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Volatility Modeling of the Impact of Geopolitical Risk on Commodity Markets

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Abstract: This study analyses the impact of the Geopolitical Risk Index (GPR) on the volatility of commodity futures returns from 4 January 2010 to 30 June 2023, using Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) models. It expands the research scope to include precious metals, agricultural products, energy, and industrial metals. The study differentiates between the impacts of geopolitical threat events and actions using GPRACT and GPRTHREAT indicators. Findings reveal that negative geopolitical shocks increase commodity returns' volatility more than positive shocks. Specifically, gold, silver, and natural gas are negatively affected, while wheat, corn, soybeans, cotton, zinc, nickel, lead, WTI oil, and Brent oil experience positive effects. Platinum, cocoa, coffee, and copper show no significant impact. These insights highlight the importance of geopolitical risks on commodity market volatility and returns, aiding in risk management and portfolio diversification. Policymakers, financial market stakeholders, and investors can leverage these findings to better understand the GPR's relationship with commodity markets and develop effective strategies.

Keywords: geopolitical risk; commodity; EGARCH

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1. Introduction

After the stock market declines in the 2000s, commodities began to be seen as an asset that could reduce portfolio risk. Due to the negative correlation between commodity and stock returns, there was a significant capital inflow into the commodity markets (Tang & Xiong, 2012). Especially in the last twenty years, there has been a substantial inflow of funds into commodity markets through commodity funds (Just & Łuczak, 2020; Ding et al., 2021). Institutional investors have strengthened the connection between commodity markets and financial markets. Institutional investors' acceptance of the commodity market as an investment vehicle alongside traditional financial investment instruments is referred to as the financialization of commodities (Cheng & Xiong, 2014). Investments in commodities in both spot and futures markets serve as a hedging tool in financial markets and are sensitive to GPR (Mo et al., 2024). GPR is the potential impact of political, economic, and social factors on global or regional dynamics. Terrorism, conflicts, and tensions between governments or regions are risks that interfere with the regular peace process of international relations and are part of GPR (Caldara & Iacoviello, 2022). Caldara and Iacoviello (2022) define geopolitical risk as "the threat, realization, and escalation of negative events associated with tensions that affect the peaceful course of wars, terrorism, and conflicts between states and political actors". The GPR index focuses on the number of articles related to geopolitical actions, tensions, and threats in the leading ten global newspapers. Caldara and Iacoviello (2022) divide the GPR index into two sub-indices: geopolitical threats (GPRTHREAT) and geopolitical actions (GPRACT). GPRACT is designed to capture geopolitical actions, while GPRTHREAT captures geopolitical threats. Although both sub-indices are highly correlated with the GPR index, the GPR and GPRTHREAT indices have a low correlation (0.35). The distinction between the original GPR and these sub-indices provides an opportunity to precisely track the source of GPR affecting the commodity futures market. GPR allows us to determine whether the primary sources of price fluctuations due to geopolitical risk are the threat events themselves or the actions that follow these threats.

As seen in Figure 1, global geopolitical risks between 2010 and 2023 have been influenced by various events. Throughout this period, factors such as financial crises, regional conflicts, large-scale wars, pandemics, and economic uncertainties have contributed to the increase in geopolitical risks. Between 2010 and 2013, key events that escalated global risks included the Arab Spring in the Middle East, the escalation of the civil war in Syria, and rising tensions between Russia and the West. From 2014 to 2016, geopolitical uncertainties intensified due to Russia's invasion of Crimea, which led to sanctions imposed by the United States and European Union, the deepening refugee crisis in Europe, large-scale terrorist attacks, the Brexit referendum, and the election of Donald Trump as the President of the United States. Between 2017 and 2019, geopolitical tensions were primarily driven by the United States. During this period, heightened tensions between the U.S. and North Korea, U.S.–China trade wars, and U.S.–Iran conflicts were among the key factors contributing to the rise in global risks. After 2020, the most significant factor exacerbating geopolitical risks was the COVID-19 pandemic. In 2022, Russia's invasion of Ukraine further intensified global uncertainties. Subsequently, in 2023, rising tensions between China and Taiwan, escalating Israel–Palestine conflicts, and global energy crises contributed to the increasing geopolitical risks.

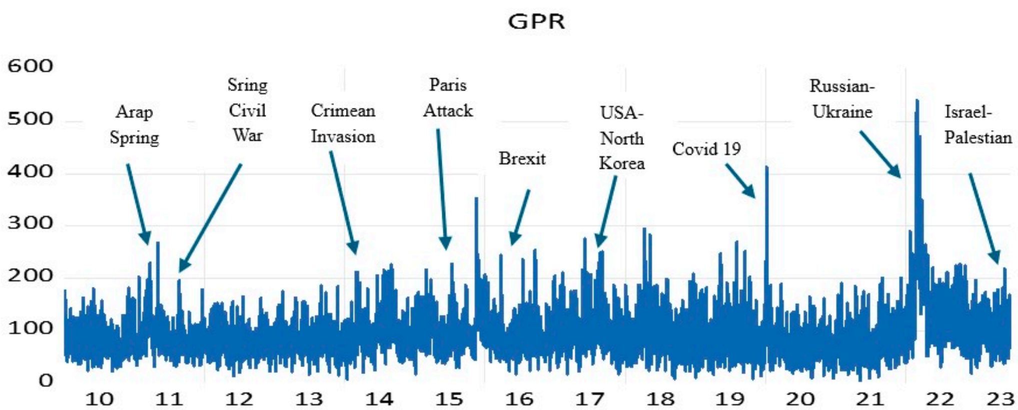

Figure 1. *Cont.*

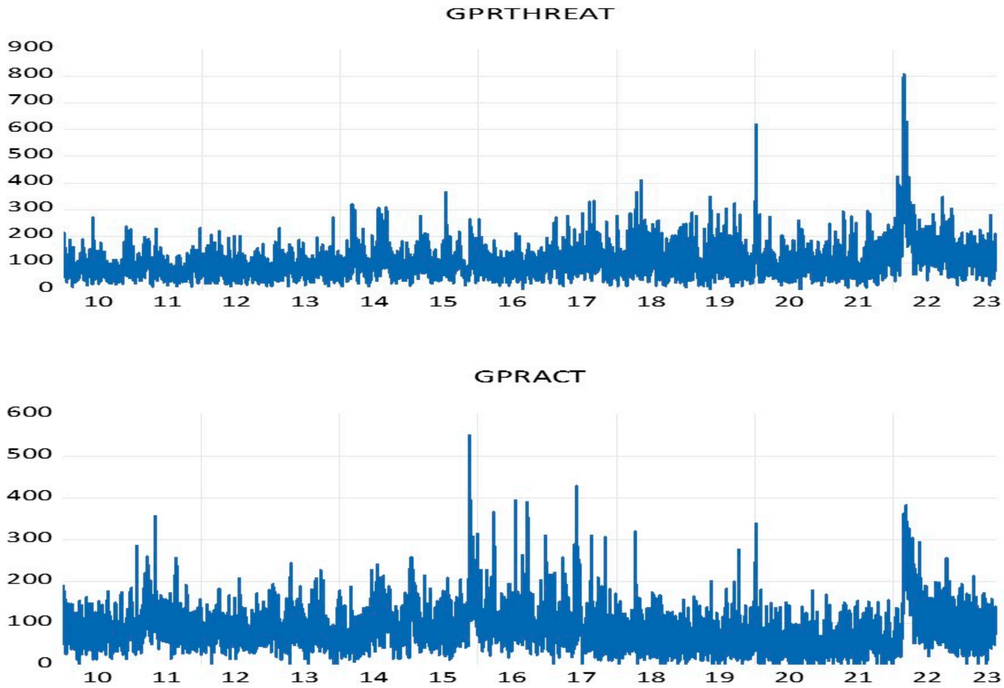

Figure 1. Geopolitical Risk Indicators. Source: author's compilation.

Geopolitical risk has been observed to have a significant impact on global markets (Elsayed & Helmi, 2021; Fiorillo et al., 2023; Bossman et al., 2023; Sheenan, 2023; Caldara et al., 2024; M. Yang et al., 2021). Several studies have demonstrated that geopolitical risks influence commodity markets, including those by Hammoudeh (2024), Gong and Xu (2022), Mitsas et al. (2022), Shahzad et al. (2023), and Foglia et al. (2023). Therefore, policymakers and investors must monitor geopolitical risks to make informed decisions regarding investments and strategies. There are a limited number of studies in the literature examining the relationship between commodity market volatility and geopolitical risk (GPR). Wang et al. (2022) demonstrated the impact of GPR on volatility spillovers among commodity markets, including energy, metals, and agricultural products. Qian et al. (2022), Smales (2021), and Pan et al. (2023) investigated the effect of GPR on oil price volatility. Mitsas et al. (2022) analyzed the impact of GPR, GPRACT, and GPRTHREAT indices on the monthly return volatility of various U.S. commodity futures (oil, gold, platinum, silver, and sugar) using the EGARCH (1,1) model. This study applied the same volatility model to each commodity market. However, since the characteristics of individual commodity markets differ, using the same model may lead to misleading results. To conduct a more detailed analysis, it is essential to apply the most appropriate volatility model for each commodity market. Moreover, no study has been found that examines the persistence of shocks in commodity market volatility through volatility half-life. This research could provide more meaningful insights for both investors and portfolio managers.

The primary motivation of this study is to separately examine the effects of the GPR, GPRACT, and GPRTHREAT indices on commodity market volatility and to determine the persistence of volatility in these markets. Accordingly, this study aims to analyze the impact of geopolitical risk indices on the volatility of commodity futures returns using daily data from 4 January 2010 to 30 June 2023 through EGARCH models. In financial markets, good and bad news (shocks) do not have the same effect on volatility and impact it asymmetrically. This phenomenon is referred to in the literature as the leverage effect. Therefore, the EGARCH model is employed in this study. Additionally, the use of standardized errors instead of past values of the error term in the EGARCH model provides a more natural explanation regarding the persistence and magnitude of shocks (Korkmaz &

Çevik, 2009). The duration for which volatility persists daily and the time required for the market to revert to its previous level after a shock is defined as the half-life of volatility. In this study, the persistence of volatility (volatility half-life) is calculated for each commodity to examine the effects of geopolitical risks. Commodity markets are categorized into four groups: precious metals (gold, silver, platinum), agricultural commodities (soybeans, wheat, corn, cocoa, cotton, coffee), industrial metals (copper, nickel, lead, zinc), and energy products (natural gas, WTI crude oil, and Brent crude oil).

To structure our empirical investigation, we define the following research questions:

1. How does geopolitical risk (GPR) influence the volatility of different commodity classes, including precious metals, agricultural products, energy, and industrial metals?
2. Do geopolitical threat actions (GPRACT) and geopolitical events (GPRTHREAT) have differentiated effects on commodity price volatility?
3. How do geopolitical shocks affect the persistence of volatility in commodity markets?

Based on these questions, we formulate the following hypotheses:

H1: *Geopolitical risks (GPR) significantly increase commodity market volatility.*

H2: *Geopolitical actions (GPRACT) have a stronger impact on commodity volatility than geopolitical events (GPRTHREAT).*

H3: *Geopolitical risks reduce the persistence of commodity market volatility.*

These hypotheses will be tested using an EGARCH modeling framework, allowing for asymmetric effects of geopolitical risk shocks on commodity returns. The increasing role of geopolitical factors in shaping global commodity market dynamics underscores the need for a deeper understanding of how political tensions influence price volatility across different commodity groups. Geopolitical risks, including conflicts, trade tensions, and policy uncertainties, create new risks for commodity market participants and require refined risk management strategies. While previous studies have acknowledged the impact of geopolitical uncertainty on financial markets, research focusing on its differentiated effects across various commodity classes remains limited.

This study contributes to the literature by (i) employing a broad set of commodities, including precious metals, agricultural products, energy, and industrial metals, (ii) distinguishing between the effects of geopolitical threats (GPRTHREAT) and geopolitical actions (GPRACT) on price volatility, (iii) applying an EGARCH model to capture asymmetric volatility responses to geopolitical shocks, and (iv) calculating the persistence duration (the volatility half-life) of commodity market volatility. By doing so, our study provides valuable insights for investors, policymakers, and financial market participants seeking to manage exposure to geopolitical risks.

The remainder of the study is organized as follows. Section 1 presents the introduction. Section 2 provides a review of the relevant literature. Section 3 discusses the data, and Section 4 addresses the methodology and statistical techniques. Section 5 presents empirical results and policy recommendations.

2. Literature Review

The effects of GPR vary across markets. The literature discusses the impact of GPR on stock markets (M. Yang et al., 2021; J. Yang & Yang, 2021; Choi, 2022; Hao et al., 2024; Elsayed & Helmi, 2021; Fiorillo et al., 2023), foreign exchange markets (Bossman et al., 2023), investment and bond costs (Sheenan, 2023; Yu & Wang, 2023; Truong et al., 2024), inflation (Caldara et al., 2024), and cryptocurrency markets (Nouir & Hamida, 2023), with varying findings reported across studies.

It has also been identified that precious metals traded in the commodity market have demonstrated safe-haven characteristics in response to increasing GPRs, particularly during different periods and specifically in the recent Russia–Ukraine war (Shahzad et al., 2023; Baur & Smales, 2020; Raza et al., 2024).

The GPR index is divided into geopolitical threats (GPRTHREAT) and geopolitical actions (GPRACT). In the literature, the interaction with commodity markets is often studied without distinguishing between GPRTHREAT and GPRACT (Hammoudeh, 2024; Shahzad et al., 2023; Raza et al., 2024; Khurshid et al., 2024). While there are studies on commodity markets that take into account the distinction between GPRACT and GPRTHREAT, these studies are limited in number (Mo et al., 2024; Gong & Xu, 2022; Liu et al., 2024; Micallef et al., 2023; Hao et al., 2024). The responses to GPRTHREAT are primarily similar to the outcomes of GPR (Mo et al., 2024; Gong & Xu, 2022; Hao et al., 2024). This indicates that geopolitical risk primarily stems from the threat of adverse geopolitical events. Studies have shown that the GPRACT and GPRTHREAT sub-indices affect commodities differently. In the case of agricultural commodities, GPRTHREAT influences the future prices of soybean oil, coffee, wheat, and oats, whereas GPRACT only impacts the future price of oats (Micallef et al., 2023).

Foglia et al. (2023) examined the dynamic effects of country-specific geopolitical risk indices on commodity prices (energy, metals, food) in G8 countries. He found that GPR had a greater impact on energy commodities than on metals and food and that shocks tended to dissipate within a year. Mo et al. (2024) examined an example of energy, food, metal, and agricultural commodities, considering both the GPRTHREAT and GPRACT dimensions of geopolitical risks. The findings suggest that the impact of GPR on the energy sector may be more pronounced compared to non-energy commodities. The study shows that both GPRTHREAT and GPRACT positively influence commodity markets during periods of general market sentiment and investor optimism. Hammoudeh (2024) investigated the impact of geopolitical risks caused by conflicts on nine global commodities. The study demonstrates that commodities are resilient to excessively negative GPR shocks during conflict-free periods. Variance decompositions highlight the limited contribution of GPR shocks in explaining commodity price volatility. Additionally, the spillover analysis reveals a low level of correlation between GPR and the nine commodities, indicating a high degree of protection against GPR shocks.

Gong and Xu (2022) show that geopolitical risk (GPR) affects volatility spillovers in energy, precious metals, industrial metals, agricultural, and livestock commodity markets. The impact of GPR on the net linkages of different commodity markets varies from market to market. Specifically, GPR has a positive effect on the net linkages of energy, agricultural, and livestock commodity markets. GPRACT has a more significant impact on the spillover level in commodity markets compared to GPRTHREAT, and it is statistically more significant. The direction of the effect of GPR on the net linkages of commodity markets differs across markets. In particular, in energy, agricultural, and livestock commodity markets, GPR significantly increases the net linkage. Similar to Gong and Xu (2022), Wang et al. (2022) examined the impact of GPR on volatility spillovers across commodity markets. They found that during the Russia–Ukraine war, volatility spillovers in commodity markets were higher than during the pandemic. Despite differences in volatility spillovers among commodities, an increase in GPR significantly affects volatility spillovers at a high level of significance.

Although the number of studies examining the effects of GPR indices on commodity market volatility is limited, such studies do exist in the literature. Smales (2021) investigated the impact of the GPR index on oil return volatility using daily data from January 1986 to May 2018 with the EGARCH (1,1) model. The findings indicate that negative news has a greater effect on oil return volatility than positive news. Additionally, geopolitical risk was found to have a significant impact on oil return volatility, with volatility persistence being prolonged. Qian et al. (2022) examined the predictability of geopolitical risk on oil market volatility using an Autoregressive Markov Regime-Switching Model with daily data from 2 January 1986 to 31 May 2018. The results suggest that high GPR can lead to significant fluctuations in the oil market. Moreover, the geopolitical risk threat index is more useful in predicting oil price volatility compared to the geopolitical risk actions index. Pan et al. (2023) compared the impact of geopolitical risk on crude oil volatility for oil-importing and oil-exporting countries. The study analyzed monthly data from January 1992 to March 2022 using the GARCH-MIDAS model. It was found that crude oil return volatility is more strongly associated with the geopolitical risks of oil-importing countries than those of oil-exporting countries.

The study by Mitsas et al. (2022) investigates the impact of real-time global GPR (GPRs), actions (GPRACT), and threats (GPRTHREAT) indices on the monthly returns and volatility of various American commodity futures, including corn, crude oil, heating oil, gold, platinum, silver, and sugar. To analyze volatility, the study employed the EGARCH model using monthly data from January 1985 to July 2019. The findings indicate that GPRs and GPRTHREAT negatively affect the returns of crude oil, gold, platinum, and silver futures. At the same time, GPRTHREAT has a weak positive effect on the volatility of corn futures. Additionally, GPRACT was found to negatively impact the return volatility of crude oil, heating oil, platinum, and sugar futures.

Liu et al. (2024) examined the impact of GPR and its sub-indices on the volatility of natural resources (Brent crude oil and natural gas) using daily data from 1 January 2008 to 30 September 2022 with the GARCH-MIDAS model. The study results indicate that geopolitical risks and their sub-indices have an asymmetric effect on the short-term volatility of Brent crude oil; specifically, negative news leads to higher volatility than positive news. Additionally, the GPRACT and GPRTHREAT sub-indices affect commodity volatility differently in the long run. An increase in GPRTHREAT has a greater impact on Brent crude oil return volatility, while GPRACT exerts a stronger effect on natural gas return volatility.

A brief evaluation of the findings in the literature suggests that the GPR index has a significant impact on commodity market volatility. Most existing studies have focused on the effects of GPR on oil return volatility. Only Mitsas et al. (2022) have examined the impact of GPR indices on the return volatility of different commodities. As seen, there are very few studies investigating the effects of GPR indices on commodity market volatility. In this context, by analyzing the separate effects of GPR indices on four different commodity groups, this study is expected to provide valuable insights to investors regarding commodity market volatility while also making a significant contribution to the limited academic literature on the subject.

While existing studies primarily focus on the impact of geopolitical risk on financial markets (stocks, bonds, cryptocurrencies), fewer have examined its direct effects on commodity markets (Hammoudeh, 2024; Gong & Xu, 2022).

Recent studies highlight how geopolitical risk impacts commodity price volatility through supply chain disruptions, investment sentiment, and policy-driven factors (Liu et al., 2024). By expanding on this literature, our study bridges this gap by exploring sector-specific volatility responses and distinguishing between geopolitical threats (GPRTHREAT) and geopolitical actions (GPRACT).

3. Data

The study examines commodity futures market volatility across four different commodity groups. The products included in each group are (1) precious metals: gold, silver, and platinum; (2) agricultural products: wheat, corn, soybeans, cotton, cocoa, and coffee; (3) industrial products: copper, zinc, nickel, and lead; (4) energy products: WTI crude oil, Brent crude oil, and natural gas. The selection of commodity products is based on information from Bloomberg News, which identifies them as having the highest trading volumes and being good representatives of global commodity markets.

The simultaneous inclusion of multiple commodity classes allows for a comparative assessment of how different markets respond to geopolitical risks. Given the distinctive price dynamics of precious metals, energy, agriculture, and industrial metals, we verified the robustness of our approach by conducting sub-sample regressions for each commodity group.

The results suggest that while energy and industrial metals exhibit co-movements under geopolitical uncertainty, agricultural commodities tend to be more influenced by trade policies and supply-side shocks. This supports our decision to analyze all commodities within a single framework while controlling for sectoral differences.

Additionally, the study employs the Geopolitical Risk (GPR) index along with its two sub-indices (Geopolitical Threats—GPRTHREAT and Geopolitical Actions—GPRACT) to represent the level of geopolitical risk. The commodity supercycle is an economic cycle that typically spans several decades, characterized by long-term, large-scale upward and downward trends in global commodity prices. Since the early 2000s, the industrialization of emerging economies such as China and India has significantly increased the demand for metals, energy, and agricultural products, leading to peak commodity prices in the early 2010s (Jacks, 2019). Therefore, the data period of this study has been defined as 4 January 2010–30 June 2023. and is of daily frequency. Commodity futures data are obtained from the investing data terminal, while data for the GPR indices are sourced from matteoiacoviello.com (accessed on 15 January 2025). The analysis is conducted using the EViews 12 econometric software package (EViews 12 econometric software package—University). Commodity futures returns are calculated using the logarithmic return formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

Here, R_t represents the return on day t, P_t denotes the closing price on day t, and P_{t-1} indicates the closing price on day $t - 1$. The graphs of the commodity futures return series included in the study can be examined in Figure A1 (Appendix A).

Figure A1 (Appendix A) presents commodity returns, illustrating periods of increase and decrease that align with geopolitical risks. The gold return series exhibits higher volatility during specific periods. In 2013, geopolitical risks such as the Syrian crisis, the coup in Egypt, and threats from North Korea led to short-term increases in gold prices. However, the primary determining factors were the Federal Reserve's policies and improvements in the U.S. economy; 2013 is considered one of the worst-performing years for gold in the past three decades. In contrast, in 2020, gold emerged as a safe-haven asset during the COVID-19 pandemic, leading to its price reaching record highs. Other precious metals, such as silver and platinum, displayed a performance similar to gold in response to geopolitical risks. The highest volatility was observed among the analyzed precious metal commodities during the COVID-19 pandemic.

The response of agricultural commodities' return to geopolitical events varies. In 2022, wheat and cotton returns exhibited high levels of volatility. Since Russia and Ukraine play a key role in the export of these commodities, the conflict between the two countries resulted in heightened volatility in their returns. However, soybean, cocoa, and sweet corn did not experience a similar increase in volatility during the same period. Cocoa commodity returns, in particular, exhibited high volatility in 2019, which can be attributed to political instability and extreme weather conditions in West African countries, where cocoa production is concentrated. In contrast, volatility in coffee returns is primarily driven by uncertainties in Brazil, the world's largest coffee producer, rather than by global geopolitical risks.

Regarding industrial commodities, all commodities except nickel exhibited high volatility. However, the most notable volatility was observed in nickel in 2022. The primary reason for this was the Russia–Ukraine war and the subsequent sanctions imposed on Russian firms, which are among the largest nickel exporters.

Energy commodity returns were among the most affected by the COVID-19 pandemic. The sharp decline in economic and transportation activities during this period led to a significant decrease in demand for oil, resulting in dramatic declines in energy commodity returns. While natural gas returns did not experience a similar effect, the escalation of tensions between Russia and Ukraine toward the end of 2021 and Russia's threats to cut gas supply to European countries increased natural gas return volatility in 2021–2022.

Upon examining the time series graphs of commodity futures products, volatility clustering is observed in all commodity futures returns over specific periods. Before commencing the analysis, descriptive statistics and unit root test results for the commodity futures returns included in the study are provided in Table 1 below.

Table 1. Preliminary Statistics and Unit Root Test.

Variables	Mean	Std. Dev.	Skewness	Kurtosis	Jarque–Bera	ADF	Daily Obs.
			Precious Metal Returns				
Gold	0.00020	0.01006	−0.4665	8.7275	4873.116 ***	−60.3988 ***	3473
Silver	0.00026	0.01914	−0.5590	9.0742	5504.280 ***	−60.2246 ***	3463
Platinum	-3.06×10^{-5}	0.01558	−0.1304	7.2010	2508.463 ***	−57.3803 ***	3398
			Agriculture Returns				
Wheat	0.00024	0.02010	0.5773	9.4547	6365.446 ***	−57.7576 ***	3553
Sweetcorn	0.00023	0.01708	−0.5445	10.3031	7796.677 ***	−57.1446 ***	3432
Soybean	0.00016	0.01341	−0.4207	7.7027	3375.133 ***	−60.2916 ***	3549
Cotton	0.00016	0.01701	−0.3262	9.3578	5848.005 ***	−54.5985 ***	3436
Cocoa	0.00014	0.01656	0.1425	10.8018	8627.077 ***	−59.0430 ***	3397
Coffee	0.00025	0.02047	0.3753	4.7391	512.961 ***	−59.7895 ***	3431
			Industry Returns				
Copper	0.00012	0.01415	−0.0546	4.981	565.849 ***	−59.9523 ***	3449
Zinc	0.00011	0.01649	−0.0260	4.8955	499.945 ***	−57.7483 ***	3337
Nickel	0.00036	0.02724	8.0383	242.8670	801.4190 ***	−20.1711 ***	3328
Lead	8.14×10^{-5}	0.01628	−0.0167	6.5012	1701.034 ***	−56.0326 ***	3330
			Energy Returns				
WTI Oil	0.00034	0.02738	−0.1857	48.634	303,544.7 ***	−29.4367 ***	3498
Brent Oil	0.00024	0.02294	−0.7066	22.007	52,511.42 ***	−59.2347 ***	3469
Natural gas	0.00037	0.03457	0.8008	15.9469	24,216.30 ***	−63.4216 ***	3415
			Explanatory Variables				
GPR	96.04948	46.9787	2.0746	13.3264	25,420.63 ***	−6.2154 ***	4926
GPRACT	84.69949	53.1313	1.6319	8.8962	9322.093 ***	−8.6815 ***	4926
GPRTRHEAT	105.9285	64.5715	2.6162	18.8489	57,176.18 ***	−5.6631 ***	4926

*** indicates 1% significance level. Source: author's compilation.

When examining the descriptive statistics of daily commodity returns included in the analysis, it is observed that the platinum futures return is negative. In contrast, all other commodity futures returns are positive. The commodity futures group that provides the highest returns is energy products. Natural gas has the highest standard deviation, a measure of risk, whereas gold futures have the lowest standard deviation. The Jarque–Bera

Test determines whether the data follows a normal distribution based on skewness and kurtosis (Bera & Jarque, 1987). According to the Jarque–Bera values, the commodity futures return and the geopolitical risk indices do not exhibit a normal distribution. Table 1 also presents the Augmented Dickey–Fuller (ADF) test results, which indicate whether the data series are stationary (Dickey & Fuller, 1979). According to the ADF test, all series are stationary at the level.

4. Methodology and Model Specification

In the literature, various methods are used. Gong and Xu (2022) use the TVP-VAR-SV model based on the enhanced Diebold and Yilmaz method to analyze the dynamic linkages among energy, precious metals, industrial metals, agricultural, and livestock commodity markets using data from June 2008 to December 2020. Hammoudeh (2024) uses the QVAR model, momentum response functions, variance decompositions, and spillover approach. They investigated the impact of geopolitical risk induced by conflicts only on nine global commodities from 3 January 2023 to 18 December 2023. In our study, we propose to use a volatility model that must be able to forecast volatility. This is the central requirement in almost all financial applications. One of the commonly used volatility models is the Autoregressive Conditional Heteroskedasticity (ARCH) family of models. There are two general classes of volatility models in widespread use. The other model is the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (R. Engle & Patton, 2007). In this study, the volatilities of commodity futures returns will be modeled using ARCH models.

While EGARCH models effectively capture volatility clustering and asymmetric responses to geopolitical shocks, they do not explicitly account for spillover effects between commodities.

To address this, we conducted a correlation analysis between commodity price volatilities, which revealed significant linkages between energy and industrial metals markets. Future research may explore multivariate GARCH models (e.g., DCC-GARCH, BEKK-GARCH) or TVP-VAR-SV models, which better capture volatility spillovers and interdependencies (Gong & Xu, 2022).

Despite this, EGARCH remains valuable as it helps quantify volatility asymmetries, an important feature given the negative shocks from geopolitical risks tend to have a stronger impact than positive shocks.

The EGARCH model was selected due to its ability to capture asymmetric volatility responses to geopolitical risk. Unlike standard GARCH models, EGARCH accounts for the fact that negative shocks tend to create larger volatility spikes than positive shocks, which aligns with market behavior under geopolitical uncertainty.

To ensure robustness, we also compared EGARCH with GARCH-MIDAS and HAR-RV models and found that EGARCH provided superior explanatory power in modeling volatility clustering and asymmetries. Future studies could extend this analysis using nonlinear Markov-switching models or high-frequency GARCH approaches.

The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model has proven to be a powerful tool in addressing volatility dynamics in commodity markets. It is particularly adept at capturing asymmetric effects, which are commonplace in financial time series, especially commodities subject to sudden market shocks and persistent volatility structures. The EGARCH model's ability to model volatility clustering is fundamental, as highlighted by several studies demonstrating its effectiveness against traditional GARCH frameworks.

For instance, Chkili et al. explore the implications of asymmetry and long memory in forecasting volatility in key commodities such as oil, gold, and natural gas, solidifying the efficacy of GARCH-type methodologies in capturing complex market behaviors (Chkili et al., 2014). Additionally, Mahalik et al. and R. L. and Mishra confirm the applicability of EGARCH across various market segments, indicating its robustness in examining price discovery and volatility spillover effects in both spot and futures markets, particularly in the Indian context (Mahalik et al., 2014; R. L. & Mishra, 2020). They employ advanced econometric frameworks, including the Vector Error Correction Model (VECM), alongside EGARCH to discern inter-market dynamics.

Research also suggests that hybrid models integrating EGARCH and machine learning methodologies can enhance forecasting accuracy. Kakade et al. propose a sophisticated hybrid model combining GARCH and Long Short-Term Memory (LSTM) methods, showing significantly improved volatility predictability in commodities over traditional models (Kakade et al., 2022). This advancement reflects a shift toward utilizing technology to capture the intricate relationships within commodity price movements. Similarly, the work by Bakas and Triantafyllou underscores the effectiveness of GARCH family models in forecasting performance (Bakas & Triantafyllou, 2019).

Furthermore, the application of the EGARCH framework is supported by its versatility in various economic contexts. Dutta employed the EGARCH model to examine the impact of crude oil volatility on the ethanol market, demonstrating how asymmetrical responses to shocks play a critical role in volatility assessments (Dutta, 2018). This empirical finding further strengthens the argument for the EGARCH model's relevance, illustrating its utility in both theoretical and practical applications in financial econometrics.

Moreover, the literature maintains a consensus on the importance of addressing various global and local market factors when applying these models. For example, the studies by Mensi et al. delve into the correlations and spillover effects between commodity and stock markets, indicating that understanding these dynamics is essential for effective investment strategies (Mensi et al., 2013). Consequently, the amalgamation of findings from different studies portrays the EGARCH model as a versatile and robust tool for volatility forecasting in commodity markets.

The wide application of the EGARCH model for analyzing and forecasting volatility in commodity markets is reinforced by its adaptability to asymmetric effects, long memory characteristics, and the integration of modern computational techniques. The ongoing research illustrates the model's supremacy in capturing the complexities of market behaviors prevalent among commodities.

4.1. Autoregressive Moving Average (ARMA)

The ARMA model, introduced by Box and Jenkins (1976) for forecasting univariate time series, is commonly referred to as the Box–Jenkins (BJ) method (Gujarati, 2003). One of the model's key assumptions is that the series, which consists of observations obtained at equal time intervals, must be stationary and stable. If the time series is stationary, it can be examined in three categories: the Autoregressive (AR) model, the Moving Average (MA) model, and the ARMA model (Enders, 2004). AR models describe a time series by expressing the value of any observation in a given period as a function of a specific number of past observations and an error term. An AR model of order p is referred to as an AR(p) model and is defined by Equation (2) (Gujarati, 2003).

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots\cdots + \varphi_p y_{t-p} + u_t \tag{2}$$

MA models describe a time series by expressing the value of any observation in a given period as a linear combination of the error term in the same period and a specific number of past error terms. An MA model of order q is referred to as an MA(q) model and is defined by Equation (3) (Gujarati, 2003).

$$y_t = u_t - \theta_1 u_{t-1} - \theta_2 u_{t-2} - \cdots\cdots - \theta_q u_{t-q} \quad (3)$$

The combination of an AR(p) model and an MA(q) model forms the ARMA(p,q) model, which is defined by Equation (4).

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} + u_t - \theta_1 u_{t-1} - \cdots - \theta_q u_{t-q} \quad (4)$$

Alternatively, it is represented symbolically, as shown in Equation (5).

$$y_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i y_{t-i} - \sum_{i=1}^{q} \theta_i u_{t-i} + u_t \quad (5)$$

Here, y_t represents the current daily price, φ_0 is a constant term, θ_i denotes the parameters of the autoregressive component of order p, θ_i denotes the parameters of the moving average component of order q, and u_t represents the error term. The orders p and q are non-negative integers.

4.2. Volatility Modeling

Volatility modeling is an important indicator for understanding market behaviors and dynamics. The ARCH model is commonly used in the volatility modeling of time series. ARCH models enable the modeling of conditional variance. These models are expressed using the squares of residuals obtained from the ARMA model, as shown below (Ramanathan, 1998).

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 \quad (6)$$

Here, q denotes the order of the model. ω represents the constant term, and α_i represents the parameters of the model. In ARCH models, there are certain constraints on the α_i parameters. The conditional variance (h_t) cannot be negative. Therefore, h_t must be positive for all observed values of u_t. Consequently, the conditions $\omega > 0$ and $\alpha_i \geq 0$ must be satisfied. Another constraint is that each α_i, or their sum, must be less than 1. This constraint is also necessary to ensure the stationarity of the ARCH process. Otherwise, the process would have an infinite variance.

In most applications of ARCH models, the number of lags must be taken quite significantly for the conditional variance equation to be adequately defined.

Unlike the ARCH model, the GARCH model developed by Bollerslev (1986) is a volatility model where the conditional variance depends not only on the lagged values of the squared error terms but also on its own lagged values. The GARCH(p,q) model is written as follows (Enders, 2004).

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \quad (7)$$

As in ARCH models, there are certain constraints on the α_i parameters in GARCH models. For these models, the conditions $q > 0$, $p \geq 0$, $\omega > 0$, $\alpha_i \geq 0$, and $\beta_i \geq 0$ must be satisfied. Additionally, the sum of the α_i and β_i parameters must be less than one. Satisfying this constraint indicates that the process is stationary. If the sum of the α_i and β_i parameters is equal to or greater than one, the volatility estimation becomes statistically infeasible (R. F. Engle, 2002).

GARCH models assume that positive and negative error terms have symmetric effects on volatility. However, in the financial time series, good and bad news (shocks) do not have the same impact on volatility and affect it asymmetrically. This phenomenon is referred to as the leverage effect in the literature. In his study, Nelson (1991) developed the EGARCH (Exponential GARCH) model, which allows for modeling the leverage effect.

In financial markets, volatility often reacts asymmetrically to positive and negative shocks, a phenomenon known as the leverage effect (Korkmaz & Çevik, 2009). The EGARCH model is particularly well-suited to capturing this asymmetry, as it models the nonlinear dependence of volatility on past shocks, reflecting the often-erratic market responses to geopolitical and economic uncertainty. Previous studies, including those by Mitsas et al. (2022) and Liu et al. (2024), have demonstrated the advantages of using EGARCH in modeling commodity market volatility under geopolitical risk conditions. Korkmaz and Çevik (2009) further emphasize the role of standardized errors in EGARCH modeling, which provides a more natural interpretation of shock persistence and magnitude, making it a suitable choice for this study.

The EGARCH model has been widely applied in financial market volatility studies, particularly in times of crisis. Özdemir et al. (2021) and Dewasiri et al. (2024) utilized EGARCH to analyze return volatility in major stock indices before and during the COVID-19 pandemic, demonstrating its effectiveness in capturing asymmetric responses to shocks. Similarly, Grima and Caruana (2017); Özdemir et al. (2024) examined sovereign credit default swap (SCDS) market volatility using EGARCH, reinforcing its role in modeling uncertainty in financial markets. These findings support the application of EGARCH in this study, as geopolitical risk similarly introduces asymmetric volatility in commodity markets, making EGARCH a suitable framework for capturing these effects (Özdemir et al., 2024; Sharma et al., 2024).

The EGARCH model is expressed as follows.

$$\log(\mathrm{h_t}) = \omega + \sum_{j=1}^{p} \beta_j \log(\mathrm{h_{t-j}}) + \sum_{i=1}^{q} \alpha_i \frac{|\mathrm{u_{t-i}}|}{\sqrt{\mathrm{h_{t-i}}}} + \sum_{i=1}^{q} \gamma_i \frac{\mathrm{u_{t-i}}}{\sqrt{\mathrm{h_{t-i}}}} \tag{8}$$

Here, ω represents the constant term, α_i and β_j denote the standard ARCH and GARCH terms, respectively. The parameter γ_i indicates the leverage effect, demonstrating that the conditional variance responds asymmetrically to shocks. If γ_i is significant ($\gamma_i \neq 0$) it indicates asymmetric shock effects. Specifically, if $\gamma_i < 0$ and is significant, a negative shock in the past increases volatility more than a positive shock.

The EGARCH model allows modeling the leverage effect compared to the GARCH model and offers additional advantages. In the EGARCH model, the conditional variance is modeled in logarithmic form, eliminating the non-negativity constraint on the parameters as in the GARCH model. Additionally, using standardized errors instead of past values of the error term provides a more natural explanation regarding the persistence and magnitude of shocks (Korkmaz & Çevik, 2009).

This article uses EGARCH models, incorporating additional independent variables to predict the effects of (GPR) on the return volatility of selected commodities traded in future markets. The EGARCH model includes GPR, GPRACT, and GPRTHREAT indices as regressor variables.

$$\log(\mathrm{h_t}) = \omega + \sum_{j=1}^{p} \beta_j \log(\mathrm{h_{t-j}}) + \sum_{i=1}^{q} \alpha_i \frac{|\mathrm{u_{t-i}}|}{\sqrt{\mathrm{h_{t-i}}}} + \sum_{i=1}^{q} \gamma_i \frac{\mathrm{u_{t-i}}}{\sqrt{\mathrm{h_{t-i}}}} + \delta GPR_t \tag{9}$$

If the δ coefficient in the equation is negative and significant, this indicates a relationship between GPR and a decrease in commodity return volatility. If the δ coefficient is positive and significant, this indicates a relationship between GPR and an increase in commodity return volatility.

4.3. Model Selection

When selecting the most appropriate model among alternatives, Akaike information criterion (AIC) and Schwart's Bayesian information criterion (SBIC) criteria are taken into consideration. AIC and SBIC evaluate the goodness of fit of the model by taking into account the number of terms in the model. They aim to minimize the residual sum of squares and assist in selecting the correct model using a penalty function. AIC and SBIC are calculated using the following formulas (Brooks, 2008):

$$AIC = ln\left[\frac{SSR}{T}\right] + \frac{2k}{T} \tag{10}$$

$$SBIC = ln\left[\frac{SSR}{T}\right] + \frac{k}{T}lnT \tag{11}$$

Equations (10) and (11) represent the residual sum of squares (SSR), the number of observations T, and k = p + q + 1, which denotes the total number of parameters. On the right-hand side of these equations, there are two terms. The first term is desired to be low. Increasing the number of independent variables in the model reduces this first term, as each additional variable has a diminishing effect on this residual term. At this point, an additional term becomes a balancing force. The second term in the equations acts as a penalizing term. Each added independent variable reduces the first term while increasing the penalty term. Therefore, the model that includes the number of variables resulting in the lowest total score of these two terms is preferred as the most suitable model.

4.4. Model Specification Tests

Model specification refers to a series of tests conducted to determine whether a model is correctly defined. These tests examine whether there are omitted variables, incorrect functional forms, or whether the error terms are appropriately modeled. Model adequacy tests help in selecting the correct model, thereby ensuring the reliability of the results. The Ljung–Box Q test, ARCH LM test, and Ramsey RESET test are commonly used to determine the suitability of ARMA and GARCH models. The Ljung–Box Q test is a statistical test used to examine whether there is autocorrelation in a time series up to a specified lag. If the p-value of the test statistic is less than 0.05, it indicates that the error terms of the model are not independent, and the model may not be suitable (Gujarati, 2003). The ARCH LM test is a statistical test used to detect the presence of heteroskedasticity in time series data, particularly to assess whether volatility changes over time. Proposed by Robert Engle in 1982, this test forms the basis for ARCH (Autoregressive Conditional Heteroskedasticity) models. If volatility clustering is present in the data, ARCH models should be considered. If the p-value of the ARCH LM test statistic is less than 0.05, heteroskedasticity exists, and ARCH or GARCH models are recommended (Brooks, 2008). The Ramsey RESET (Regression Equation Specification Error Test) is a statistical test used to determine whether a regression model is correctly specified. Proposed by James B. Ramsey in 1969, this test identifies whether the model suffers from omitted variables, incorrect functional form, or issues with linearity. If the p-value of the test statistic is less than 0.05, it suggests that the model may be misspecified and require adjustment (Brooks, 2008).

4.5. Comparing Volatilities

The predicted volatilities were compared based on specific criteria after determining the most suitable volatility forecasting models for commodity futures returns.

The large values of ARCH and GARCH parameters affect conditional volatility differently. If the sum of ARCH parameters is close to 1, it indicates that the effects of shocks are more pronounced in subsequent periods. In contrast, if the sum of GARCH parameters is close to 1, it suggests that the effects of shocks are more persistent. Therefore, a significant ARCH parameter implies short-term high volatility, whereas a large GARCH parameter signifies long-term volatility (Nazlioglu et al., 2013).

The duration for which volatility persists daily and the period it takes to return to its previous level due to a shock in the market is referred to as the volatility half-life. In other words, while changes in returns due to any shock initially increase volatility, the change returns to normal levels after some time. The volatility half-life can be calculated using the following formula (Kalaycı et al., 2010):

$$\text{Half-Life} = \ln(0.5)/\ln(\beta_i) \tag{12}$$

5. Results

To model the volatility of time series data, it is initially essential to examine whether an ARCH effect (volatility) is present in the series. The ARCH LM test is used to ascertain the presence of volatility in the series. This test involves estimating the autoregressive moving average (ARMA) model.

Within the scope of the study, the most suitable AR and MA structures for the examined return series were determined based on the results of the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). Models were constructed using combinations of p = 0, 1,. . ., 4 and q = 0, 1,. . ., 4, and those with the lowest AIC and SIC values were decided as the most appropriate ARMA structures, as shown in Table 2. Subsequently, the presence of heteroskedasticity and autocorrelation issues in the error terms of the return series was examined. Heteroskedasticity was tested using the ARCH-LM test, while autocorrelation was assessed through the correlograms of the error terms.

Table 2. The Results of ARMA (p,q) for Best Selection.

Variables	Model	AIC	SIC	LogL	Q^2 (15)	ARCH LM (15)	Ramsey Reset (15)
			Precious Metal Returns				
Gold	ARMA(3,3)	−6.3570	−6.3428	11,046.97	246.59 ***	9.7442 ***	3.4075 ***
Silver	ARMA(2,2)	−5.0725	−5.0618	8789.04	483.11 ***	18.8287 ***	1.5553 *
Platinum	ARMA(4,4)	−5.4938	−5.4758	9344.07	943.05 ***	33.7951 ***	6.5076 ***
			Agriculture Returns				
Wheat	ARMA(4,3)	−4.9780	−4.9624	8852.536	967.38 ***	35.7909 ***	11.8816 ***
Sweetcorn	ARMA(4,3)	−5.3013	−5.2852	9106.167	155.75 ***	7.8521 ***	2.2949 ***
Soybean	ARMA(2,2)	−5.7850	−5.7746	10,271.59	319.82 ***	13.4562 ***	1.8115 **
Cotton	ARMA(2,4)	−5.3147	−5.3004	9138.689	307.62 ***	11.2292 ***	1.9443 **
Cocoa	ARMA(4,3)	−5.3657	−5.3495	9122.770	497.28 ***	45.7879 ***	1.5160 *
Coffee	ARMA(0,0)	−4.9388	−4.9370	8473.580	364.67 ***	14.2092 ***	-
			Industry Returns				
Copper	ARMA(2,2)	−5.678	−5.668	9799.15	440.86 ***	14.4108 ***	1.7067 **
Zinc	ARMA(4,4)	−5.374	−5.356	8978.15	405.64 ***	13.6463 ***	1.7036 **
Nickel	ARMA(4,3)	−4.406	−4.390	7341.96	1583.9 ***	207.9627 ***	63.2875 ***
Lead	ARMA(3,3)	−5.400	−5.386	9000.31	540.23 ***	19.8349 ***	3.8950 ***
			Energy Returns				
WTI Oil	ARMA(3,3)	−4.376	−4.362	7662.14	2142.0 ***	112.4582 ***	23.7406 ***
Brent Oil	ARMA(4,4)	−4.710	−4.692	8179.88	1075.8 ***	45.9100 ***	8.6682 ***
Natural Gas	ARMA(0,1)	−3.896	−3.891	6656.73	316.87 ***	15.7338 ***	4.5511 ***

***, ** and * indicate 1%, 5%, and 10% significance levels, respectively. Source: author's compilation.

ARCH LM test results have been found statistically significant up to the 15th lag for commodity futures returns. According to the ARCH test results, the null hypothesis testing the absence of changing variance in error terms across all commodity returns has been rejected. The error terms of all return series exhibit ARCH effects. An examination of the Q-statistic probability values revealed the presence of autocorrelation in commodity futures return series up to the 15th lag. Following the identification of heteroskedasticity and autocorrelation issues in the return series, the presence of nonlinear elements in the series was investigated using the Ramsey Regression Equation Specification Error Test. The results indicated that the return series contained nonlinear components. However, test results could not be obtained for coffee futures returns due to the inability to estimate an ARMA process. Considering the presence of heteroskedasticity, autocorrelation issues, and nonlinear elements in the commodity futures return series, it was concluded that a GARCH-type model is necessary to model the volatility of each commodity futures product appropriately.

In financial time series, good and bad news (shocks) do not impact volatility equally; instead, they asymmetrically affect volatility. This phenomenon is referred to in the literature as the leverage effect. The volatility of commodity futures returns has been estimated considering the leverage effect using the EGARCH model. Models were constructed using combinations of p = 0, 1,. . ., 3 and q = 0, 1,. . ., 3, and those with the lowest AIC and SIC values, as well as no autocorrelation issues in the error terms, were decided as the most suitable EGARCH models.

Geopolitical risk indices have been added as regressor variables to the EGARCH models established to analyze their impact on the volatility of future returns of precious metal commodity futures. Diagnostic test statistics for the EGARCH models are also presented in Table 3.

Table 3. Diagnostic Statistic.

Variables		Model	Diagnostic Statistic				
			AIC	SIC	LogL	Q^2 (15)	ARCH LM (15)
Gold	Without GPR	EGARCH(3,1)	−6.4570	−6.4464	11,218.75	13.778 (0.542)	0.9319 (0.5273)
	With GPR		−6.4573	−6.4449	11,220.15	13.113 (0.594)	0.8871 (0.5786)
	With GPRACT		−6.4567	−6.4443	11,219.08	13.348 (0.575)	0.9043 (0.5588)
	With GPRTHREAT		−6.4573	−6.4449	11,220.17	13.368 (0.574)	0.9034 (0.5599)
Silver	Without GPR	EGARCH(3,2)	−5.2484	−5.2360	9094.705	19.642 (0.186)	1.2963 (0.1951)
	With GPR		−5.2493	−5.2351	9097.253	18.715 (0.227)	1.2450 (0.2295)
	With GPRACT		−5.2482	−5.2340	9095.425	19.108 (0.209)	1.2682 (0.2134)
	With GPRTHREAT		−5.2494	−5.2352	9097.490	18.885 (0.219)	1.2521 (0.2245)
Platinum	Without GPR	EGARCH(1,2)	−5.6588	−5.649836	9619.399	19.775 (0.181)	1.2733 (0.2100)
	With GPR		−5.6582	−5.647474	9619.450	19.467 (0.193)	1.2556 (0.2220)
	With GPRACT		−5.6586	−5.647804	9620.011	19.098 (0.209)	1.2343 (0.2373)
	With GPRTHREAT		−5.6582	−5.647451	9619.411	19.923 (0.175)	1.2817 (0.2044)

Source: author's compilation.

Following the estimated EGARCH models, an ARCH-LM test was conducted again to determine whether the ARCH effect in the residual series had disappeared. The ARCH-LM test statistics calculated up to the 15th lag were statistically insignificant, indicating that the conditional variance effect has been eliminated in the series. Additionally, when examining autocorrelation in the model series using the Ljung–Box Q^2 test up to the 15th lag, no autocorrelation issues were found. These results confirm the adequacy of the EGARCH models. The results of the EGARCH models conducted to assess the impact of GPRon precious metal return volatility are presented in Table 4.

Table 4. Geopolitic Risk and Precious Metal Return Volatility.

Variables		Model	Coefficients										
			ω	α_1	α_2	γ	β_1	β_2	β_3	δ	$\sum \alpha_i$	$\sum \beta_i$	**Half-Life**
Gold	Without GPR	EGARCH(3,1)	−0.1863 (0.000)	0.0831 (0.000)	-	−0.0049 (0.064)	1.9695 (0.000)	−1.7617 (0.000)	0.7786 (0.000)	-	0.0831	0.986	51
	With GPR		−0.1848 (0.000)	0.0827 (0.000)	-	−0.0043 (0.110)	1.9671 (0.000)	−1.7556 (0.000)	0.7740 (0.000)	-6.20×10^{-5} (0.041)	0.0827	0.9858	48
	With GPRACT		−0.1821 (0.000)	0.0829 (0.000)	-	−0.0047 (0.076)	1.9699 (0.000)	−1.7538 (0.000)	0.7704 (0.000)	-3.03×10^{-5} (0.275)	0.0829	0.9865	51
	With GPRTHREAT		−0.1897 (0.000)	0.0830 (0.000)	-	−0.0044 (0.105)	1.9661 (0.000)	−1.7603 (0.000)	0.7796 (0.000)	-4.16×10^{-5} (0.036)	0.0830	0.9854	47
Silver	Without GPR	EGARCH(3,2)	−0.5088 (0.000)	0.1573 (0.000)	0.1826 (0.000)	0.0105 (0.029)	−0.7150 (0.000)	0.8216 (0.000)	0.8605 (0.000)	-	0.3399	0.9671	21
	With GPR		−0.4981 (0.000)	0.1568 (0.000)	0.1808 (0.000)	0.0102 (0.023)	−0.7356 (0.000)	0.8220 (0.000)	0.8780 (0.000)	−0.0002 (0.001)	0.3376	0.9644	19
	With GPRACT		−0.5038 (0.000)	0.1580 (0.000)	0.1848 (0.000)	0.0097 (0.039)	−0.7236 (0.000)	0.8253 (0.000)	0.8646 (0.000)	−0.0001 (0.056)	0.3428	0,9663	20
	With GPRTHREAT		−0.5039 (0.000)	0.1574 (0.000)	0.1783 (0.000)	0.0107 (0.016)	−0.7358 (0.000)	0.8181 (0.000)	0.8821 (0.000)	−0.0002 (0.000)	0.3357	0.9644	19
Platinum	Without GPR	EGARCH(1,2)	−0.1009 (0.000)	0.1733 (0.000)	−0.0898 (0.000)	−0.0224 (0.000)	0.9957 (0.000)	-	-	-	0.0835	0.9957	161
	With GPR		−0.0994 (0.000)	0.1740 (0.000)	−0.0904 (0.000)	−0.0226 (0.000)	0.9957 (0.000)	-	-	-1.08×10^{-5} (0.741)	0.0836	0.9957	164
	With GPRACT		−0.0983 (0.000)	0.1764 (0.000)	−0.0933 (0.000)	−0.0230 (0.000)	0.9955 (0.000)	-	-	-3.67×10^{-5} (0.210)	0.0831	0.9955	156
	With GPRTHREAT		−0.1017 (0.000)	0.1731 (0.000)	−0.0896 (0.000)	−0.0224 (0.000)	0.9956 (0.000)	-	-	3.52×10^{-6} (0.867)	0.0834	0.9956	159

Source: author's compilation.

The leverage parameter (γ) is negative and significant for gold and platinum return volatilities. A negative parameter indicates the presence of a leverage effect, where the impact of negative shocks on the volatility of these precious metals is more significant than that of positive shocks. A low ARCH parameter suggests that shocks have a lesser effect on precious metal returns. The higher ARCH parameters for silver commodities indicate that shocks in the markets predominantly affect silver return volatility in the short term. A high GARCH parameter implies that shock effects are more persistent. Volatility in platinum returns tends to be more persistent compared to other commodity returns. To determine how long volatility in precious metal returns lasts daily, the half-life (HL) measure was calculated. Accordingly, shock persistence in gold lasts approximately 50 days, 20 days for silver, and 161 days for platinum.

The EGARCH model has been expanded by including index data (GPR, GPRACT, and GPRTHREAT) as regressor variables to determine their impact on precious metal return volatilities. Table 4 presents the results of the EGARCH models that incorporate these regressor variables into the conditional variance equation. For gold return volatility, GPR and GPRTREAT indices have a negative and significant effect, while the effect of GPRACT is insignificant. When GPR, GPRACT, and GPRTREAT indices are included in the model, the persistence of shocks in gold return volatility is approximately 48, 51, and 47 days, respectively.

For silver return volatility, GPR, GPRACT, and GPRTHREAT indices have a negative and significant effect, whereas they have an insignificant effect on platinum return volatility. Including GPR, GPRACT, and GPRTREAT indices in the model, the persistence of shocks in silver return volatility is approximately 19, 20, and 19 days, respectively. The persistence of shocks in platinum return volatility is approximately 163, 156, and 159 days, respectively.

Geopolitical risk indices were added as regressor variables to the EGARCH models to analyze the impact of GPR on agricultural commodity futures return volatility. Diagnostic test statistics for the EGARCH models are also provided in Table 5.

Following the specified EGARCH models, an ARCH-LM test was conducted again to determine whether the ARCH effect in the agricultural commodity return series had disappeared. It was found that the ARCH-LM test statistics calculated up to the 15th lag were not statistically significant, indicating the elimination of the conditional variance effect in the series. Additionally, autocorrelation analysis in the model series was performed using the Ljung–Box Q^2 test up to the 15th lag, and no autocorrelation issues were detected. These findings confirm the adequacy of the EGARCH models. The results of the EGARCH models conducted to assess the impact of GPR on agricultural return volatility are presented in Table 6.

The leverage parameter (γ) is negative and significant for corn, soybean, and cocoa return volatilities. A negative parameter indicates the presence of a leverage effect, where the impact of negative shocks on the volatility of these agricultural products is greater than that of positive shocks.

Wheat, cocoa, and coffee products have lower ARCH parameters than other agricultural products. This indicates that the effect of shocks in the market on these products is lower in the short term. The total GARCH parameter for cocoa agricultural products is closest to 1. This suggests that the effects of shocks in the market are more persistent on cocoa return fluctuations.

Table 5. Diagnostic Statistic.

Variables		Model	Diagnostic Statistic				
			AIC	SIC	LogL	Q^2 (15)	ARCH LM (15)
Wheat	Without GPR	EGARCH(1,1)	−5.1204	−5.1135	9100.556	17.087 (0.195)	1.3056 (0.2012)
	With GPR		−5.1211	−5.1124	9102.768	16.975 (0.200)	1.2987 (0.2053)
	With GPRACT		−5.1201	−5.1114	9100.962	16.836 (0.207)	1.2864 (0.2129)
	With GPRTHREAT		−5.1214	−5.1128	9103.342	17.499 (0.177)	1.3396 (0.1817)
Sweetcorn	Without GPR	EGARCH(3,3)	−5.4614	−5.4471	9379.804	19.676 (0.185)	1.3491 (0.1638)
	With GPR		−5.4610	−5.4449	9380.112	20.034 (0.171)	1.3725 (0.1513)
	With GPRACT		−5.4612	−5.4451	9380.534	20.097 (0.168)	1.37021 (0.1525)
	With GPRTHREAT		−5.4608	−5.4447	9379.816	19.744 (0.182)	1.3539 (0.1612)
Soybean	Without GPR	EGARCH(3,3)	−5.9184	−5.9044	10,510.21	19.066 (0.211)	1.2316 (0.2393)
	With GPR		−5.9154	−5.8998	10,506.05	16.019 (0.381)	1.0246 (0.4255)
	With GPRACT		−5.9149	−5.8993	10,505.13	16.064 (0.378)	1.0422 (0.4072)
	With GPRTHREAT		−5.9145	−5.8988	10,504.29	16.892 (0.325)	1.0767 (0.3726)
Cotton	Without GPR	EGARCH(3,2)	−5.4833	−5.4708	9427.460	7.4696 (0.943)	0.4884 (0.9477)
	With GPR		−5.4907	−5.4764	9441.028	10.743 (0.771)	0.7006 (0.7863)
	With GPRACT		−5.4886	−5.4743	9437.543	11.453 (0.720)	0.7522 (0.7320)
	With GPRTHREAT		−5.4895	−5.4752	9439.072	10.549 (0.784)	0.6881 (0.7987)
Cocoa	Without GPR	EGARCH(1,2)	−5.4543	−5.4453	9269.206	16.169 (0.184)	1.3164 (0.2013)
	With GPR		−5.4540	−5.4432	9269.739	16.255 (0.180)	1.3246 (0.1967)
	With GPRACT		−5.4540	−5.4431	9269.635	16.255 (0.180)	1.3260 (0.1959)
	With GPRTHREAT		−5.4540	−5.4431	0.924662	16.226 (0.181)	1.3212 (0.1986)
Coffee	Without GPR	EGARCH(3,2)	−5.0083	−4.9957	8598.758	19.621 (0.187)	1.3067 (0.1886)
	With GPR		−5.0081	−4.9937	8599.395	20.333 (0.160)	1.3577 (0.1591)
	With GPRACT		−5.0078	−4.9935	8599.041	19.498 (0.192)	1.2994 (0.1931)
	With GPRTHREAT		−5.0080	−4.9937	8599.343	20.535 (0.152)	1.3714 (0.1519)

Source: author's compilation.

To determine how long volatility in agricultural product returns lasts daily, the half-life (HL) measure has been calculated. Accordingly, shock persistence in wheat returns lasts approximately 23 days, 9 days for corn, 8 days for soybeans, 23 days for cotton, 79 days for cocoa, and 36 days for coffee.

The EGARCH model has been expanded by including index data (GPR, GPRACT, and GPRTREAT) as regressor variables to determine their impact on agricultural product return volatilities. Table 6 presents the results of the EGARCH models that incorporate these regressor variables into the conditional variance equation. For wheat return volatility, GPR and GPRTREAT indices have a positive and significant effect, while the effect of GPRACT is insignificant. When GPR, GPRACT, and GPRTHREAT indices are included in the model, the persistence of shocks in wheat return volatility is approximately 20, 22, and 20 days, respectively. For corn return volatility, the GPRACT index has a positive and significant effect, while the effects of the GPR and GPRTHREAT indices are insignificant. Including GPR, GPRACT, and GPRTHREAT indices in the model, the persistence of shocks in corn return volatility is approximately 9, 8, and 9 days, respectively.

GPR, GPRACT, and GPRTHREAT indices have a positive and significant effect on soybean and cotton return volatilities, while they have an insignificant effect on cocoa and coffee return volatilities. When GPR, GPRACT, and GPRTHREAT indices are included in the model, the persistence of shocks in soybean return volatility is approximately 8, 9, and 6 days, respectively. Cotton return volatility is approximately 20, 21, and 21 days, respectively. For cocoa return volatility, the persistence of shocks is approximately 75, 72, and 77 days, respectively, and for coffee return volatility, it is approximately 36, 36, and 35 days, respectively.

Table 6. Geopolitic Risk and Agriculture Return Volatility.

Variables		Model	Coefficients											
			ω	α_1	α_2	α_3	γ	β_1	β_2	β_3	δ	$\sum \alpha_i$	$\sum \beta_i$	**Half-Life**
Wheat	Without GPR	EGARCH(1,1)	−0.3636 (0.000)	0.1639 (0.000)	-	-	0.0162 (0.015)	0.9699 (0.000)	-	-	-	0.1639	0.9699	23
	With GPR		−0.4118 (0.000)	0.1594 (0.000)	-	-	0.0161 (0.018)	0.9656 (0.000)	-	-	0.00016 (0.002)	0.1594	0.9656	20
	With GPRACT		−0.3829 (0.000)	0.1640 (0.000)	-	-	0.0174 (0.0107)	0.9682 (0.000)	-	-	6.81×10^{-5} (0.321)	0.1640	0.9682	22
	With GPRTHREAT		−0.4061 (0.000)	0.1583 (0.000)	-	-	0.0148 (0.0299)	0.9658 (0.000)	-	-	0.00012 (0.000)	0.1583	0.9658	20
Sweetcorn	Without GPR	EGARCH(3,3)	−1.0433 (0.000)	0.1995 (0.000)	0.2886 (0.000)	0.0942 (0.000)	−0.0604 (0.000)	−0.4066 (0.000)	0.4956 (0.000)	0.8376 (0.000)	-	0.5824	0.9266	9
	With GPR		−1.0682 (0.000)	0.1998 (0.000)	0.2907 (0.000)	0.0939 (0.000)	−0.0605 (0.000)	−0.4086 (0.000)	0.4967 (0.000)	0.8376 (0.000)	0.00015 (0.302)	0.4906	0.9258	9
	With GPRACT		−1.1327 (0.000)	0.2043 (0.000)	0.2933 (0.000)	0.1034 (0.000)	−0.0549 (0.000)	−0.4199 (0.000)	0.4851 (0.000)	0.8551 (0.000)	0.00024 (0.099)	0.6010	0.9203	8
	With GPRTHREAT		−1.0442 (0.000)	0.1993 (0.000)	0.2888 (0.000)	0.0937 (0.000)	−0.0608 (0.000)	−0.4064 (0.000)	0.4965 (0.000)	0.8367 (0.000)	2.03×10^{-5} (0.826)	0.5819	0.9268	9
Soybean	Without GPR	EGARCH(3,3)	−1.0904 (0.000)	0.1610 (0.000)	0.2323 (0.000)	0.1421 (0.000)	−0.0074 (0.012)	−0.3620 (0.000)	0.3154 (0.000)	0.9675 (0.000)	-	0.5355	0.9209	8
	With GPR		−1.1819 (0.000)	0.1870 (0.000)	0.2287 (0.000)	0.1651 (0.000)	0.0079 (0.000)	−0.3200 (0.000)	0.2620 (0.000)	0.9741 (0.000)	0.00019 (0.003)	0.5809	0.9161	8
	With GPRACT		−1.0897 (0.000)	0.1759 (0.000)	0.2145 (0.000)	0.1534 (0.000)	0.0037 (0.051)	−0.3194 (0.000)	0.2686 (0.000)	0.9736 (0.000)	0.00012 (0.013)	0.5439	0.9227	9
	With GPRTHREAT		−1.5023 (0.000)	0.1942 (0.000)	0.2381 (0.000)	0.1723 (0.000)	0.0064 (0.001)	−0.3310 (0.000)	0.2490 (0.000)	0.9636 (0.000)	0.00017 (0.001)	0.6047	0.8816	6
Cotton	Without GPR	EGARCH(3,2)	−0.4516 (0.000)	0.1456 (0.000)	0.1363 (0.000)	-	0.0098 (0.021)	−0.3776 (0.003)	0.9792 (0.000)	0.3693 (0.003)	-	0.2820	0.970	23
	With GPR		−0.5625 (0.000)	0.1598 (0.000)	0.1435 (0.000)	-	0.0238 (0.002)	−0.5294 (0.000)	0.6277 (0.000)	0.8683 (0.000)	0.00054 (0.000)	0.3034	0.9666	20
	With GPRACT		−0.5367 (0.000)	0.1615 (0.000)	0.1474 (0.000)	-	0.0268 (0.000)	−0.5563 (0.000)	0.6298 (0.000)	0.8941 (0.000)	0.00039 (0.000)	0.3089	0.9676	21
	With GPRTHREAT		−0.5345 (0.000)	0.1605 (0.000)	0.1401 (0.000)	-	0.0229 (0.003)	−0.5199 (0.000)	0.6216 (0.000)	0.8655 (0.000)	0.00031 (0.000)	0.3006	0.9672	21

Table 6. *Cont.*

Variables		Model	Coefficients											
			ω	α_1	α_2	α_3	γ	β_1	β_2	β_3	δ	$\sum\alpha_i$	$\sum\beta_i$	**Half-Life**
Cocoa	Without GPR	EGARCH(1,2)	−0.1207 (0.000)	0.2131 (0.000)	−0.1496 (0.000)	-	−0.0124 (0.013)	0.9913 (0.000)	-	-	-	0.0634	0.9913	79
	With GPR		−0.1233 (0.000)	0.2128 (0.000)	−0.1474 (0.000)	-	−0.0128 (0.015)	0.9907 (0.000)	-	-	-3.34×10^{-5} (0.299)	0.0654	0.9907	75
	With GPRACT		−0.1264 (0.000)	0.2118 (0.000)	−0.1470 (0.000)	-	−0.0139 (0.012)	0.9903 (0.000)	-	-	-3.16×10^{-5} (0.2080)	0.0648	0.9903	72
	With GPRTHREAT		−0.1219 (0.000)	0.2134 (0.000)	−0.1483 (0.000)	-	−0.0121 (0.018	0.9910 (0.000)	-	-	-1.95×10^{-5} (0.376)	0.0651	0.9910	77
Coffee	Without GPR	EGARCH(3,2)	−0.2107 (0.000)	0.1185 (0.000)	−0.0391 (0.081)	-	0.0239 (0.000)	1.9544 (0.000)	−1.7125 (0.000)	0.7389 (0.000)	-	0.0793	0.9808	36
	With GPR		−0.2167 (0.000)	0.1190 (0.000)	−0.0403 (0.070)	-	0.0253 (0.000)	1.9538 (0.000)	−1.7109 (0.000)	0.7377 (0.000)	4.48×10^{-5} (0.233)	0.0787	0.9806	36
	With GPRACT		−0.2141 (0.000)	0.1185 (0.000)	−0.0395 (0.075)	-	0.0248 (0.000)	1.9569 (0.000)	−1.7142 (0.000)	0.7380 (0.000)	3.01×10^{-5} (0.383)	0.079	0.9807	36
	With GPRTHREAT		−0.2157 (0.000)	0.1192 (0.000)	−0.0405 (0.070)		0.0249 (0.000)	1.9532 (0.000)	−1.7108 (0.000)	0.7382 (0.000)	2.85×10^{-5} (0.268)	0.0787	0.9806	35

Source: author's compilation.

Geopolitical risk indices were added as regressor variables to the models to observe their impact on industrial commodity futures return volatility, and EGARCH models were re-created accordingly. Diagnostic test statistics for the EGARCH models are also provided in Table 7.

Table 7. Diagnostic Statistic.

Variables	Model		Diagnostic Statistic				
			AIC	SIC	LogL	Q^2 (15)	ARCH LM (15)
Copper	Without GPR	EGARCH(1,2)	−5.7674	−5.7585	9950.958	11.481 (0.718)	0.7546 (0.7294)
	With GPR		−5.766	−5.7561	9950.987	11.546 (0.713)	0.7592 (0.7244)
	With GPRACT		−5.7668	−5.7561	9950.994	11.613 (0.708)	0.7635 (0.7197)
	With GPRTHREAT		−5.7668	−5.7561	9950.999	11.522 (0.715)	0.7576 (0.7261)
Zinc	Without GPR	EGARCH(3,3)	−5.4890	−5.4743	9166.457	11.798 (0.694)	0.7984 (0.6806)
	With GPR		−5.4908	−5.4743	9170.402	12.329 (0.654)	0.8398 (0.6333)
	With GPRACT		−5.4894	−5.4729	9168.196	11.673 (0.704)	0.7952 (0.6843)
	With GPRTHREAT		−5.4903	−5.4738	9169.647	12.602 (0.633)	0.8572 (0.6131)
Nickel	Without GPR	EGARCH(2,3)	−4.9733	−4.9605	8282.710	6.417 (0.972)	0.4150 (0.9756)
	With GPR		−5.0246	−5.0099	8368.947	12.949 (0.606)	0.8379 (0.6355)
	With GPRACT		−4.9912	−4.9765	8313.411	3.2536 (0.999)	0.2119 (0.9994)
	With GPRTHREAT		−5.0200	−5.0053	8361.315	13.390 (0.572)	0.8669 (0.6020)
Bullet	Without GPR	EGARCH(2,3)	−5.5545	−5.5416	9255.308	15.789 (0.396)	1.0375 (0.4121)
	With GPR		−5.5571	−5.5425	9260.733	17.324 (0.300)	1.139 (0.3141)
	With GPRACT		−5.5572	−5.5425	9260.768	15.303 (0.430)	0.9998 (0.4519)
	With GPRTHREAT		−5.5558	−5.5412	9258.558	17.377 (0.297)	1.1444 (0.3096)

Source: author's compilation.

The ARCH-LM test was applied again to the specified EGARCH models, and it was found that the ARCH-LM test statistics calculated up to the 15th lag indicate the absence of conditional variance effects in the series. Additionally, autocorrelation analysis using the Ljung–Box Q^2 test up to the 15th lag revealed no autocorrelation issues in the model series. These findings confirm the adequacy of the EGARCH models. The results of the EGARCH models conducted to examine the effects of GPRon industrial return volatility are presented in Table 8.

The leverage parameter (γ) is negative and significant for copper, zinc, and lead return volatilities. A negative parameter indicates the presence of a leverage effect, where the impact of negative shocks on the volatility of these industrial products is greater than that of positive shocks.

The total ARCH parameters for copper commodity products are lower than those of other industrial products. This suggests that the effect of shocks in the market on copper return volatility is lower in the short term. The total GARCH parameters for lead commodity products are closest to 1. This indicates that the effects of shocks in the market are more persistent in lead return volatility. To determine how long volatility in industrial product returns lasts daily, the half-life (HL) measure has been calculated. Accordingly, shock persistence in copper returns lasts approximately 35 days, 19 days for zinc, 35 days for nickel, and 99 days for lead.

The EGARCH model has been expanded by including index data (GPR, GPRACT, and GPRTREAT) as regressor variables to determine their impact on industrial product return volatilities. Table 8 presents the results of the EGARCH models that incorporate these regressor variables into the conditional variance equation. GPR, GPRACT, and GPRTHREAT indices have a positive and significant effect on zinc, nickel, and lead return volatilities, while they have an insignificant effect on copper return volatility.

Table 8. Geopolitic Risk and Industry Return Volatility.

Variables		Model	Coefficients											
			ω	α_1	α_2	α_3	γ	β_1	β_2	β_3	δ	$\sum \alpha_i$	$\sum \beta_i$	**Half-Life**
Copper	Without GPR	EGARCH(1,2)	−0.2389 (0.000)	0.1518 (0.000)	−0.0625 (0.022)	-	−0.0409 (0.000)	0.9801 (0.000)	-	-	-	0.0892	0.9801	35
	With GPR		−0.2410 (0.000)	0.1517 (0.000)	−0.0623 (0.022)	-	−0.0409 (0.000)	0.9800 (0.000)	-	-	1.08×10^{-5} (0.766)	0.0894	0.9800	34
	With GPRACT		−0.2410 (0.000)	0.1521 (0.000)	−0.0627 (0.021)	-	−0.0407 (0.000)	0.9800 (0.000)	-	-	1.22×10^{-5} (0.751)	0.0894	0.9800	34
	With GPRTHREAT		−0.2409 (0.000)	0.1514 (0.000)	−0.0620 (0.023)	-	−0.0410 (0.000)	0.9800 (0.000)	-	-	8.40×10^{-6} (0.723)	0.0894	0.9800	34
Zinc	Without GPR	EGARCH(3,3)	−0.5794 (0.000)	0.1018 (0.000)	0.1593 (0.000)	0.0877 (0.000)	−0.0178 (0.005)	−0.7449 (0.000)	0.7443 (0.000)	0.9638 (0.000)	-	0.3489	0.9632	19
	With GPR		−0.5940 (0.000)	0.0994 (0.000)	0.1467 (0.000)	0.0807 (0.000)	−0.0208 (0.002)	−0.7295 (0.000)	0.7434 (0.000)	0.9500 (0.000)	0.0003 (0.001)	0.3268	0.9638	19
	With GPRACT		−0.6142 (0.000)	0.1018 (0.000)	0.1531 (0.000)	0.0837 (0.000)	−0.0211 (0.003)	−0.7297 (0.000)	0.7437 (0.000)	0.9465 (0.000)	0.0002 (0.047)	0.3387	0.9605	17
	With GPRTHREAT		−0.5652 (0.000)	0.0992 (0.000)	0.1473 (0.000)	0.0806 (0.000)	−0.0213 (0.002)	−0.7314 (0.000)	0.7433 (0.000)	0.9540 (0.000)	0.0002 (0.003)	0.3272	0.9659	20
Nickel	Without GPR	EGARCH(2,3)	−0.2999 (0.000)	0.4662 (0.000)	0.1050 (0.014)	−0.3773 (0.000)	0.0751 (0.000)	0.4200 (0.000)	0.5600 (0.000)	-	-	0.1939	0.9801	35
	With GPR		−1.1087 (0.000)	0.2293 (0.000)	0.1188 (0.021)	−0.1228 (0.000)	0.0295 (0.018)	0.5548 (0.001)	0.3498 (0.031)	-	0.0017 (0.000)	0.2253	0.9047	7
	With GPRACT		−1.8623 (0.000)	0.3388 (0.000)	0.2542 (0.000)	−0.1765 (0.000)	0.0838 (0.000)	0.1408 (0.001)	0.6878 (0.000)	-	0.0022 (0.000)	0.4164	0.8287	4
	With GPRTHREAT		−0.7102 (0.000)	0.2389 (0.000)	0.0700 (0.260)	−0.1277 (0.000)	0.0178 (0.102)	0.7619 (0.000)	0.1774 (0.395)	-	0.0007 (0.000)	0.1812	0.9394	11
Lead	Without GPR	EGARCH(2,3)	−0.1464 (0.000)	0.1592 (0.000)	0.0318 (0.003)	−0.0784 (0.004)	−0.0183 (0.000)	0.0153 (0.036)	0.9776 (0.000)	-	-	0.1126	0.9930	99
	With GPR		−0.1393 (0.000)	0.1542 (0.000)	0.0252 (0.015)	−0.0764 (0.007)	−0.0152 (0.001)	0.0164 (0.015)	0.9784 (0.000)	-	0.0001 (0.000)	0.1030	0.9948	135
	With GPRACT		−0.1590 (0.000)	0.1537 (0.000)	0.0249 (0.014)	−0.0757 (0.008)	−0.0172 (0.000)	0.0152 (0.015)	0.9770 (0.000)	-	0.0001 (0.000)	0.1029	0.9923	90
	With GPRTHREAT		−0.1355 (0.000)	0.1576 (0.000)	0.0285 (0.006)	−0.0780 (0.005)	−0.0155 (0.001)	0.0160 (0.020)	0.9790 (0.000)	-	7.72×10^{-5} (0.001)	0.1081	0.9950	139

Source: author's compilation.

When GPR, GPRACT, and GPRTHREAT indices are included in the model, the persistence of shocks in copper return volatility is approximately 34, 34, and 34 days, respectively. Zinc return volatility is approximately 19, 17, and 20 days, respectively. Nickel return volatility shows persistence of shocks of approximately 7, 4, and 11 days, respectively. Lead return volatility exhibits a persistence of shocks of approximately 135, 90, and 139 days, respectively.

To examine the impact of GPRon energy commodity futures return volatility, EGARCH models were re-established by adding geopolitical risk indices as regressor variables to the model. Diagnostic test statistics for the EGARCH models are also provided in Table 9.

Table 9. Diagnostic Statistic.

Variables		Model	Diagnostic Statistic				
			AIC	SIC	LogL	Q^2 (15)	ARCH LM (15)
WTI Oil	Without GPR	EGARCH(1,2)	−4.9416	−4.9328	8647.933	8.9155 (0.882)	0.5820 (0.8909)
	With GPR		−4.9472	−4.9367	8658.802	8.0978 (0.920)	0.5286 (0.9264)
	With GPRACT		−4.9412	−4.9306	8648.181	8.6214 (0.896)	0.5641 (0.9037)
	With GPTHREAT		−4.9496	−4.9390	8662.938	8.2772 (0.912)	0.5412 (0.9187)
Brent Oil	Without GPR	EGARCH(3,1)	−5.0952	−5.0846	8843.765	9.5802 (0.845)	0.6460 (0.8385)
	With GPR		−5.0983	−5.0859	8850.085	11.647 (0.706)	0.7889 (0.6914)
	With GPRACT		−5.0947	−5.0823	8843.800	9.5680 (0.846)	0.6447 (0.8396)
	With GPTHREAT		−5.1004	−5.0880	8853.697	12.744 (0.622)	0.8614 (0.6084)
Natural Gas	Without GPR	EGARCH(3,3)	−4.1585	−4.1441	7108.664	7.9408 (0.926)	0.5363 (0.9217)
	With GPR		−4.1682	−4.1520	7126.245	8.3381 (0.910)	0.5678 (0.9011)
	With GPRACT		−4.1518	−4.1356	7098.254	9.4736 (0.851)	0.6327 (0.8502)
	With GPTHREAT		−4.1585	−4.142	7109.776	5.5131 (0.987)	0.3651 (0.9872)

Source: author's compilation.

The ARCH-LM test was re-applied to the specified EGARCH models, and it was found that the ARCH-LM test statistics calculated up to the 15th lag indicate the absence of conditional variance effects in the series. Additionally, autocorrelation analysis using the Ljung–Box Q^2 test up to the 15th lag revealed no autocorrelation issues in the model series. These findings confirm the adequacy of the EGARCH models. The results of the EGARCH models conducted to examine the effects of GPR on energy return volatility are presented in Table 10.

The leverage parameter (γ) is negative and significant for WTI and Brent crude oil return volatilities. A negative parameter indicates the presence of a leverage effect, where the impact of negative shocks on the volatility of these energy products is greater than that of positive shocks.

The total ARCH parameters for crude oil commodities are lower than those for natural gas parameters. This suggests that the short-term effect of market shocks on crude oil return volatility is lower. The total GARCH parameters for crude oil commodities are closest to 1. This indicates that the effects of shocks in the market are more persistent in terms of crude oil return volatility. To determine how long volatility in energy product returns lasts daily, the half-life (HL) measure has been calculated. Accordingly, shock persistence in WTI crude oil returns lasts approximately 37 days, 49 days for Brent crude oil, and 18 days for natural gas.

The EGARCH model has been expanded by adding GPR, GPRACT, and GPRTHREAT indices as regressor variables to determine their impact on energy product return volatilities. Table 10 presents the results of EGARCH models with regressor variables included in the conditional variance equation. GPR and GPRTREAT indices have a positive and significant effect on WTI crude oil and Brent crude oil return volatilities. In contrast, only the GPRACT index has a negative and significant effect on natural gas return volatility.

Table 10. Geopolitics Risk and Energy Return Volatility.

Variables		Model	Coefficients											
			ω	α_1	α_2	α_3	γ	β_1	β_2	β_3	δ	$\sum\alpha_i$	$\sum\beta_i$	**Half-Life**
WTI Oil	Without GPR	EGARCH(1,2)	−0.2649 (0.000)	0.2438 (0.000)	−0.0840 (0.000)	-	−0.0829 (0.000)	0.9815 (0.000)	-	-	-	0.1597	0.9815	37
	With GPR		−0.2861 (0.000)	0.2278 (0.000)	−0.0847 (0.000)	-	−0.0894 (0.000)	0.9808 (0.000)	-	-	0.0003 (0.000)	0.1431	0.9808	36
	With GPRACT		−0.2721 (0.000)	0.2429 (0.000)	−0.0831 (0.000)	-	−0.0831 (0.000)	0.9811 (0.000)	-	-	4.40×10^{-5} (0.312)	0.1598	0.9811	36
	With GPTHREAT		−0.2700 (0.000)	0.2236 (0.000)	−0.0876 (0.000)	-	−0.0919 (0.000)	0.9816 (0.000)	-	-	0.0002 (0.000)	0.1359	0.9816	37
Brent Oil	Without GPR	EGARCH(3,1)	−0.2355 (0.000)	0.1657 (0.000)	-	-	−0.0686 (0.000)	1.3123 (0.000)	−0.6754 (0.001)	0.3490 (0.000)	-	0.1657	0.9859	49
	With GPR		−0.2524 (0.000)	0.1493 (0.000)	-	-	−0.0741 (0.000)	1.3629 (0.000)	−0.7666 (0.000)	0.3886 (0.000)	0.0002 (0.000)	0.1493	0.9850	46
	With GPRACT		−0.2339 (0.000)	0.1663 (0.000)	-	-	−0.0687 (0.000)	1.3079 (0.000)	−0.6693 (0.001)	0.3474 (0.000)	-1.61×10^{-5} (0.694)	0.1663	0.9860	49
	With GPRTHREAT		−0.2471 (0.000)	0.1448 (0.000)	-	-	−0.0773 (0.000)	1.3627 (0.000)	−0.7735 (0.000)	0.3959 (0.000)	0.0002 (0.000)	0.1448	0.9850	46
Natural Gas	Without GPR	EGARCH(3,3)	−0.6987 (0.000)	0.1814 (0.000)	0.2190 (0.000)	0.1773 (0.000)	0.0060 (0.004)	−0.2016 (0.000)	0.1768 (0.000)	0.9876 (0.000)	-	0.5778	0.9629	18
	With GPR		−0.7251 (0.000)	0.2026 (0.000)	0.2381 (0.000)	0.1600 (0.000)	0.0055 (0.115)	−0.2728 (0.000)	0.2513 (0.000)	0.9826 (0.000)	-5.16×10^{-5} (0.473)	0.6007	0.9611	17
	With GPRACT		−1.4425 (0.000)	0.2495 (0.000)	0.3088 (0.000)	0.2433 (0.000)	0.0042 (0.000)	−0.2288 (0.000)	0.1420 (0.000)	0.9622 (0.000)	−0.0004 (0.000)	0.8017	0.8754	5
	With GPRTHREAT		−0.5821 (0.000)	0.1862 (0.000)	0.1659 (0.000)	0.1549 (0.000)	0.0195 (0.000)	0.0476 (0.000)	−0.0537 (0.000)	0.9765 (0.000)	-8.18×10^{-5} (0.290)	0.5070	0.4768	1

Source: author's compilation.

When GPR, GPRACT, and GPRTHREAT indices are included in the model, the persistence of shocks in WTI crude oil return volatility is approximately 36, 36, and 37 days, respectively. For Brent crude oil return volatility, the persistence of shocks is approximately 46, 49, and 46 days, respectively. Natural gas return volatility shows persistence of shocks of approximately 17, 5, and 1 day, respectively.

6. Discussion

In this study, data collected at a daily frequency from 4 January 2010 to 30 June 2023 were used to model the impact of the GPR on the volatilities of commodity futures returns using EGARCH models and conducting volatility analysis. The analysis provides a foundation to help investors and policymakers understand the relationship between GPR and commodity markets. In the futures commodity markets, 10 out of 16 traded products exhibit greater responsiveness to adverse events than to positive ones. In other words, there is a leverage effect in commodity markets. This implies that negative shocks increase the volatility of commodity returns more than positive shocks do. The findings are similar to those of Mitsas et al. (2022), Smales (2021), and Liu et al. (2024). The leverage parameter is negative and significant for the return volatility of gold and platinum from precious metal commodities, the return volatility of corn, soybean, and cocoa from agricultural products, the return volatility of copper, zinc, and lead from industrial products, and the return volatility of WTI oil and Brent oil from energy products. The statistical significance of the leverage parameter indicates the presence of a leverage effect on the volatility of these commodity returns.

The models incorporating geopolitical risk indices (GPR, GPRACT, and GPRTHREAT) determined that the GPR indices reduce the return volatility of gold, silver, and platinum. However, the effect on platinum return volatility was not found to be significant. When comparing the short-term impact of market shocks on the return volatility of precious metals, it is observed that there is not much difference between the models. However, when comparing the long-term effects of shocks, GPR indices reduce the duration of return volatility for precious metals. The findings obtained are similar to those in the study by Mitsas et al. (2022). It is observed that the impact of GPR on the precious metals commodity market differs from its impact on other markets. Increased geopolitical risk plays a negative role in this market, which contradicts the findings of studies by Khurshid et al. (2024) and Fiorillo et al. (2023). Their findings suggest a more profound impact on the returns of precious metals. One possible reason is that precious metals exhibit more stable performance when faced with sudden shocks. Additionally, it has been demonstrated that they act as safe-haven assets during crisis periods, providing hedging properties against risks (Shahzad et al., 2023). Therefore, under the influence of geopolitical risk, the volatility of these metals may be less affected by increased uncertainty.

In agricultural products, the GPR, GPRACT, and GPRTHREAT indices significantly positively affect the return volatility of soybean and cotton. In contrast, their effects on the return volatility of cocoa and coffee are insignificant. The GPR and GPRTHREAT indices have a significant positive effect on the return volatility of wheat. In contrast, the GPRACT index has a significant positive effect on the return volatility of corn. The effect of the GPRTHREAT index on corn is consistent with the findings of Mitsas et al. (2022). When comparing the short-term effects of shocks in the markets, geopolitical risk indices have been found to enhance the return volatility of agricultural products. When comparing the long-term effects of shocks, it has been observed that geopolitical risk indices reduce the duration of return volatilities of agricultural products. The impact of GPR and GPRTHREAT indices on wheat return volatility is consistent with the findings in the literature, specifically the study by Micallef et al. (2023). Agricultural commodities, in particular, show a more significant response to changes in GPR due to the high degree of government intervention in the agricultural market.

In industrial products, it has been found that the GPR, GPRACT, and GPRTHREAT indices have a significant enhancing effect on the volatility of zinc, nickel, and lead returns. In contrast, their effects on copper return volatility are insignificant. Comparing the short-term impact of market shocks on the return volatility of industrial products, geopolitical risk indices have a low impact on the return volatility of zinc and lead. The GPR and GPRACT indices have a large impact on the volatility of nickel returns in the short term, while the GPRTHREAT index has a low impact on nickel return volatility. When comparing the long-term effects of shocks, it has been found that GPR indices do not significantly alter the duration of zinc return volatilities. In contrast, they significantly reduce the duration of nickel return volatilities. In the long term, the GPR and GPRTHREAT indices increase the duration of lead return volatilities, while the GPRACT index has reduced the duration of return volatilities.

In energy products, GPR and GPRTHREAT indices have a positive impact on the volatility of WTI crude oil and Brent crude oil returns. On the other hand, the GPRACT index has a negative impact on the volatility of natural gas returns. Comparing the short-term impact of market shocks on the volatility of energy product returns, geopolitical risk indices have a low impact on the volatility of WTI crude oil and Brent crude oil returns. In contrast, they have a large impact on the volatility of natural gas returns. In the long term, geopolitical risk indices have reduced the duration of volatility in energy product returns. Specifically, the GPRACT index has significantly shortened the persistence of volatility in natural gas returns. The negative leverage effect on oil among energy commodities indicates that negative shocks in energy commodities are more impactful on the return volatility of oil. Our findings are consistent with those of Smales (2021), Mitsas et al. (2022), Shahzad et al. (2023), Mo et al. (2024), Foglia et al. (2023), and Liu et al. (2024). A noteworthy finding is that the GPRACT index reduces the volatility of natural gas returns in the long term, which differs from the study by Liu et al. (2024). This difference is likely due to the volatility in natural gas returns beginning with the emergence of threats.

In the short term, GPRare increases the volatility of nickel and natural gas returns. However, relative decreases in volatility are observed in other commodities. In the long term, GPR persistently increases the volatility of lead returns. However, the duration of volatility in other commodities is relatively short. The persistence of shocks on natural gas returns decreases from 18 days, according to the GPRACT index, to 5 days. For nickel returns, the persistence of shocks decreases from 35 days to approximately 7, 4, and 11 days, according to the GPR, GPRACT, and GPRTHREAT indices, respectively. Shocks have a significant long-term impact on lead returns. The persistence of shocks on lead return volatility increases from 99 days to 135 and 139 days, according to the GPR and GPRTREAT indices, respectively, while it decreases to 90 days for the GPRACT index. The persistence of shocks on other commodity return volatility does not differ across GPR indices.

The observed differences in volatility responses across commodity classes can be attributed to the unique transmission mechanisms through which geopolitical risk affects these markets:

- ✓ Energy commodities (oil, gas): Highly sensitive to supply shocks from geopolitical conflicts in major producing regions (Middle East, Russia–Ukraine).
- ✓ Precious metals (gold, silver): Serve as safe-haven assets, attracting investors during geopolitical instability.
- ✓ Agricultural commodities (wheat, corn): Vulnerable to trade restrictions, export bans, and climate-related risks exacerbated by conflicts.

✓ Industrial metals (copper, nickel): Affected indirectly through global trade policies, sanctions, and industrial demand fluctuations.

This explains why geopolitical risk has stronger and more persistent effects on energy and metals, while agricultural commodities experience more localized and temporary volatility spikes.

7. Conclusions

The study examines the impact of geopolitical risk indices on commodity futures return volatility using asymmetric GARCH models, specifically EGARCH models. The findings indicate the presence of the leverage effect in most of the commodities analyzed. Key results include (i) the volatility of precious metals such as gold and platinum, often considered safe-haven assets, is more sensitive to negative shocks. This can be attributed to heightened demand fluctuations during periods of crisis as investors seek refuge in these assets. (ii) The return volatility of corn, soybean, and cocoa increases more significantly following negative shocks as supply-side risks disrupt price stability. (iii) The asymmetric volatility structure observed in copper, zinc, and lead suggests that global economic downturns or trade wars amplify price volatility by dampening demand. (iv) In crude oil markets, negative shocks have a more pronounced effect on volatility, which can be explained by the energy sector's sensitivity to global economic growth and uncertainties on the supply side. Commodity investors should anticipate how adverse developments impact markets and adjust their risk management strategies accordingly.

The results examining the impact of geopolitical risks on commodity market volatility indicate that (i) the finding that GPR indices reduce the return volatility of precious metals suggests that the H1 hypothesis does not hold in the precious metals market. Precious metals (e.g., gold and silver) tend to exhibit safe-haven characteristics. (ii) The observation that GPR indices increase the return volatility of agricultural and industrial commodities supports the H1 hypothesis in these markets. Agricultural commodities respond to supply chain disruptions linked to geopolitical instability (e.g., wheat prices surged due to the Russia–Ukraine war). (iii) GPR indices increase the return volatility of WTI and Brent crude oil (H1 accepted), whereas they decrease the return volatility of natural gas (H1 rejected). The negative impact of the natural gas market can be explained by the low supply elasticity in the natural gas market and the fact that it is more stably affected by geopolitical risks due to regional supply contracts. These findings highlight that the effects of geopolitical risks on commodity markets are not homogeneous, as each commodity type responds through distinct mechanisms.

The results examining the impact of geopolitical actions (GPRACT) and geopolitical threat events (GPRTHREAT) on commodity price volatility indicate that both factors influence commodity price fluctuations. However, when analyzed at the commodity group level, (i) the GPRACT index has a more significant impact on the return volatility of silver, corn, coffee, nickel, and natural gas (H2 accepted). (ii) The GPRTHREAT index significantly affects soybean return volatility (H2 rejected). (iii) The return volatility of the remaining commodities is equally affected by both indices. These findings suggest that most commodities are influenced by overall geopolitical risks rather than distinct effects stemming from actions or threats.

The results examining the impact of geopolitical risks on the persistence of commodity return volatility indicate that the hypothesis "Geopolitical risks reduce the persistence of commodity market volatility" (H3) is accepted for all commodity products. Notably, geopolitical risks significantly affect the persistence of return volatility in nickel, lead, and natural gas. While geopolitical risks initially increase volatility, this effect is not long-lasting, suggesting that commodity markets can absorb shocks over time.

These findings reinforce the critical role of GPR in shaping commodity price volatility, with important implications for investors, policymakers, and market participants. They contribute to the existing literature by highlighting the sensitivity of commodity return volatilities to geopolitical risks. The study emphasizes the importance of considering the varying return volatilities of different commodities under GPR. Notably, the distinction between geopolitical actions (GPRACT) and geopolitical threats (GPRTHREAT) have differing effects on commodity market volatility dynamics, offering a critical insight for risk management. This suggests that market participants should consider the overall level of geopolitical risk and the source and nature of the risk when formulating hedging and investment strategies.

Investors operating in commodity futures markets can diversify their portfolios by considering geopolitical risks, enhancing their resilience to market shocks. Policymakers, on the other hand, should develop proactive measures to address potential supply–demand imbalances. From a risk management perspective, monitoring market reactions following geopolitical shocks can facilitate the development of short-term strategies. However, for long-term investors, geopolitical risks do not appear to pose a persistent challenge. Therefore, accurate risk assessment and diversification strategies can enable sound investment decisions during periods of financial uncertainty.

The study relies on publicly available geopolitical risk indices, which may not fully capture all aspects of geopolitical uncertainty. Future research could explore alternative measures, such as sentiment analysis from news sources or geopolitical forecasting models. The EGARCH model effectively captures volatility clustering and asymmetry, but comparisons can be made with alternative econometric frameworks such as Markov-variation models or machine learning approaches. Our study examines broad commodity classes; however, future studies could focus on industry-specific responses, such as the energy sector's dependence on geopolitical disruptions in major oil-producing regions. In future research, the GPR indices created by Caldara and Iacoviello specifically for different countries can be used to study these countries' commodity futures markets. They should explore the dynamic interaction between geopolitical risk, macroeconomic factors, and financial stability, further enriching our understanding of this evolving global phenomenon.

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Appendix A. Returns of Commodity Futures Series

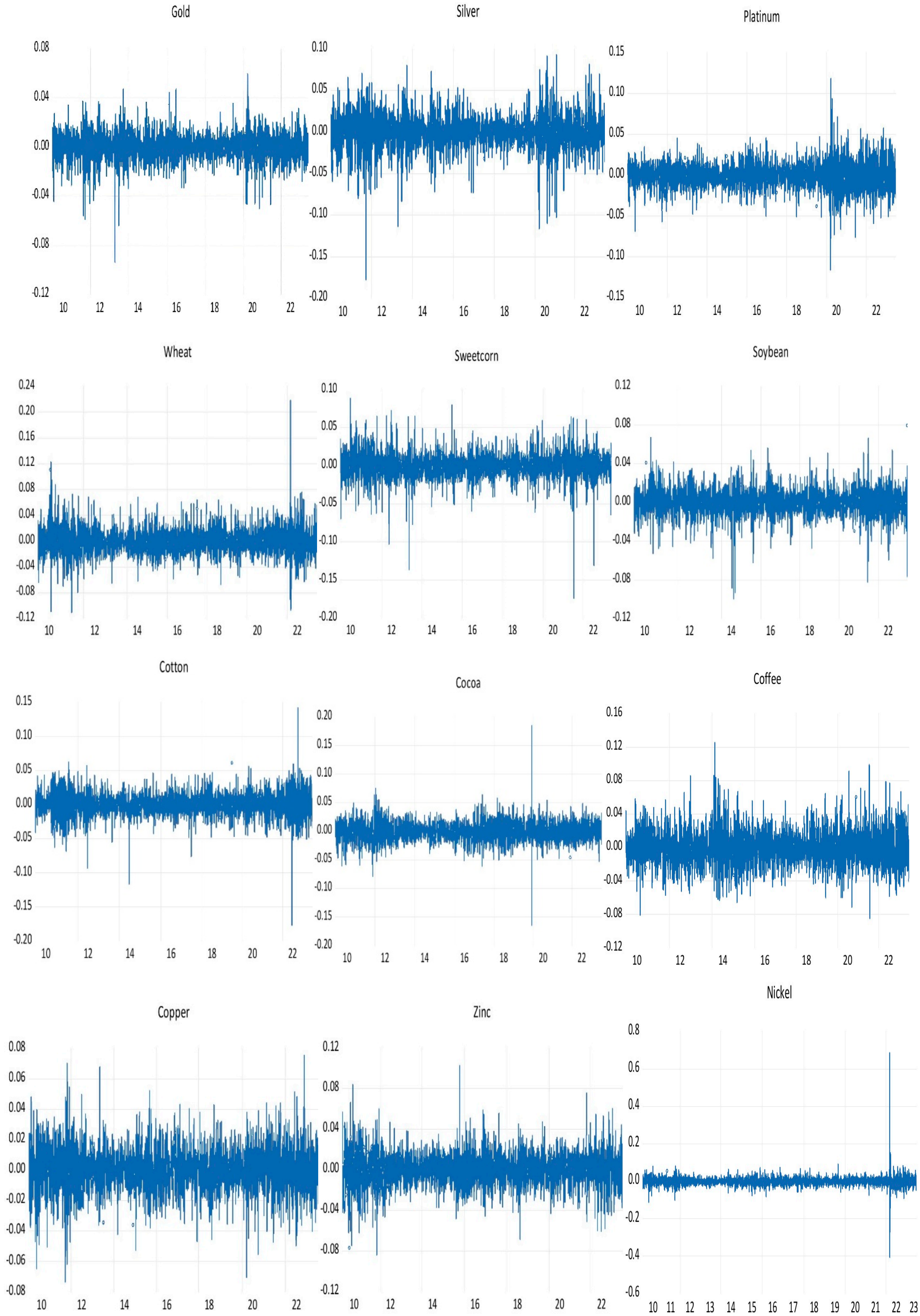

Figure A1. *Cont*.

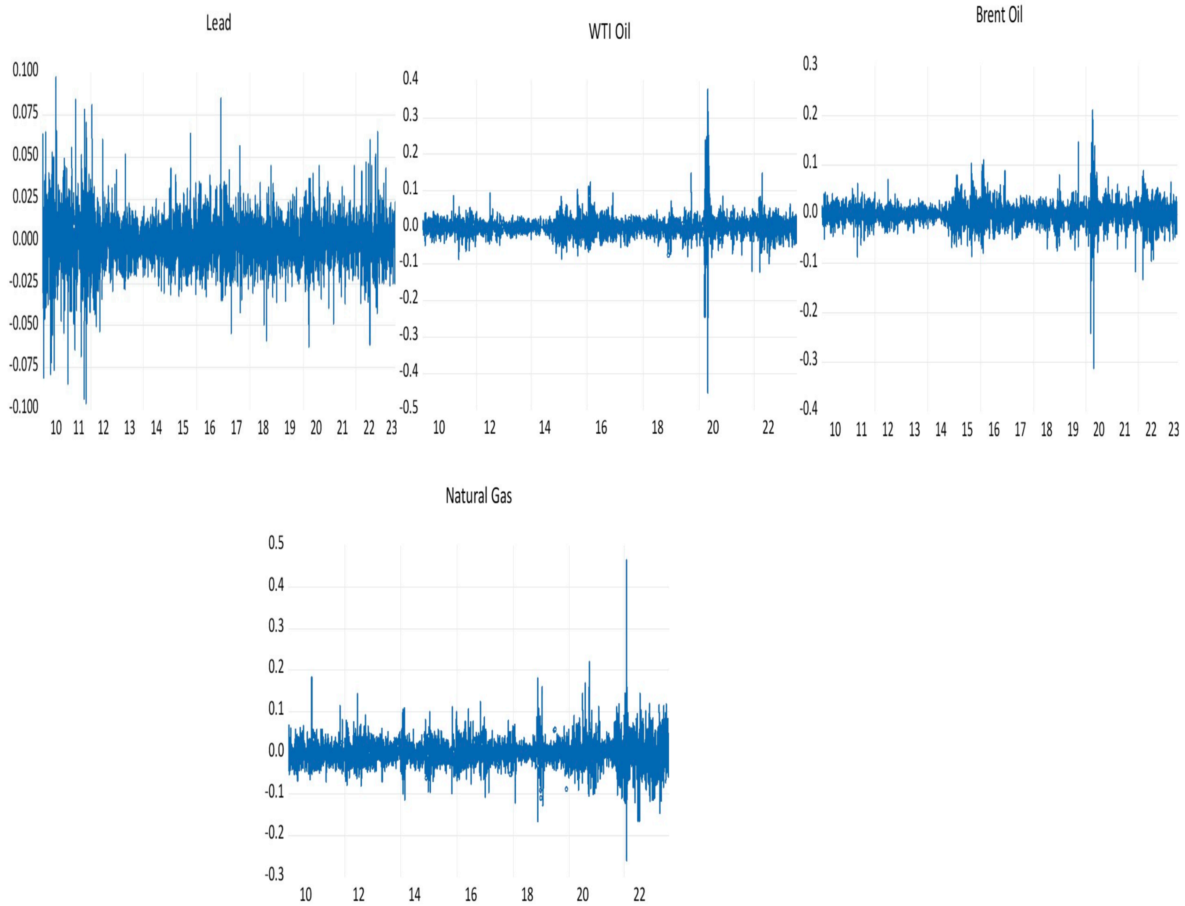

Figure A1. Returns of commodity futures series.

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