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# Dynamic interdependence between gold and oil markets: Evidence from multivariate time-series analysis (2007–2026)

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**Abstract:** Commodity markets play a central role in global financial systems, with gold and crude oil representing strategic assets characterized by distinct economic functions and responses to market uncertainty. This study examines the dynamic interdependence between gold and oil markets using daily observations from 2007 to 2026. Gold is represented by SPDR Gold Shares, while West Texas Intermediate (WTI) and Brent crude oil are considered as major oil benchmarks. Daily logarithmic returns are analyzed using descriptive statistics, correlation analysis, Augmented Dickey–Fuller tests, Vector Autoregression (VAR), Impulse Response Functions (IRFs), and Forecast Error Variance Decomposition (FEVD). The findings reveal heterogeneous and asymmetric relationships across the commodity markets. While significant short-run transmission effects emerge between gold and WTI returns, cross-market shocks generally dissipate rapidly, indicating limited persistence. Gold remains comparatively insulated from energy-market disturbances, whereas WTI exhibits greater responsiveness to gold-market shocks. Overall, the evidence suggests that gold–oil interdependence is predominantly short-term and asymmetric rather than persistent. These findings contribute to understanding commodity-market transmission mechanisms and provide implications for portfolio diversification, risk management, and investment decision-making.

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## 1. Introduction

Commodity markets play a fundamental role in the global financial system by influencing investment decisions, inflation expectations, industrial production, and portfolio risk management. Among internationally traded commodities, crude oil and gold occupy particularly important positions because they perform distinct yet complementary economic functions. Crude oil serves as a primary input for industrial production, transportation, and economic growth, making its price highly sensitive to changes in global demand, geopolitical developments, and supply disruptions. Gold, in contrast, is widely regarded as a safe-haven asset and store of value that attracts investors during periods of financial uncertainty, inflationary pressure, and heightened market volatility. Consequently, understanding the interactions between these two strategic commodities has become increasingly important for investors, policymakers, and researchers seeking to evaluate market integration, risk transmission, and diversification opportunities.

Growing financial integration and repeated episodes of global economic disruption have substantially increased interest in the dynamic relationships between commodity markets. Previous studies demonstrate that the strength and direction of interactions between gold and oil are not constant over time but vary across investment horizons, market conditions, and major economic events. Stronger interdependence is frequently observed during periods of financial crises, geopolitical conflicts, and elevated market uncertainty, suggesting that commodity markets respond differently under normal and turbulent conditions (Bonato et al., 2020; Cevik et al., 2018; Raggad & Bouri, 2023; Tran et al., 2026).

Recent research has increasingly adopted advanced econometric techniques to capture the complexity of commodity market interactions. Wavelet analysis, Dynamic Conditional Correlation GARCH (DCC-GARCH), BEKK-GARCH, quantile connectedness, transfer entropy, and time-varying Granger causality have revealed that relationships among commodity prices exhibit considerable nonlinearities, asymmetries, and frequency-dependent characteristics. These studies consistently report that spillovers intensify during extreme market conditions, while connectedness generally weakens during relatively stable economic periods. Furthermore, evidence suggests that crude oil frequently acts as a major transmitter of shocks, whereas gold alternates between transmitting and absorbing market disturbances depending on the prevailing economic environment and investment horizon (Lee et al., 2023; Shang & Hamori, 2024; Torun, 2025; Uddin et al., 2018; Yang et al., 2025).

Despite this growing body of literature, empirical evidence remains mixed regarding the magnitude, persistence, and direction of interactions between gold and oil markets. Some studies report substantial return and volatility spillovers, particularly during periods of global financial stress and geopolitical crises, whereas others find relatively weak or highly time-dependent relationships. These inconsistent findings suggest that the interdependence between the two markets remains sensitive to the choice of methodology, sample period, benchmark oil price, and frequency of analysis (Bonato et al., 2020; Raggad & Bouri, 2023; Sahadudheen & Kumar, 2025).

Most existing studies primarily emphasize volatility spillovers, nonlinear dependence, or multiscale connectedness using sophisticated econometric frameworks. While these approaches provide valuable insights into evolving market dynamics, relatively fewer studies offer a comprehensive assessment of the short-run transmission mechanisms between gold and oil returns using a conventional multivariate time-series framework that combines descriptive analysis, stationarity testing, Vector Autoregression (VAR), Impulse Response Functions (IRFs), and Forecast Error Variance Decomposition (FEVD). Such an integrated framework remains valuable because it provides transparent evidence regarding lagged transmission effects, dynamic shock propagation, and the relative importance of internal and external sources of market variability.

Accordingly, this study investigates the dynamic relationship between gold and oil markets using daily observations covering the period from 2007 to 2026. Specifically, the analysis examines historical price behaviour, return characteristics, statistical dependence, stationarity, dynamic interactions, shock transmission, and forecast error variance decomposition between gold and two major international crude oil benchmarks. By combining descriptive analysis with multivariate time-series techniques, this study seeks to determine whether the observed co-movements between gold and oil represent persistent market interdependence or merely temporary short-run adjustments driven by changing economic conditions. The findings contribute to the literature by providing updated evidence spanning multiple episodes of global financial instability, including the Global Financial Crisis, the COVID-19 pandemic, and recent geopolitical disruptions, thereby offering useful implications for investors, portfolio managers, and policymakers concerned with commodity market integration and risk management.

## 2. Materials and Methods

### 2.1 Data

This study examines the dynamic relationship between gold and crude oil markets using daily financial market data covering the period from January 2007 to 2026. Gold prices are represented by the SPDR Gold Shares (GLD), while crude oil markets are represented by the West Texas Intermediate (WTI) and Brent Crude Oil Futures, which together capture the two principal international oil benchmarks. The sample period encompasses several major episodes of global economic and geopolitical uncertainty, including the Global Financial Crisis, the European sovereign debt crisis, the COVID-19 pandemic, and recent geopolitical conflicts, thereby providing a comprehensive environment for evaluating commodity market interactions. Daily closing prices were obtained from publicly available financial market databases. To ensure comparability across assets with different price levels, all analyses were conducted using continuously compounded logarithmic returns rather than raw price levels. Daily log returns were calculated as:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100 \qquad (1)$$

where $P_t$ denotes the closing price on trading day $t$. Logarithmic returns are widely used in financial econometrics because they stabilize the variance, facilitate statistical inference, and reduce non-stationarity commonly observed in asset price series.

### 2.2 Descriptive Analysis

The empirical analysis begins with descriptive statistics to summarize the principal characteristics of the return distributions. Measures including the mean, standard deviation, minimum, maximum, quartiles, skewness, kurtosis, and the Jarque–Bera statistic are reported to evaluate central tendency, dispersion, distributional asymmetry, tail behaviour, and deviations from normality. Historical price series and daily return plots are also presented to provide an initial visual assessment of market behaviour, volatility clustering, and potential co-movement between gold and crude oil prices over the sample period (Table 1).

### 2.3 Correlation Analysis

To provide preliminary evidence regarding the association between commodity markets, Pearson correlation coefficients were computed using daily logarithmic returns. Scatter plots were additionally employed to visualize the strength and direction of the linear relationship between gold and oil prices. Although correlation provides an initial measure of contemporaneous association, it does not establish dynamic dependence or predictive relationships. Consequently, further multivariate time-series analysis is required to investigate the transmission of shocks between markets.

### 2.4 Stationarity Testing

Before estimating the multivariate time-series model, the stationarity properties of each return series were evaluated using the Augmented Dickey–Fuller (ADF) unit root test. The ADF test examines whether a series contains a stochastic trend by testing the null hypothesis of a unit root against the alternative hypothesis of stationarity. Since Vector Autoregressive (VAR) models require stationary variables to avoid spurious estimation, the ADF procedure serves as an essential diagnostic before model estimation. Rejection of the null hypothesis indicates that the return series fluctuate around a stable mean and variance, satisfying the assumptions necessary for subsequent dynamic modelling.

### 2.5 Vector Autoregressive Model

Dynamic interactions between gold and crude oil returns were examined using a Vector Autoregressive (VAR) model. The VAR framework treats each variable as endogenous, allowing current returns to depend on their own past values as well as the lagged values of the other variables within the system. This approach captures feedback effects and dynamic interdependence without imposing strong theoretical restrictions regarding causal direction. The general VAR($p$) specification is expressed as:

$$\mathrm{Y}_t = \mathrm{c} + \sum_{i=1}^{p} \mathrm{A}_i \, \mathrm{Y}_{t-i} + \varepsilon_t \tag{2}$$

where $\mathrm{Y}_t$represents the vector of return series, cis a vector of constants, $\mathrm{A}_i$denotes coefficient matrices associated with lag $i$, and $\varepsilon_t$is the vector of innovation terms. The optimal lag length was determined using standard information criteria, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan–Quinn Information Criterion (HQIC), and Final Prediction Error (FPE). Based on these criteria, the selected lag order was subsequently used for all dynamic analyses.

### 2.6 Impulse Response Analysis

Following VAR estimation, Impulse Response Functions (IRFs) were employed to evaluate how unexpected shocks originating in one commodity market propagate through the system over subsequent periods. IRFs trace the temporal adjustment path following a one-standard-deviation innovation while holding the remaining structural relationships constant. This analysis enables the identification of both the magnitude and persistence of cross-market transmission effects and illustrates whether market disturbances dissipate rapidly or generate prolonged responses across commodities.

### 2.7 Forecast Error Variance Decomposition

To complement the impulse response analysis, Forecast Error Variance Decomposition (FEVD) was conducted to quantify the proportion of forecast uncertainty attributable to own-market shocks and shocks originating from other markets within the VAR system. Variance

decomposition provides additional insight into the relative importance of internal and external sources of market variability over different forecast horizons. High own-market variance contributions indicate relatively independent market dynamics, whereas larger cross-market contributions suggest stronger interdependence and information transmission between commodity markets.
All statistical analyses were conducted using Python. Data preprocessing, descriptive statistics, econometric estimation, and graphical visualizations were implemented using widely adopted scientific computing libraries for financial time-series analysis, ensuring the reproducibility and transparency of the empirical results.

## 3. Results

### 3.1 Historical Price Behavior

Figure 1 presents the historical evolution of Gold and oil prices across the primary volatile sub-period of 2016 to 2026 for visual clarity, while the broader econometric analysis utilizes the full 2007 to 2026 sample framework. Because the assets differ substantially in price magnitude, separate vertical axes are used to improve interpretability and avoid visual compression of lower-valued series. The figure demonstrates that gold and oil exhibit notably different long-term price dynamics, suggesting that their underlying economic drivers are not identical. Oil prices display stronger cyclical behavior and greater short-term volatility, while gold follows a comparatively smoother long-term appreciation path. From 2016 to 2019, oil experienced sustained upward momentum, reflecting stronger economic conditions and increased energy demand. During the same period, gold remained relatively stable with modest appreciation, suggesting limited contemporaneous integration between the markets.

A substantial structural disruption emerges in 2020. Oil prices experienced an abrupt decline followed by recovery, whereas gold moved upward during the same interval. This divergence reflects the differing economic roles of the commodities: oil is closely linked to industrial activity and demand expectations, while gold frequently functions as a defensive asset during periods of uncertainty. Between 2021 and 2022, both markets entered a temporary recovery phase and demonstrated periods of positive co-movement. However, this relationship weakened again after 2023 as oil experienced renewed instability while gold entered a stronger upward trend. Overall, historical price movements indicate that although periods of co-movement exist, a stable long-run relationship is not visually apparent. Consequently, further econometric analysis is required to determine whether statistical interdependence exists beyond descriptive observation.

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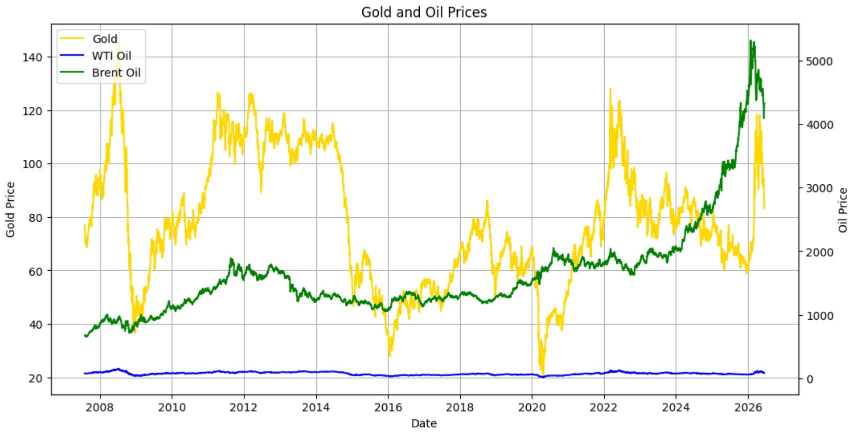


Figure 1. Historical Prices

**Note.** Daily closing prices are shown in USD. Gold prices are represented by SPDR Gold Shares and oil prices by Brent Oil Futures. Separate y-axes are used due to differences in scale and should not be interpreted as indicating comparable rates of change. The figure focuses on the 2016–2026 timeline for visual clarity and is intended for descriptive analysis only and does not establish causality or predictive relationships between variables.

### 3.2 Return Dynamics and Distribution Characteristics

To evaluate short-run market behavior independent of long-term price trends, price levels were transformed into daily logarithmic returns. All return series fluctuate around zero, providing preliminary evidence of stationarity and enabling comparison of short-run market volatility across commodities. Most observations remain concentrated around their average values; however, periods of elevated volatility are visible throughout the sample. These visual variations are robustly supported by the descriptive statistics presented in Table 1. Average daily returns remain relatively close to zero across all markets, a pattern standard in financial return time series. However, the standard deviations reveal distinctly different levels of underlying risk exposure. West Texas Intermediate (WTI) exhibits the highest short-run variability ($SD$ = 2.740), followed closely by Gold ($SD$ = 2.381), while Brent crude demonstrates a substantially lower overall dispersion ($SD$ = 1.156). Furthermore, WTI records an exceptionally high kurtosis (*17.464*), signaling significant fat-tail risk and a higher probability of extreme market corrections compared to the other assets.

Distributional measures indicate departures from normality. Negative skewness observed in gold and Brent suggests a greater frequency of downside movements, while elevated kurtosis across all series indicates heavier tails and a higher likelihood of extreme outcomes than expected under a normal distribution. Jarque–Bera statistics strongly reject normality assumptions across all return series. These findings support the use of econometric methods designed to accommodate financial data characteristics including volatility clustering and non-normal distributions.

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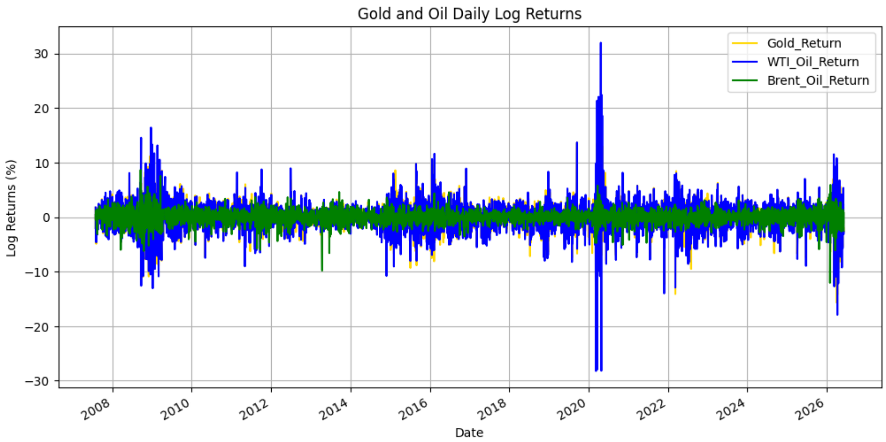



Figure 2. Daily Log Returns

**Note.** The figure displays daily logarithmic returns calculated from commodity closing prices. Log returns are expressed as percentages and computed as the first difference of the natural logarithm of consecutive price observations. Positive values indicate price increases relative to the previous trading period, while negative values indicate price declines. Values centered around zero indicate that the transformed series fluctuate around a stable mean over time.

Table 1. Descriptive Statistics

| Statistic | Gold Return (%) | WTI Oil Return (%) | Brent Oil Return (%) |
|---|---|---|---|
| Observations | 4,687 | 4,687 | 4,687 |
| Mean | 0.012 | 0.016 | 0.040 |
| Standard Deviation | 2.381 | 2.740 | 1.156 |
| Minimum | -27.575 | -28.221 | -12.066 |
| 25th Percentile | -1.041 | -1.247 | -0.490 |
| Median | 0.074 | 0.089 | 0.048 |
| 75th Percentile | 1.166 | 1.315 | 0.632 |
| Maximum | 19.077 | 31.963 | 8.643 |
| Skewness | -0.496 | 0.005 | -0.534 |
| Kurtosis | 8.988 | 17.464 | 7.487 |
| Jarque–Bera Statistic | 15,929.98 | 59,429.72 | 11,142.30 |
| Jarque–Bera p-value | <0.001 | <0.001 | <0.001 |

**Note**. Returns are calculated as daily logarithmic percentage changes. The Jarque–Bera (JB) test evaluates departure from normality; p-values below 0.05 indicate rejection of the null hypothesis of normally distributed returns.

### 3.3 Preliminary Dependence Analysis

Initial examination of market relationships was conducted using scatter plots and correlation analysis. The scatter plot of price levels suggests a weak positive association with considerable dispersion around the fitted trend line. In contrast, return-based correlation analysis reveals a highly benchmark-specific structure; a substantially stronger contemporaneous relationship is observed exclusively between Gold and WTI returns ($r$ = 0.88), suggesting intense short-run co-movement between precious metals and US domestic crude benchmarks. Conversely, the contemporaneous association between Gold and Brent returns remains notably weak ($r$ = 0.16). These findings imply that levels of market integration differ across commodity groups. However, correlation measures contemporaneous association only and cannot determine predictive influence or causal transmission.

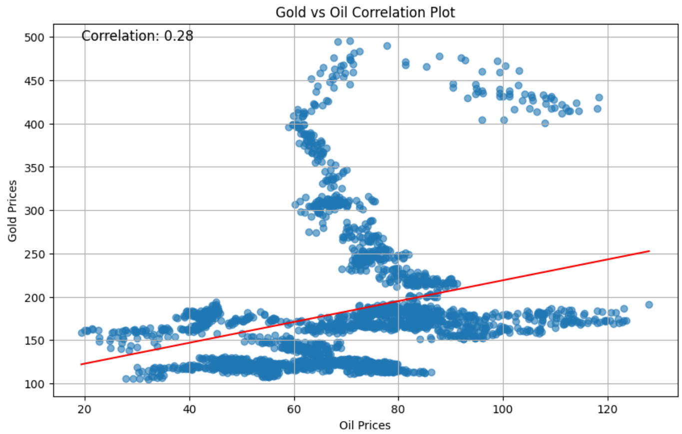
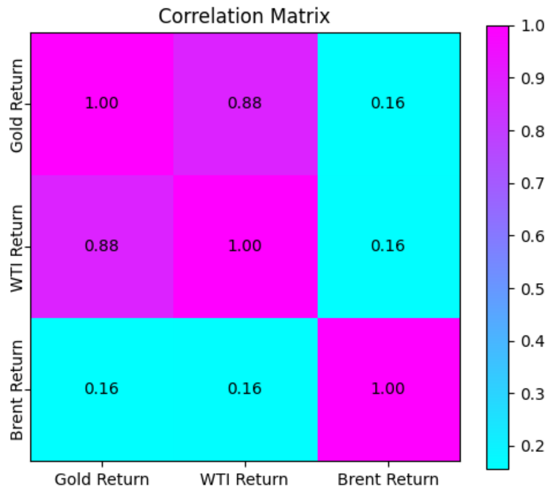



Figure 3. Scatter Plot

**Note.** The figure displays a scatter plot of daily gold and oil price observations with a fitted linear trend line. The reported correlation coefficient measures the strength and direction of the linear association between variables. Correlation values closer to +1 indicate stronger positive relationships, values closer to −1 indicate stronger negative relationships, and values near zero indicate weak linear association. The observed relationship should not be interpreted as evidence of causality.

Figure 4. Correlation Matrix




**Note.** Values represent Pearson correlation coefficients calculated using daily logarithmic returns. Correlation coefficients range from −1 to +1, where values closer to ±1 indicate stronger linear relationships.

### 3.4 Stationarity and Model Specification

Before estimating dynamic relationships, stationarity testing was performed using the Augmented Dickey–Fuller (ADF) procedure. All return series rejected the null hypothesis of a unit root at conventional significance levels, indicating stationarity. This confirms that transformed returns fluctuate around a stable mean and variance and therefore satisfy a key assumption required for multivariate time-series modelling. Because all asset series are stationary in their first-differenced log return formats, as confirmed by the highly significant ADF test statistics exceeding critical thresholds, the subsequent lag selection criteria are evaluated directly on daily returns to avoid spurious regression. Lag-order selection criteria produced mixed recommendations. Although AIC and FPE suggested longer lag structures, BIC and HQIC selected a more parsimonious specification. To balance explanatory power and model simplicity, a VAR(3) specification was selected for subsequent analysis. Although lower information criterion values were observed at higher lag lengths, the VAR(3) specification was selected to preserve model parsimony while adequately capturing short-run market dynamics.

Table 2. ADF Results

| Test Statistic | Gold Return | WTI Oil Return | Brent Oil Return |
|---|---|---|---|
| ADF Statistic | -15.009 | -12.053 | -69.302 |
| p-value | <0.001 | <0.001 | <0.001 |
| Stationarity Decision | Stationary | Stationary | Stationary |

**Note.** The Augmented Dickey–Fuller (ADF) test was conducted to assess stationarity of the return series. The null hypothesis assumes the presence of a unit root (non-stationarity). Rejection of the null hypothesis at conventional significance levels indicates that the series is stationary.

Table 3. Lag Selection

| Lag | AIC | BIC | FPE | HQIC |
|---|---|---|---|---|
| 0 | 2.247 | 2.249 | 9.456 | 2.248 |
| 1 | 2.242 | 2.250 | 9.408 | 2.244 |
| 2 | 2.231 | 2.245 | 9.312 | 2.236 |
| 3 | 2.219 | **2.238** | 9.194 | **2.225** |
| 4 | 2.219 | 2.244 | 9.200 | 2.228 |
| 5 | 2.219 | 2.249 | 9.198 | 2.230 |
| 6 | 2.216 | 2.252 | 9.175 | 2.229 |
| 7 | 2.216 | 2.257 | 9.166 | 2.230 |
| 8 | 2.214 | 2.260 | 9.149 | 2.230 |
| 9 | 2.212 | 2.264 | 9.132 | 2.230 |
| 10 | **2.209** | 2.267 | **9.103** | 2.229 |

**Note.** AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; FPE = Final Prediction Error; HQIC = Hannan–Quinn Information Criterion. Lower values indicate preferred model specifications.

### 3.5 Dynamic Market Interactions: VAR Estimation

The VAR(3) estimation provides strong empirical evidence of short-run interactions and lag transmission dynamics between commodity markets. Looking at the Gold Return equation, first-lagged WTI crude returns exert a statistically significant positive effect ($\beta = 0.095$, $p < 0.001$), demonstrating an immediate, short-run transmission running from energy markets into precious metals. Conversely, the transmission from precious metals back to energy markets operates with an asymmetric, delayed momentum. In the WTI Oil Return equation, a positive shock in Gold returns exerts a short-lived, statistically insignificant negative drag at the first lag ($\beta = -0.052$, $p = 0.143$). However, a powerful reversal occurs over a multi-day horizon: Gold returns at lag 2 ($\beta = 0.164$, $p < 0.001$) and lag 3 ($\beta = 0.092$, $p = 0.011$) exert highly significant positive predictive effects on WTI returns. This demonstrates that while immediate cross-market shocks from gold to oil are initially muted or slightly negative, a pronounced positive momentum systematically develops after a two-to-three-day operational lag.

Table 4. Vector Autoregression (VAR(3)) Estimation Results for Gold and WTI Oil Returns

| **Dependent Variable** | **Variable** | **Coefficient** | **Std. Error** | **t-statistic** | **p-value** |
|---|---|---|---|---|---|
| Gold Return | Const | 0.009967 | 0.034740 | 0.287 | 0.774 |
| | **L1.Gold_Return** | **-0.122974** | 0.031201 | **-3.941** | **0.000** |
| | **L1.WTI_Oil_Return** | **0.094971** | 0.027147 | **3.498** | **0.000** |
| | L2.Gold_Return | 0.055447 | 0.031191 | 1.778 | 0.075 |
| | L2.WTI_Oil_Return | -0.045003 | 0.027083 | -1.662 | 0.097 |

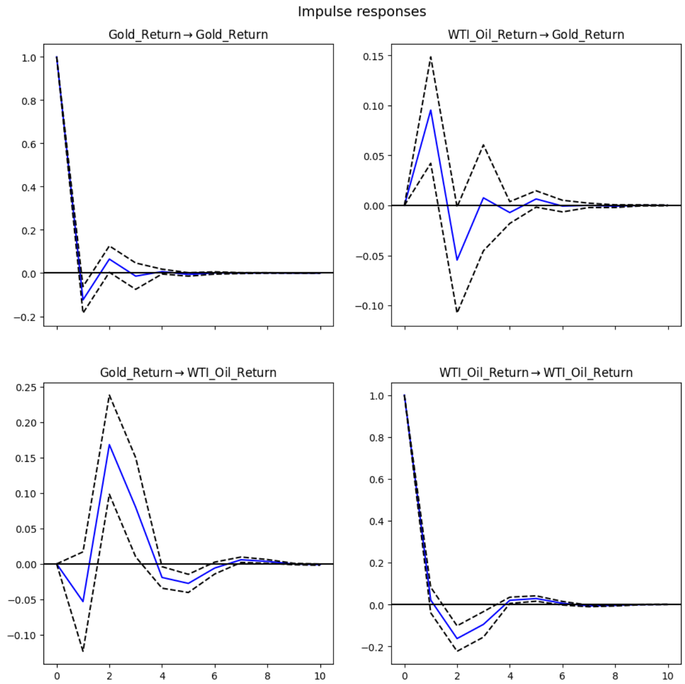
| | | | | | |
|---|---|---|---|---|---|
| | L3.Gold_Return | -0.017703 | 0.031222 | -0.567 | 0.571 |
| | L3.WTI_Oil_Return | 0.012222 | 0.027188 | 0.450 | 0.653 |
| WTI Oil Return | Const | 0.015264 | 0.039874 | 0.383 | 0.702 |
| | L1.Gold_Return | -0.052450 | 0.035811 | -1.465 | 0.143 |
| | L1.WTI_Oil_Return | 0.021511 | 0.031158 | 0.690 | 0.490 |
| | **L2.Gold_Return** | **0.163940** | 0.035800 | **4.579** | **0.000** |
| | **L2.WTI_Oil_Return** | **-0.157474** | 0.031085 | **-5.066** | **0.000** |
| | **L3.Gold_Return** | **0.091664** | 0.035835 | **2.558** | **0.011** |
| | **L3.WTI_Oil_Return** | **-0.105753** | 0.031205 | **-3.389** | **0.001** |

**Note**. L1–L3 represent lag periods in the VAR(3) model. Bold values indicate statistical significance at $p < .05$. Coefficients represent estimated effects of lagged returns on current-period returns. Negative coefficients indicate inverse relationships, while positive coefficients indicate direct relationships. Note that while Brent Crude returns are utilized in subsequent impulse response and variance decomposition horizons to check baseline consistency across alternative energy benchmarks, they are omitted from this primary VAR estimation matrix due to the exceptionally weak contemporaneous correlation highlighted in preliminary baseline testing.

### 3.6 Shock Transmission and Persistence

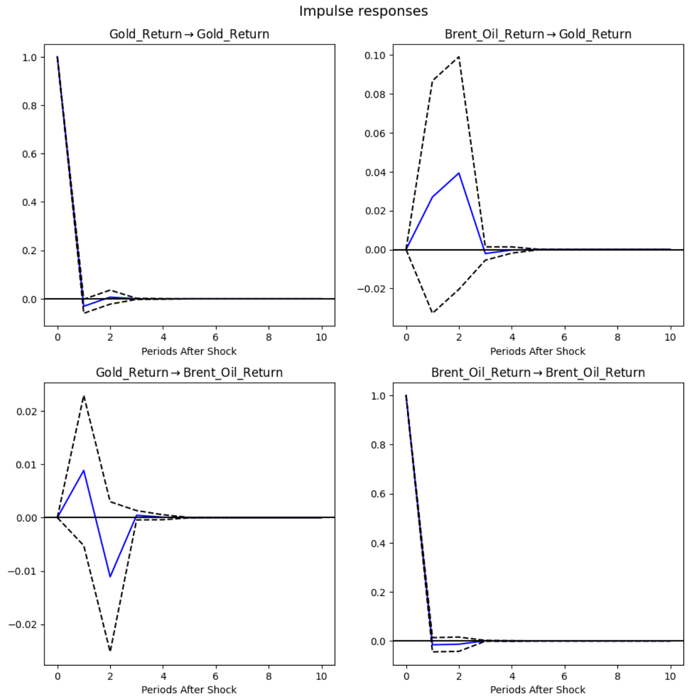
Impulse Response Functions (IRFs) were estimated to evaluate how shocks propagate across markets over time. Results show that each market responds most strongly to shocks originating within itself. These own-market effects decline rapidly and converge toward equilibrium within several forecast periods, suggesting limited persistence. Cross-market responses are present but considerably smaller. Oil shocks generate temporary responses in gold returns, while gold shocks produce comparatively modest adjustments in oil markets. When Brent oil is examined separately, transmission effects appear weaker and dissipate more quickly. The rapid convergence of responses toward zero supports the VAR findings and indicates limited long-run persistence of cross-market shocks. Overall, IRFs indicate that commodity market disturbances are predominantly short-lived and that both markets adjust rapidly following external shocks.

Figure 5. Impulse Response Functions for Gold and WTI Oil Returns



**Note.** The figure reports impulse response functions estimated from a VAR(3) model using daily logarithmic returns for Gold and WTI oil. Solid lines represent estimated responses following a one-standard-deviation shock, while dashed lines indicate approximate confidence intervals. The horizontal axis represents forecast periods after the shock and the vertical axis represents response magnitude. Responses converging toward zero indicate diminishing shock effects over time.

Figure 6. Impulse Response Functions for Gold and Brent Oil Returns

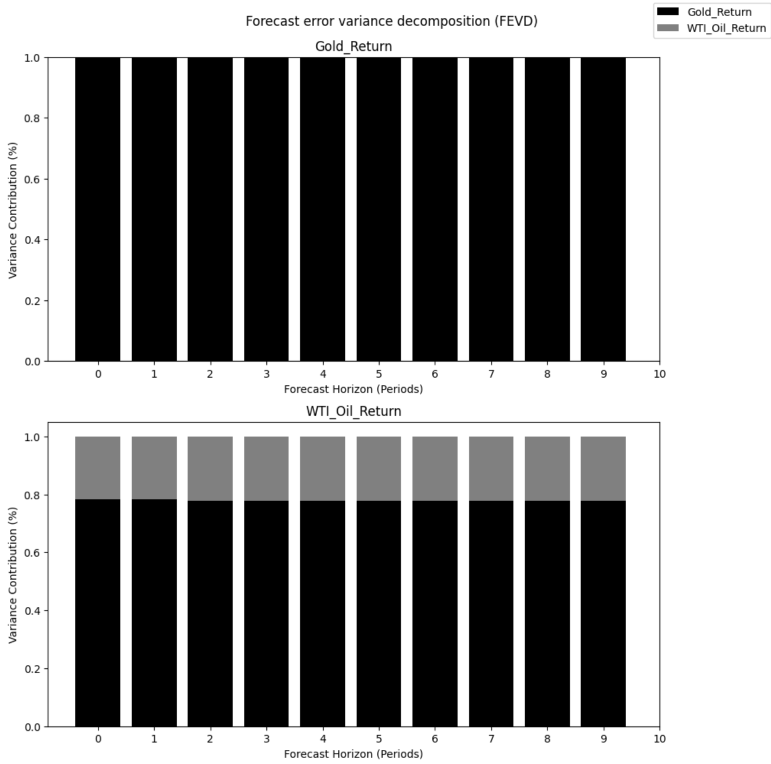



**Note.** Impulse response functions were estimated using a VAR(3) specification based on daily logarithmic returns. Solid lines represent estimated responses to a one-standard-deviation shock and dashed lines represent confidence intervals. The horizontal axis shows forecast periods after the initial shock and the vertical axis measures response magnitude. Responses converging toward zero indicate diminishing effects of shocks over time.

### 3.7 Forecast Error Variance Decomposition

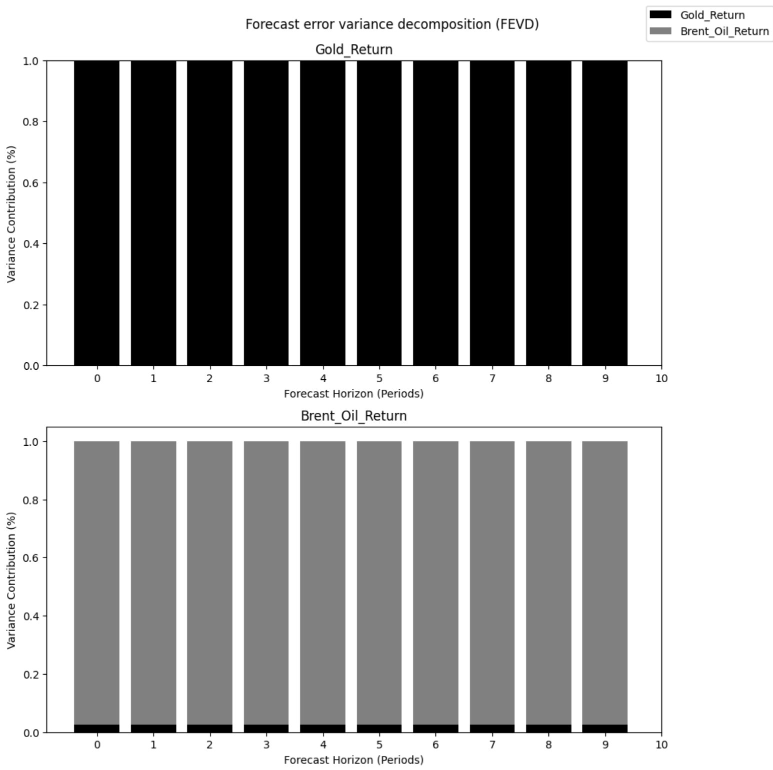
Forecast Error Variance Decomposition (FEVD) was used to determine the proportion of future variability attributable to internal and external shocks. FEVD results indicate that gold returns remain entirely internally driven, with own-market shocks accounting for approximately 100% of their forecast error variance across all horizons. Conversely, WTI returns exhibit a striking susceptibility to external shocks, with gold market disturbances accounting for an estimated 78% of WTI's forecast variance, leaving own-market shocks to explain only the remaining 22% of energy return variance. Variance contributions stabilize relatively quickly, suggesting that the importance of each shock source becomes established early in the adjustment process. These findings indicate asymmetric interdependence across commodity markets, where gold appears comparatively insulated while oil markets demonstrate greater responsiveness to external information.

Figure 7. Forecast Error Variance Decomposition for Gold and WTI Returns




**Note.** Daily closing prices in USD (2016–2026). Left axis: Gold (SPDR Gold Shares); right axis: Oil (Brent Futures). Scales differ by asset class; movements reflect descriptive historical trends and do not imply direct mathematical parity.

Figure 8. Forecast Error Variance Decomposition for Gold and Brent Returns



**Note**. Daily logarithmic returns (%) for Gold, WTI Oil, and Brent Oil from 2007 to 2026. The series fluctuate around a stable mean of zero, satisfying preliminary stationarity conditions. The distinct variance profiles highlight the differing risk exposures between precious metals and energy benchmarks, notably the higher extreme-value susceptibility of domestic WTI relative to international Brent crude.

## 4. Discussion

Collectively, the results suggest that relationships between gold and oil markets are dynamic, asymmetric, and largely short-run in nature. Although visual inspection and correlation analysis reveal periods of co-movement, econometric results indicate that these interactions weaken over time and do not imply persistent long-run dependence. Gold demonstrates characteristics consistent with its role as a defensive asset, while oil remains more sensitive to cyclical and external economic conditions. The evidence further highlights the importance of distinguishing correlation from causation. Observed associations reflect contemporaneous movement rather than direct predictive influence. The significant delayed positive transmission running from lagged Gold returns to WTI crude returns yields distinct macroeconomic implications. Crude oil functions as a primary driver of global industrial production and transport costs; spikes in energy prices typically signal impending inflationary pressures. Because gold operates fundamentally as a structural inflation hedge and safe-haven asset, macro-investors systematically bid up precious metals during early stages of global economic uncertainty or when anticipating inflation.

The subsequent multi-day delayed positive reaction in WTI suggests that early price movements in the gold market function as a leading indicator for broader commodity capital reallocations, explaining the statistical significance of the second-and third-order VAR coefficients. From a portfolio management perspective, these findings suggest that gold may retain diversification benefits despite periods of observed co-movement with oil markets, particularly over longer investment horizons. Limitations of this analysis include reliance on daily data, omission of broader macroeconomic controls, and assumptions embedded within VAR methodology. Nevertheless, the results provide evidence that commodity market interactions are not uniform and that dynamic relationships vary across forecast horizons and market conditions.

## 5. Conclusion

This study examined the relationship between gold and oil markets using descriptive and multivariate econometric techniques. The findings indicate that although periods of co-movement exist, market interactions are predominantly short-term, delayed, and asymmetric. Gold remains structurally insulated from energy shocks, retaining its independent role as a safe-haven asset, whereas WTI oil returns exhibit a heavy, multi-day delayed dependence on past gold shocks, highlighting gold's capacity to act as a leading macroeconomic indicator for industrial commodity reallocations. Future research may extend this framework by incorporating additional macroeconomic variables, volatility models, or higher-frequency market data to improve understanding of commodity market transmission mechanisms.

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