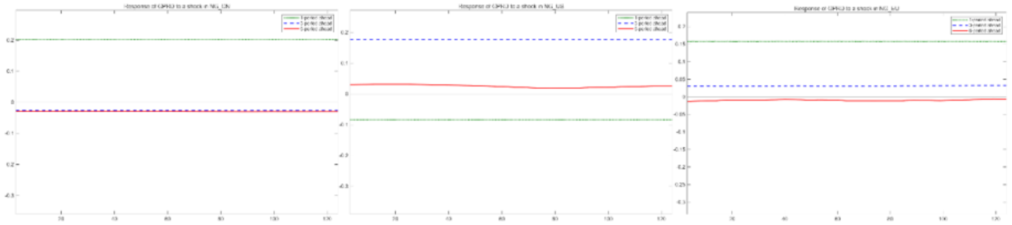

Figure 17. Geopolitical Risk Impulse Responses to Natural Gas Market Shocks.

4.3.6. Impulse Responses at Critical Event Time Points

These three figures show that response amplitudes of the three major natural gas markets to geopolitical risk are positively correlated with global impact intensity of events: shock magnitudes during the Russia-Ukraine conflict stage are significantly higher than trade friction and pandemic, with particularly violent responses in U.S. and EU markets and relatively moderate responses in the Chinese market. Regional resilience differences are obvious: the EU market shows the largest response fluctuations, reflecting stronger direct impact from geopolitical risk; the U.S. market shows the deepest negative troughs, reflecting immediate impacts of global capital flows; the Chinese market shows relatively stable responses, highlighting the role of policy buffering and industrial chain resilience. All responses converge to 0 over the long term, further verifying that geopolitical risk shocks to natural gas markets are significant in the short term but converge over the long term (As shown in Figure 18).

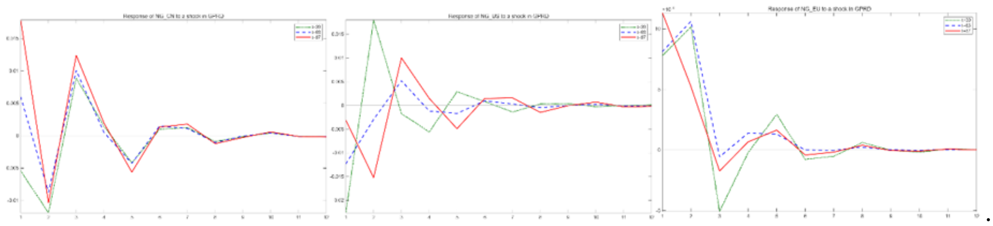

Figure 18. Impulse Responses at Critical Event Time Points.

5. Research Conclusions and Future Prospects

5.1. Research Conclusions

This paper takes the time-varying impact of global geopolitical risk on commodity markets as the core research theme, selecting three core categories-natural gas, aluminum, and copper-and segmenting markets across three key regions (China, U.S., and EU). Constructing a TVP-SVAR-SV model and employing MCMC parameter estimation, impulse response analysis, and critical event comparisons, this research systematically reveals dynamic correlation patterns between geopolitical risk and nine segmented commodity markets. Core research conclusions and innovative contributions are as follows:

First, transmission of geopolitical risk to commodity markets exhibits clear unidirectionality and time-varying characteristics. Empirical results show that all segmented markets (China, U.S., and EU natural gas, aluminum, and copper markets) show significant responses to GPR shocks, while reverse responses of GPR to shocks from various markets are extremely weak, nearly converging to 0 over the long term. This verifies that GPR is the core external factor driving commodity market volatility, rather than a variable negatively impacted by commodity market volatility.

Second, transmission effects exhibit significant horizon-dependence and short-term transience. Responses of all three major categories of commodity markets to GPR shocks follow the common pattern of "short-term negative fluctuation → medium-term adjustment rebound → long-term convergence to 0," with 1-period horizon (short-term) responses showing the most violent fluctuations, 3-period horizon (medium-term) second, and 6-period horizon (long-term) responses approaching the 0 line. This indicates that geopolitical risk impacts on commodity markets rapidly decay over time, with short-term shocks significant but dissipating over the long term, demonstrating commodity markets' self-repair capabilities relying on supply-demand fundamentals.

Third, prominent dual heterogeneity characteristics exist across categories and regions. From category differences, energy commodities show overall higher sensitivity to geopolitical risk shocks than metals, especially the EU natural gas market suffering the most violent direct impacts from geopolitical events. Among industrial metals, the copper market shows slightly greater fluctuation amplitudes than the aluminum market due to stronger financial attributes. From regional differences, Chinese commodity markets show the most moderate responses with obvious weakening trends in later shocks, demonstrating stable guarantees from complete industrial chain systems and macroeconomic policy regulation. The EU market, affected by high geopolitical risk exposure and strong external dependence in industrial chains, shows the highest sensitivity and most violent fluctuations. The U.S. market fluctuates between China and the EU, possessing both global capital flow linkage and certain domestic buffering capacity.

Fourth, critical events exhibit significant amplifying effects on transmission mechanisms. Comparing impulse responses across three critical time points-China-U.S. trade friction, COVID-19 outbreak, and Russia-Ukraine conflict-shows that as global geopolitical event intensity increases, overall shock magnitudes of GPR on various segmented markets exhibit increasing trends, with different impact characteristics across event types: the pandemic event shows more significant short-term suppression of demand-side impacts, the Russia-Ukraine conflict shows more persistent supply-side impacts on energy and related industrial metals, and trade friction impacts are relatively moderate and concentrated in industrial metal markets.

5.2. Research Limitations and Future Prospects

5.2.1. Research Limitations

Although this paper has systematically analyzed time-varying impacts of geopolitical risk on segmented commodity markets, the following limitations remain: (1) Sample period and data frequency limitations: this paper employs monthly data, failing to capture intraday high-frequency fluctuation characteristics, and sample coverage could be further expanded to include more geopolitical event cycles; (2) Variable selection limitations: only the GPR index is selected as the proxy variable for geopolitical risk without segmenting types of geopolitical risk, and without incorporating control variables such as supply-demand fundamentals and exchange rate fluctuations, potentially overlooking impacts of multi-factor interactions; (3) Insufficient depth in mechanism analysis: although time-varying characteristics and regional differences of transmission are verified, specific transmission channels are not separately identified and tested.

5.2.2. Future Research Prospects

Combining this paper's limitations with field research trends, future research could deepen in the following aspects: (1) Expand sample and variable dimensions: employ high-frequency data such as daily data, extend sample periods to cover more historical geopolitical events; simultaneously segment types of geopolitical risk, introduce control variables such as supply-demand fundamentals, exchange rates, and interest rates, construct multi-factor interaction analysis frameworks, and more precisely identify net effects of GPR. (2) Deepen transmission mechanism testing: employ methods such as mediation effect models to separately identify transmission roles of trade channels, financial channels, and expectation channels, clarifying dominant channels across different categories and regional markets. (3) Expand model specifications: introduce spatial econometrics or spillover effect models to analyze linkage effects within and between China, U.S., and EU regional commodity markets, revealing cross-regional transmission pathways of geopolitical risk.

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