Causal Relationship Analysis Between Oil Price Index and Precious Metals Price Index

Fuchun Zhan[1,a,*], Xiangmin Zhang[1,b]

[1]Economics and Management College, China University of Geosciences Beijing, Beijing, China

a. fuchunsureshen@gmail.com, b. zhangxiangmin2001@163.com

*corresponding author

Abstract. This paper examines the relationship between oil prices and precious metals (gold, silver, palladium, and platinum) prices during periods of economic turbulence and geopolitical events. Using discrete wavelet transform technology, the time series data is decomposed to extract new forms of short-term, medium-term, and long-term time series. A vector autoregression (VAR) model is then established to perform Granger causality tests and impulse response analyses between oil prices and precious metals prices. The results indicate that oil, gold, and silver have strong market influence, while platinum and palladium have relatively weaker influence. In the short term, oil has a unidirectional Granger causality effect on gold and silver. In the medium term, oil and gold, as well as oil and silver, exhibit bidirectional Granger causality. In the long term, oil and platinum demonstrate bidirectional Granger causality. Additionally, in the short term, the impulse response between gold, silver, and oil is significant, revealing notable short-term dynamic relationships among these three variables.

Keywords: Granger causality, oil price, precious metals price

1 Introduction

Oil and precious metals are two critical commodity categories in the global economy, and their price fluctuations have profound impacts on the global economy and financial markets. The oil price index reflects the supply and demand conditions in the global oil market, while the precious metals price index typically includes prices of metals such as gold and silver, which are considered safe-haven assets[1]. Studying the causal relationship between the oil price index and the precious metals price index not only helps to understand the market linkages between the two but also provides valuable references for investors and policymakers.

Over the past few decades, the oil and precious metals markets have experienced multiple significant fluctuations, often closely tied to global economic events, geopolitical risks, and changes in monetary policy[2-4]. Notably, the outbreak of the COVID-19 pandemic at the end of 2019 severely impacted the global economy, forcing a halt to production and daily life worldwide. Subsequently, the Russia-Ukraine war erupted in 2021, causing a sharp increase in oil prices as a critical energy resource. At the same time, gold, renowned as a safe-haven asset, maintained consistently high price levels. Therefore, this paper selects data from January 2020 to December 2023 to analyze the causal relationship between the oil price index and the precious metals price index, exploring the dynamic interaction mechanisms between the two and providing market participants with more accurate predictions and decision-making support.

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To comprehensively examine the causal relationship between the oil price index and the precious metals price index time series, this study first applies the discrete wavelet transform method to decompose the time series data into three different forms: short-term, medium-term, and long-term. Then, a VAR model is constructed, followed by Granger causality tests and impulse response analyses. The study investigates the interactions between oil prices and precious metals prices and explores their underlying econometric implications. This research aims to provide a new perspective and methodology for related studies and offer valuable references for practical market operations.

2 Literature Review

Oil and precious metals (such as gold and silver) play critical roles in the global economy. As one of the primary energy sources, oil is vital for global industrial production, transportation, power generation, and household energy supply. The price and supply stability of oil directly impact global economic health and growth[5]. Precious metals are not only widely used in the jewelry and decoration industries but also play essential roles in electronics, healthcare, and other industrial applications. Gold, in particular, is often regarded as the "ultimate safe haven" for currency. During periods of financial market turbulence, gold prices tend to rise as investors view it as a means of value preservation and storage[6]. Fluctuations in the prices of oil and precious metals can influence monetary policy, exchange rates, and global capital flows. The economic instability and shocks caused by the pandemic have led to dramatic fluctuations in oil production and prices.

Granger causality, introduced by economist Clive Granger in 1969[7], is a statistical hypothesis testing method used in time series analysis to determine whether one time series can predict another. In previous studies, many scholars have applied causality analysis to the field of commodity prices, such as oil, and to analyze the macroeconomic factors that influence them.

Many scholars have studied the relationship between oil and precious metals. Li Ting et al.[8] found a significant positive correlation between oil and gold prices, although during certain periods, such as financial crises, the two may exhibit a negative correlation. Y. S. Wang et al.[9] discovered mutual short-term influences between crude oil and gold prices. Liu Jie[10], after analyzing historical data and the factors influencing the relationship between oil and gold prices, observed a synchronous trend between the two prices in the same period, although some factors may cause short-term deviations. Liu Xiangyun et al.[11] reached similar conclusions. Guo Shijie[12] conducted Granger causality tests on oil rents, coal rents, and natural gas rents. Guo Mingyuan[13] used linear Granger causality tests to explore the impact of crude oil prices on China's economy from an industry perspective. C. Gharib et al.[14] studied the causal relationship between crude oil and gold spot prices to assess the economic impact of COVID-19. They identified common mild explosive periods in the WTI and gold markets, as well as bidirectional contagion effects between oil and gold market bubbles during the recent COVID-19 outbreak. Gao Xinwei et al.[15], using classical cointegration theory and VAR models, employed Johansen cointegration tests, ECM, Granger causality tests, and impulse response functions to study the quantitative relationships between international crude oil prices, the real US dollar exchange rate, and global oil rig counts, both pairwise and collectively. Their findings showed that international crude oil prices had a long-term positive impact on oil rig counts, while the real US dollar exchange rate had a long-term negative impact on oil rig counts. T. Liu et al.[16] proposed a new method for calculating time-varying volatility spillover indices using the generalized forecast error variance decomposition of a TVP-VAR-SV model. Chen

Guangying[17], using Johansen cointegration tests, Granger causality tests, impulse response, and variance decomposition, studied the relationship between international oil prices and inflation in China. Ma Duo[18] established a VEC model to investigate the relationships among international gold prices, US Federal Reserve monetary policy, the US dollar index, and oil prices. Gao Hui et al.[19] selected domestic crude oil futures market micro-indicators and renminbi internationalization indicators, using Granger causality tests, cointegration tests, and error correction models to quantitatively study the comprehensive impact of crude oil futures on renminbi internationalization. A. Bossman et al.[1] examined the asymmetric relationship between EU industry stocks and oil during periods of geopolitical turmoil, focusing on oil implied volatility, geopolitical risks, and market sentiment. Z. Dai et al.[20] analyzed the volatility spillover effects and dynamic relationships among WTI crude oil, gold, and China's new energy vehicle, environmental protection, renewable energy, coal, consumer fuel, and high-tech stock markets.

By reviewing relevant studies, it can be observed that most scholars have conducted causality analyses on oil prices and gold prices, while relatively few studies have focused on other precious metals, such as silver and platinum. Therefore, this paper incorporates four types of precious metals into the research scope to conduct an in-depth analysis of the relationship between oil prices and precious metals prices.

3 Research Methods and Data

3.1 Econometric Methods

Stationarity Test. The stationarity test is a method used to examine whether a time series is stationary, specifically testing whether the time series has a unit root (non-stationarity). In this study, two common methods for stationarity testing are employed: the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test.

The Augmented Dickey-Fuller (ADF) test, proposed by Dickey and Fuller in 1979, is used to test whether a time series contains a unit root[21]. A unit root implies that the data exhibit a trend of drift over time, indicating non-stationarity. The basic model for the ADF test is as follows:

$$\Delta Y_t = \alpha + \beta Y_{t-1} + \gamma \Delta Y_{t-1} + \delta_1 \Delta Y_{t-1} + \cdots + \delta_{p-1} \Delta Y_{t-p+1} + \varepsilon_t \tag{1}$$

Where Δ represents the first difference, Y_t is the time series data, α is the intercept, β is the coefficient for the unit root test, γ represents whether there is a time-varying trend in the data. The ADF test evaluates whether the data have a unit root by examining the estimated coefficients. If the coefficient β is sufficiently close to zero, the null hypothesis of a unit root can be rejected, indicating that the data are stationary. The Phillips-Perron (PP) test is another statistical method used to detect unit roots in time series data. It is an improved version of the ADF test, primarily designed to address issues of autocorrelation and heteroskedasticity. The core idea of the PP test is to adjust the error term in the ADF test using non-parametric methods.

Vector Autoregression Model. The Vector Autoregression (VAR) Model, commonly abbreviated as the VAR model, is a widely used econometric model introduced by economist Christopher A. Sims in 1980[22]. The VAR model regresses all current variables in the model on the lagged values of all variables. By adjusting the lag order of the variables, the model regresses each variable on itself and expands the univariate autoregressive model into an autoregressive model composed of multivariate time series variables.

The typical formula for the VAR model is as follows:

$$x_t = \mathrm{c} + \Phi_1 x_{t-1} + \cdots + \Phi_p x_{p-1} + \varepsilon_t \tag{3}$$

Where p≥1, c is a k*1constant vector, Φ_i is a K*K constant matrix, i=1,…,p. ε_t is a vector of white noise.

Before constructing the VAR model, it is essential to determine the order of the model, typically denoted as p. The order of the VAR model determines the number of lag periods included in the model, that is, how many historical periods of data are considered when predicting the current value. Suitable lag orders can be selected using information criteria such as FPE (Final Prediction Error), AIC (Akaike Information Criterion), or BIC (Bayesian Information Criterion), or through empirical methods[23].

The Final Prediction Error (FPE) criterion is a type of information criterion used in selecting time series models. FPE evaluates the performance of time series models with different lag orders to help identify the optimal model order. During the model selection process, FPE values for various lag orders are compared, and the model with the smallest FPE value is chosen as the best model. The specific formula for FPE is as follows:

$$\mathrm{FPE} = \frac{n+p+1}{n-p-1} * \hat{\delta}^2 \tag{2}$$

Where n represents the number of observations in the time series, p denotes the lag order of the model, $\hat{\delta}^2$ is the estimated mean squared error (MSE) of the model, typically calculated using the residual variance from the model estimates. FPE aims to strike a balance between the model's goodness-of-fit and its complexity. Specifically, a smaller FPE value indicates better performance of the model in fitting the data. However, increasing the model order may lead to overfitting, where the model becomes overly complex and fits the noise in the data rather than its underlying patterns. Thus, FPE provides a method to balance fit quality and model complexity, aiding in the selection of an appropriate model order. In time series analysis, different model orders are usually tested, and the FPE value is calculated for each. The model with the smallest FPE value is selected as the optimal model. This approach ensures that the chosen model fits the data well without being excessively complex, thereby avoiding overfitting.

Granger Causality Test. The Granger Causality Test is a statistical method used to examine the causal relationship between time series. It is based on the principle of Granger causality, which states that if one time series can predict changes in another time series, the former is considered to have a causal influence on the latter. In practice, the Granger Causality Test is often used to determine whether one time series can effectively explain the variations in another time series. Granger causality indicates that the changes in one set of time series are caused by the changes in another set of time series.

The model for the Granger Causality Test is as follows:

$$x_t = \alpha_i + \sum_{m=1}^{p} \beta_m x_{t-m} + \sum_{m=1}^{p} \beta_m y_{t-m} + \varepsilon_t$$

$$y_t = \gamma_i + \sum_{m=1}^{p} \delta_m y_{t-m} + \sum_{m=1}^{p} \beta_m x_{t-m} + \varepsilon_t \tag{4}$$

$$H_0 = \beta_1 = \beta_2 = \cdots = \beta_p = 0$$

$$H_1 = \gamma_1 = \gamma_2 = \cdots = \gamma_i = 0$$

Where p is the lag order, $\alpha, \beta, \gamma, \delta$ are regression coefficients. The null hypothesis tests whether the past values of X provide no predictive information for the future values of Y. If only one of the two hypotheses is rejected, it indicates a unidirectional causal relationship between X and Y. If both hypotheses are rejected, it implies a bidirectional causal relationship between X and Y. If neither hypothesis is rejected, it suggests that there is no causal relationship between X and Y. Thus, Granger causality represents a dynamic correlation, indicating whether one variable has the predictive ability to explain changes in another variable.

For unidirectional causality, If the test rejects H_0 but does not reject H_1, it indicates that the explanatory variable Y influences the dependent variable X, meaning that Y has a causal impact on X. Conversely, if H_1 is rejected but H_0 is not, it implies that the explanatory variable X influences the dependent variable Y, meaning X has a causal impact on Y.

For bidirectional causality, If the test simultaneously rejects both H_0 and H_1, it indicates that a bidirectional causal relationship exists between the two variables. This means that changes in the X variable lead to changes in the Y variable, and changes in the Y variable, in turn, influence the X variable.

For no causal relationship, If the test fails to reject both H_0 and H_1, it suggests that there is no causal relationship between X and Y, indicating that the two variables are independent of each other.

Impulse Response. Impulse Response is an important tool for analyzing the dynamics of a VAR model. It describes the dynamic response of each variable in the system when the system is subjected to a unit shock (or impulse).

$$Y_t = \mathrm{c} + \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t \tag{5}$$

Based on the VAR model described above, suppose a unit shock is applied to the j-th variable at time t, meaning that the corresponding position in the j-th column is set to 1 while all other positions are set to 0. At time t, the responses of all variables can be expressed as:

$$IRF_{j,t} = \sum_{i-0}^{t} A_j^{\mathrm{icj}} \tag{6}$$

Where $IRF_{j,t}$ represents the impulse response value of the j-th variable at time t, A_j^i is the i-th power of the j-th column of matrix $A_j(A_j^0 = I_k$, the identity matrix), cj is the j-th element of c, representing the initial shock applied to the j-th variable.

Discrete Wavelet Transform. The Discrete Wavelet Transform (DWT) is a signal processing technique used to decompose signals into frequency components at different scales. The principle of DWT is based on multi-resolution analysis, which decomposes a signal into approximation coefficients and detail coefficients to analyze its characteristics across varying levels of detail. DWT leverages the multi-resolution property of signals by breaking them down into frequency components at different scales, progressively revealing the signal's features from coarse to fine detail. It employs low-pass and high-pass filters to filter the signal, extracting approximate and detailed components. A downsampling operation is then applied to the filtered signal to reduce data size while preserving key information. DWT decomposes a signal into approximation coefficients and detail coefficients at various levels, and the original signal can be reconstructed using the inverse DWT.

$$c_{j,k} = \sum_n x[n]\psi_{j,k}[n] \quad (7)$$

Where $c_{j,k}$ are the wavelet coefficients, $x[n]$ is the original signal, $\psi_{j,k}[n]$ is the discrete wavelet function, j is the scale parameter, k is the translation parameter.

3.2 Research Data and Preliminary Statistical Results

Variable Selection and Descriptive Statistics. When selecting variables, data availability and general applicability were considered. For oil prices, the WTI Crude Oil Price Index (West Texas Intermediate) was chosen. For precious metals prices, daily closing price data from the LBMA (London Bullion Market Association) were used.

Table 1. Variable Selection and Descriptions

Variables type	Name of variables	Symbol used
Oil Price Index	WTI Crude Oil Price Index	WTI
Precious Metals Price Index	LBMA GOLD Price Index	GOLD
	LBMA SILVER Price Index	SILV
	LBMA PLATINUM Price Index	PLATNUM
	LBMA PALLADIUM Price Index	PALLDINUM

The data range spans from January 1, 2020, to December 29, 2023, providing 996 observations after aligning the datasets based on the variable with the least number of statistical days. The return rates for each index were calculated as $R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100$.

Due to the COVID-19 pandemic outbreak in 2019, the global economy faced significant disruptions, with production and daily life coming to a standstill. Between June 2019 and June 2020, the five variables experienced considerable volatility. In 2021, the outbreak of the Russia-Ukraine war caused oil prices, as a critical energy resource, to surge rapidly. Meanwhile, gold, known as a safe haven, maintained consistently high price levels.

Descriptive statistical analysis was conducted on the logarithmic returns of each variable.

Table 2. Summary Statistics

Variables	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
WTI	-0.0896193	4.145673	-42.58324	28.13821	-1.124619	31.9311
GOLD	-0.0315905	1.075057	-5.775362	5.113959	.245111	6.734884
SILVER	-0.0292777	2.219736	-8.917675	12.31422	.4257005	7.425141
PLATINUM	-0.0011889	2.162738	-9.931355	13.61363	.2689621	6.385696
PALLADIUM	0.0597958	2.962721	-18.62702	22.91715	.3443576	10.48247

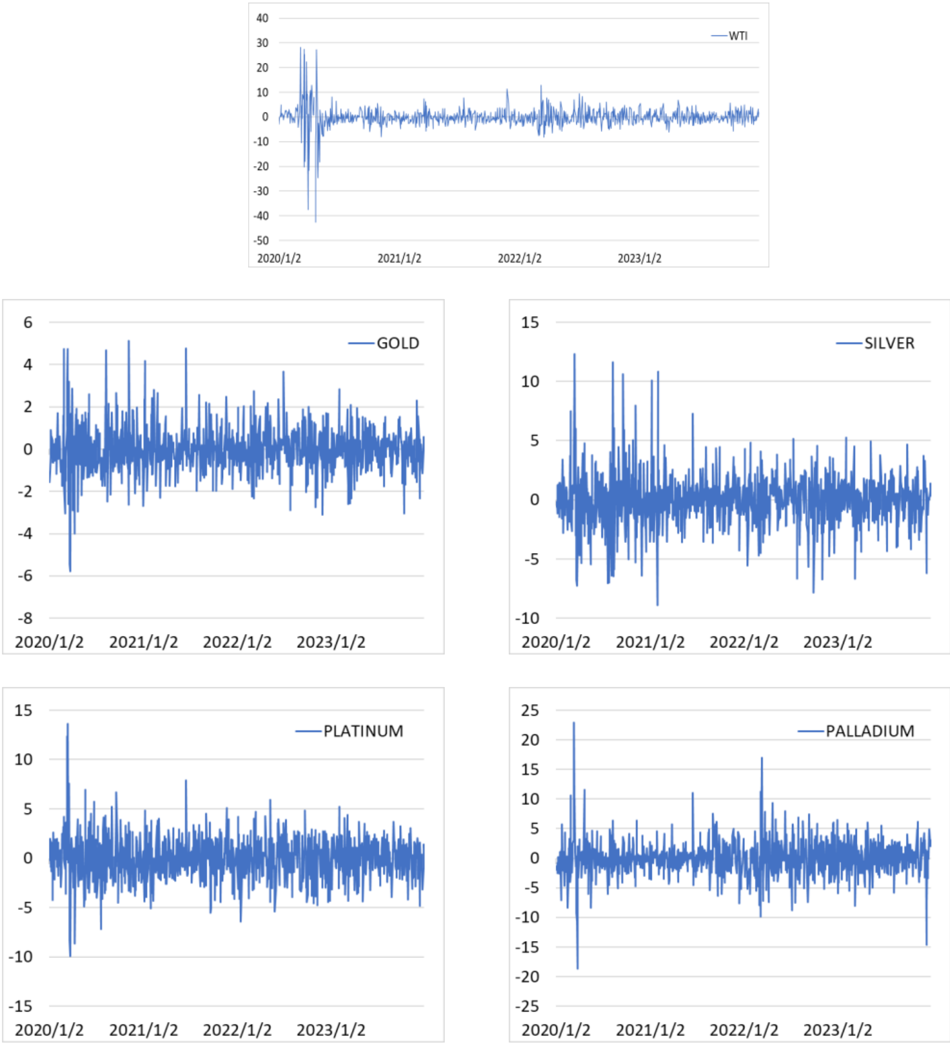


Fig. 1. Statistical Chart of Log-Transformed Data

Unit Root Test Results. Before processing time series data, it is essential to determine whether the data constitute stationary time series to avoid spurious regression issues in subsequent analysis. Therefore, this study conducts a unit root test on the data for oil prices and precious metals prices before analyzing their causal relationships. The test ensures that all variables are stationary before they are used for further analysis.

The Augmented Dickey-Fuller (ADF) unit root test is employed in this study, with the optimal lag order selected based on the Akaike Information Criterion (AIC). If the test results reject the null hypothesis of a unit root, the data are deemed stationary. For non-stationary variables, differencing is applied to transform the time series into stationary ones. The unit root test results show that all variables are stationary, allowing for subsequent wavelet correlation and causality analyses.

Table 3. Unit Root Test Results

Variables	WTI	GOLD	SILVER	PLATINUM	PALLADIUM
Adf	-33.070***	-31.301***	-31.360***	-29.749***	-27.356***
PP	-33.101***	-31.342***	-31.372***	-29.738***	-27.249***

Note: *** indicates significance at the 0.01 level, ** at the 0.05 level, and * at the 0.1 level.

Correlation Analysis

Table 4. Correlation Matrix

Variables	WTI	GOLD	SILVER	PLATINUM	PALLADIUM	WTI
WTI	1					
GOLD	0.1051*	1				
SILVER	0.1712***	0.7760***	1			
PLATINUM	0.1746***	0.5578***	0.6322***	1		
PALLADIUM	0.1798***	0.3766***	0.4600***	0.5667***	1	

4 Results and Discussion

4.1 Continuous Wavelet Transform

The data were decomposed using wavelet analysis into three scales: short-term (1–2 days), medium-term (3–4 days), and long-term (7–8 days). The decomposed results are presented in Figures 2–4:

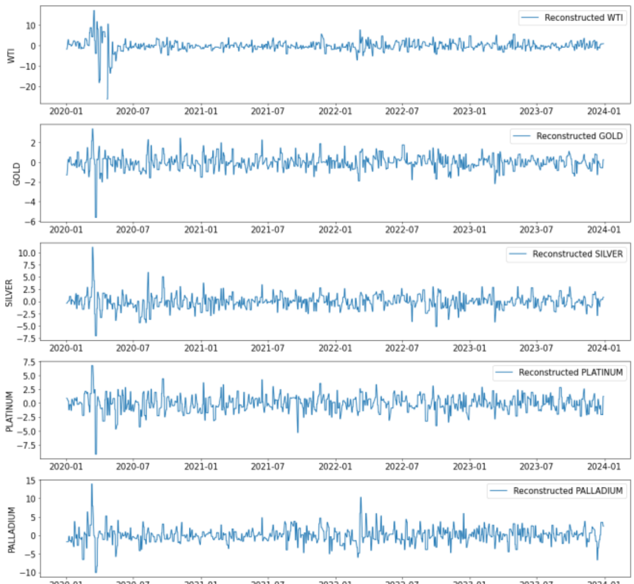


Fig. 2. Results of Short-Term Wavelet Decomposition

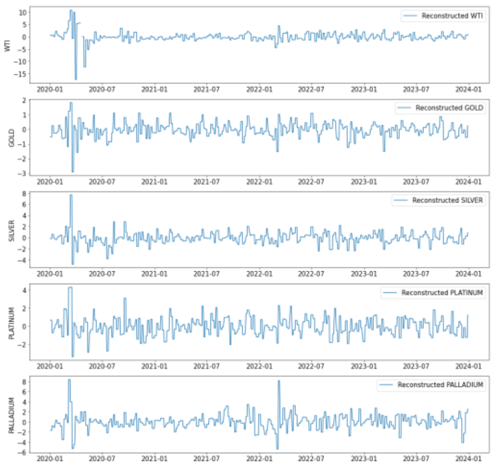


Fig. 3. Results of Medium-Term Wavelet Decomposition

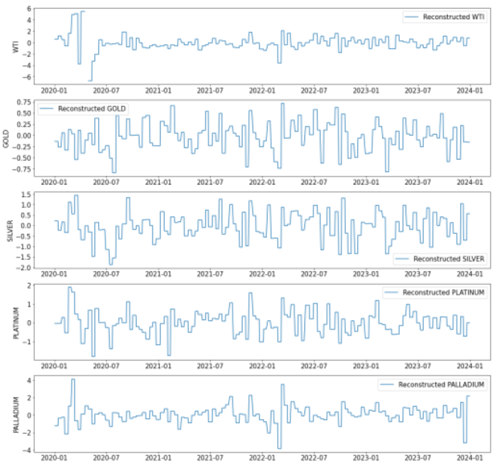


Fig. 4. Results of Long-Term Wavelet Decomposition

4.2 Granger Causality

Using the ADF and PP tests, it was confirmed that the time series for all five variables are stationary. Therefore, Granger causality tests can be conducted directly without the need for cointegration tests. Granger causality is used to determine whether one time series can predict the future values of another. The causal relationships between stationary time series can be analyzed directly using Granger causality tests.

VAR Model. The VAR model established in this study includes five variables. The specific VAR formula is as follows:

$$\Delta lnWTI_t = \alpha_0 + \sum_{i=1}^{k} \alpha_{1i}\, \Delta lnGOLD_{t-i} + \sum_{i=1}^{k} \alpha_{2i}\, \Delta lnSILV_{t-i} + \sum_{i=1}^{k} \alpha_{3i}\, \Delta lnPLAT_{t-i} + \sum_{i=1}^{k} \alpha_{4i}\, \Delta lnPALL_{t-i} + \mu_{1t} \tag{8}$$

$$\Delta lnGOLD_t = \beta_0 + \sum_{i=1}^{k} \beta_{1i}\, \Delta lnWTI_{t-i} + \sum_{i=1}^{k} \beta_{2i}\, \Delta lnSILV_{t-i} + \sum_{i=1}^{k} \beta_{3i}\, \Delta lnPLAT_{t-i} + \sum_{i=1}^{k} \beta_{4i}\, \Delta lnPALL_{t-i} + \mu_{2t} \tag{9}$$

$$\Delta lnSILV_t = \gamma_0 + \sum_{i=1}^{k} \gamma_{1i}\, \Delta lnGOLD_{t-i} + \sum_{i=1}^{k} \gamma_{2i}\, \Delta lnWTI_{t-i} + \sum_{i=1}^{k} \gamma_{3i}\, \Delta lnPLAT_{t-i} + \sum_{i=1}^{k} \gamma_{4i}\, \Delta lnPALL_{t-i} + \mu_{3t} \tag{10}$$

$$\Delta lnPLAT_t = \delta_0 + \sum_{i=1}^{k} \delta_{1i}\, \Delta lnGOLD_{t-i} + \sum_{i=1}^{k} \delta_{2i}\, \Delta lnSILV_{t-i} + \sum_{i=1}^{k} \delta_{3i}\, \Delta lnWTI_{t-i} + \sum_{i=1}^{k} \delta_{4i}\, \Delta lnPALL_{t-i} + \mu_{4t} \tag{11}$$

$$\Delta lnPALL_t = \varepsilon_0 + \sum_{i=1}^{k} \varepsilon_{1i}\, \Delta lnGOLD_{t-i} + \sum_{i=1}^{k} \varepsilon_{2i}\, \Delta lnSILV_{t-i} + \sum_{i=1}^{k} \varepsilon_{3i}\, \Delta lnPLAT_{t-i} + \sum_{i=1}^{k} \varepsilon_{4i}\, \Delta lnWTI_{t-i} + \mu_{5t} \tag{12}$$

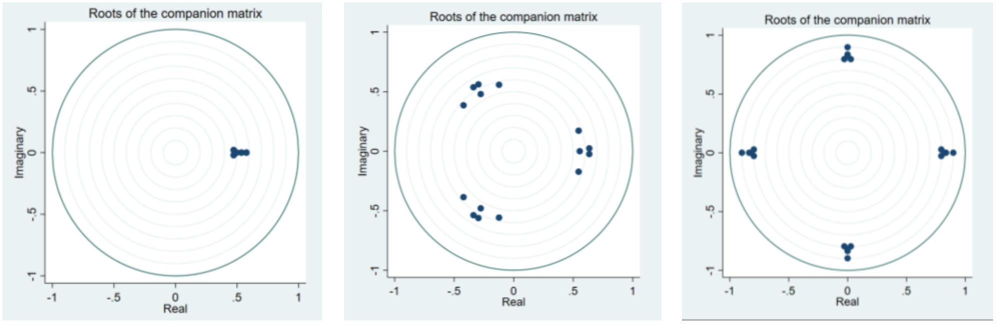
Where Δ represents the logarithmic difference of the time series, indicating the return rate. K is the optimal lag order, determined through statistical testing. t represents the time period. α_0, β_0, γ_0, δ_0, ε_0 are constants in the equations for the five variables. μ_{1t}, μ_{2t}, μ_{3t}, μ_{4t}, μ_{5t} are uncorrelated error terms with zero mean.

For the decomposed short-term, medium-term, and long-term data, lag order tests were conducted again: Short-term: Optimal lag order = 1. Medium-term: Optimal lag order = 3. Long-term: Optimal lag order = 4. Stability tests and impulse response analyses were then performed based on these lag orders.

Table 5. VAR Model Results

Period	Equation	RMSE	R-sq	chi2	P>chi2
Short-term	wti	2.36603	0.3131	438.5885	0
	gold	0.652383	0.2715	358.5682	0
	silver	1.27394	0.3242	461.5452	0
	platinum	1.31767	0.2718	358.9921	0
	palladium	1.84426	0.3036	419.3436	0
Medium-term	wti	2.12992	0.0737	76.08472	0
	gold	0.520489	0.0492	49.49378	0
	silver	1.15347	0.0487	48.91123	0
	platinum	1.036	0.0474	47.57889	0
	palladium	1.53894	0.0501	50.43206	0
Long-term	wti	1.10863	0.3234	453.9792	0
	gold	0.295153	0.2107	253.6583	0
	silver	0.604083	0.2494	315.7081	0
	platinum	0.570296	0.2331	288.7322	0
	palladium	0.927895	0.1849	215.5255	0

To verify the stability of the Vector Autoregression (VAR) model established in this study, the inverse roots of the characteristic polynomial were plotted. If all inverse roots are distributed within the unit circle, the model is considered stable and suitable for further impulse response analysis. As shown in Figure 6, all eigenvalues of the VAR model lie within the unit circle, indicating that the established VAR system is stable.



(a) Short-term (b) Medium-term (c) Long-term

Fig. 5. VAR System Stability Test

Granger Causality Analysis. This section compares the short-term, medium-term, and long-term causal relationships among variables to observe consistent patterns or variations. Before conducting the Granger causality test, all variable sequences must be stationary. If a variable sequence is non-stationary, it should be differenced to achieve stationarity. In the Granger causality test, Equation represents the dependent variable being predicted, and Excluded refers to the variable being tested as a potential Granger cause.

In the short term, the following significant causal relationships are observed: Oil has a significant causal relationship with gold, silver, and palladium. Gold exhibits a significant causal relationship with oil and silver. Silver shows a significant causal relationship with oil and palladium. Platinum has a significant causal relationship with gold and silver. All variables demonstrate significant causal relationships with oil, gold, silver, and platinum. In the medium term, the relationships are similar: Oil maintains a significant causal relationship with gold, silver, and palladium. Gold continues to exhibit a significant causal relationship with oil and silver. Silver retains a significant causal relationship with oil and palladium. Platinum still demonstrates a significant causal relationship with gold and silver. All variables show significant causal relationships with oil, gold, silver, and platinum. In the long term, the relationships shift slightly: Oil has a significant causal relationship with gold, platinum, and silver. Platinum shows a significant causal relationship with gold and palladium. All variables demonstrate significant causal relationships with oil and platinum. The overall significance of the model highlights that when all variables are considered, they exhibit complex dynamic relationships with one another.

Table 6. Granger Causality Test Results

Equa-tion	Exclu-ded	Short-term	Medi-um-term	Long-term	Equation	Exclu-ded	Short-term	Medium-term	Long-term
wti	gold	***	***		platinum	wti			***
wti	silver	***	**		platinum	gold	*		**
wti	platinum			***	platinum	silver	**		

Table 6. (continued).

wti	palladium		***	*	platinum	palladium		***	**
wti	ALL	***	***	**	platinum	ALL		**	***
gold	wti		**	*	palladium	wti			
gold	silver	*	***		palladium	gold			
gold	platinum				palladium	silver			
gold	palladium		**		palladium	platinum			
gold	ALL	*	***		palladium	ALL			
silver	wti		**	**					
silver	gold								
silver	platinum								
silver	palladium		**						
silver	ALL		***	*					

Impulse Response Analysis. Impulse response graphs illustrate how a shock (impact variable) to one variable affects another variable (response variable) over time. Each graph displays an impact variable, a response variable, and the changes in the response variable over time steps.

From the short-term impulse response graphs (Figure 6), the following observations can be made: Self-Responses: All five commodities show a gradual reduction in their self-responses over time, eventually converging to zero. Gold: Exhibits a small and insignificant response to shocks from platinum, palladium, and silver. Shows a larger and significant response to shocks from oil, with the confidence interval not including zero, indicating a notable impact. Silver: Displays small and insignificant responses to shocks from gold, platinum, and palladium. Shows a larger and significant response to shocks from oil, with the confidence interval not including zero, indicating a notable impact. Palladium: Exhibits small and insignificant responses to shocks from gold, platinum, silver, and oil, with confidence intervals including zero, indicating no significant impact. Platinum: Demonstrates small and insignificant responses to shocks from gold, palladium, silver, and oil, with confidence intervals including zero, indicating no significant impact. Oil: Shows a small and insignificant response to shocks from gold, platinum, and palladium. Displays a larger response to shocks from silver.

The medium-term (Figure 7) and long-term (Figure 8) impulse response results are largely consistent with the short-term findings: Gold: Shows significant responses to shocks from oil and silver. Oil and Silver: Show significant responses to shocks from each other. The other variables (platinum and palladium) maintain small and insignificant responses to shocks from most variables, with confidence intervals including zero.

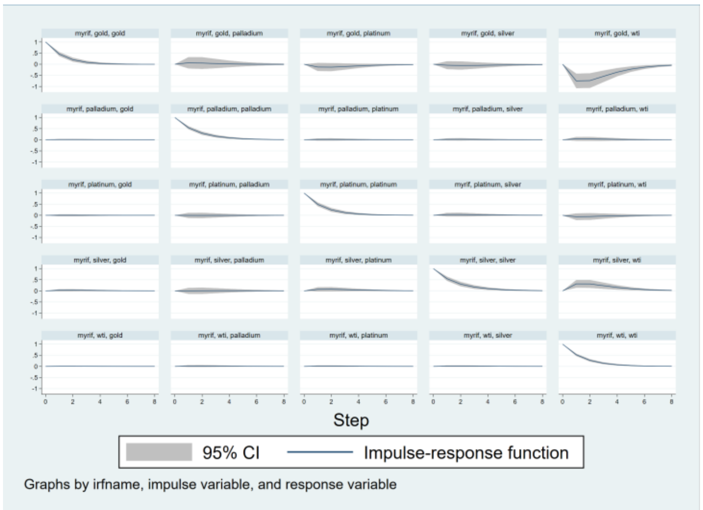


Fig. 6. Short-Term Impulse Response Results

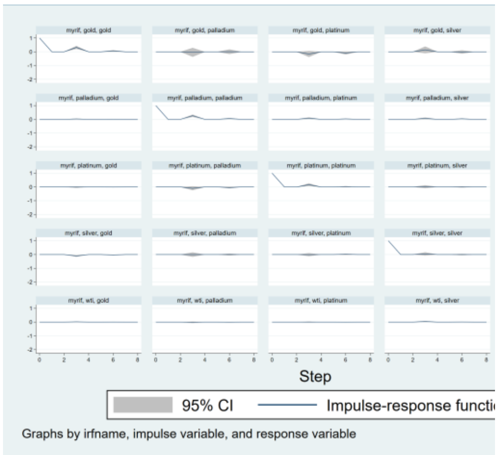


Fig. 7. Medium-Term Impulse Response Results

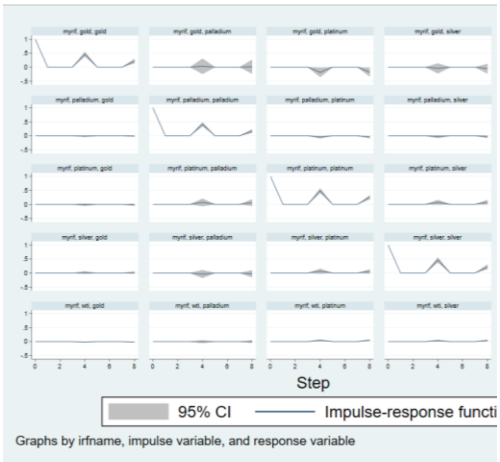


Fig. 8. Long-Term Impulse Response Results

5 Conclusion

Oil and precious metals are not only critical commercial commodities but also key factors influencing the global economy, geopolitics, and financial markets. Understanding their economic significance is essential for predicting market trends, formulating policies, and making strategic investment decisions.

This study analyzed the price indices of five commodities to explore the relationships between oil and precious metals during periods of economic turbulence and geopolitical events.

Using Discrete Wavelet Transform (DWT), the time series were decomposed into short-term, medium-term, and long-term components. A Vector Autoregression (VAR) model was then constructed to conduct Granger causality tests and impulse response analyses for oil and precious metal prices.

The results reveal the following: Oil exhibits significant causal relationships with several variables across short-term, medium-term, and long-term horizons, particularly with gold and silver. Gold and platinum also show significant causal relationships with other variables during different time periods. In the short term, oil has a unidirectional Granger causality with gold and silver. In the medium term, oil and gold, as well as oil and silver, display bidirectional Granger causality. In the long term, oil and platinum exhibit bidirectional Granger causality. Overall, oil, gold, and silver demonstrate strong market influence, whereas platinum and palladium show relatively weaker effects. In the short term, impulse response analyses reveal significant dynamic relationships among gold, oil, and silver, particularly for the impacts of gold on oil, silver on oil, and oil on silver. Conversely, the relationships among other variables are weaker or insignificant.

Future research could further explore the dynamic changes in the relationship between oil and precious metals during different economic periods. Analyzing the effects of varying policies and shifts in the global economic environment on these relationships would provide valuable insights for promoting stable global economic development.

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