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Research paper

The Role of Commodities and Institutional Investors in Shaping Stock Market Trends

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Abstract

In the complex landscape of financial markets, understanding the relationship between commodities and institutional investments is crucial for shaping effective investment strategies. Commodities—such as crude oil, gold, silver, and other primary goods—play a pivotal role not only as essential inputs in manufacturing but also as reliable hedges against inflation, especially during periods of economic uncertainty. Their movements often echo across broader financial markets, influencing investor sentiment and stock market behavior. This research paper explores the interplay between key commodities (crude oil, gold, silver) and institutional investments (FII and DII) to assess their collective impact on market volatility, specifically in the context of the NSE. Drawing on data from 2012 to 2024, the study employs BVAR, VAR, and ARMA models to analyze patterns and forecast volatility. The findings reveal strong interdependence among these variables, with shifts in commodity prices significantly influencing the NSE index. These insights highlight the intricate yet critical connections between commodity markets, institutional flows, and stock market performance. The paper also delves into the strategic implications of these dynamics for investors and policymakers alike.

Keywords: *Variance decomposition, Impulse Response Function, Financialization of Commodities, Volatility, VAR, ARMA*

1. Introduction

In today's complex financial world, understanding how commodities and institutional investments interact is incredibly important. These two areas are closely linked and together influence how markets behave, how investors make decisions, and even how the broader economy performs.

Commodities—which include things like oil, gold, agricultural products, and metals—are basic goods that people buy and sell. They are essential for manufacturing and often serve as a hedge against inflation, meaning they can protect against the loss of purchasing power when prices rise. Because of this, commodities tend to attract attention especially during uncertain economic times. On the other side, institutional investments come from large organizations such as pension funds, insurance companies, mutual funds, and hedge funds. These institutions manage huge sums of money and have a strong influence on the financial markets due to their strategic and large-scale investing. What makes this relationship so interesting is how changes in commodity prices affect institutional investors and, through them, the stock market. For example, when oil prices rise, businesses often face higher costs, which can squeeze their profits and cause stock prices to fall. On the flip side, when commodity prices drop, consumers may feel more confident and spend more, helping to lift stock market values. Institutional investors often include commodities in their portfolios because commodities tend to behave differently than stocks. This difference means commodities can help reduce overall risk and stabilize returns—acting as a safety net when the stock market is shaky. They also watch commodity trends as clues about the economy's future. For instance, if gold prices surge, it might signal that investors are worried about economic stability, leading institutions to rethink their stock investments.

However, this close connection can sometimes increase market ups and downs. Big swings in commodity prices—caused by events like geopolitical tensions, natural disasters, or supply chain issues—can quickly prompt institutional investors to change their strategies. These rapid shifts can create ripple effects across stock markets, particularly impacting industries heavily dependent on commodities, such as energy and materials. Adding to the complexity, advanced technologies like algorithmic and high-frequency trading help institutions react faster to commodity price changes. While this can create opportunities, it can also amplify the speed and intensity of market fluctuations. Overall, the interplay between commodities and institutional investments is a key driver of market trends and investor behavior. For anyone involved in markets, whether individual investors, policymakers, or analysts—grasping these relationships is vital for making informed decisions and promoting stable economic growth. In an increasingly interconnected global economy, this dynamic will continue to shape both day-to-day market moves and long-term financial developments.

2. Conceptual Framework:

The conceptual framework of this research is built around the dynamic interaction between key macroeconomic and market variables that influence stock market volatility. It suggests that fluctuations in the stock market are closely tied to the movements of Foreign Institutional Investments (FII) and Domestic Institutional Investments (DII), which often reflect both global and domestic investor sentiment. Commodities like gold and silver, traditionally seen as safe-haven assets, tend to exhibit an inverse or delayed relationship with market volatility, especially during periods of uncertainty. Crude oil prices, widely regarded as indicators of economic health and production costs, also play a significant role by affecting inflation and shaping investor expectations. By examining these interrelated factors, this framework seeks to better understand and forecast market volatility, offering deeper insights into how external economic shifts influence stock market behavior (Rani, 2021; Verma, 2023; Sireesha, 2013; Sreeya, 2022; Kumar et al., 2023).

The paper focuses on crude oil, gold, and silver because these commodities play a critical and multifaceted role in shaping financial market dynamics, especially in the context of stock markets like the NSE (National Stock Exchange of India):

- **Crude Oil**: Crude oil is a globally traded commodity that has a significant impact on inflation, interest rates, and overall economic activity. Oil price fluctuations can directly influence corporate earnings, transportation costs, and even policy decisions, making it a key macroeconomic variable that investors and policymakers closely watch. As the analysis in the paper suggests, oil market stability also has broader implications for sustainable development and firm-level behavior, such as inventory management and risk mitigation.
- **Gold**: Gold is traditionally regarded as a *safe-haven* asset. During periods of economic uncertainty or market volatility, investors often turn to gold to hedge against inflation and currency risks. Gold prices are influenced by geopolitical events, central bank policies, and investor sentiment, making it highly relevant for understanding risk transmission and portfolio diversification.
- **Silver**: Silver, while also considered a precious metal like gold, is unique due to its dual role—as both an investment asset and an industrial input. Silver prices are affected by macroeconomic factors and by trends in manufacturing, technology, and energy sectors. This dual characteristic allows silver to capture aspects of both financial market behavior and real economic activity

Together, these three commodities are representative of the broader commodity class. They exhibit strong linkages with stock markets through both direct economic effects and financial spillovers, as evidenced by the paper's review of volatility spillover, cointegration, and impulse response analyses. By studying crude oil, gold, and silver alongside market variables (such as DII, FII, and stock indices), the analysis can offer more holistic insights into how international price shocks, financialization, and investor behavior impact domestic equity markets

3. Literature Review:

3.1 Share Market Volatility

A wealth of research has emphasized the inherent volatility of stock markets and the way this volatility spills over across different indices. For example, a study examining sectoral indices in Nigeria—based on monthly data from January 2007 to December 2016—found clear trends in returns alongside bursts of volatility (Fasanya et al., 2019). In another study focused on the Indian stock market, preliminary analyses using descriptive statistics, stationarity, normality, and serial correlation tests were followed by volatility modeling through ARCH and GARCH family models. The findings suggested that despite the market's volatility, these models can provide useful insights for investors looking to make informed decisions (Mathur et al., 2021). Similarly, research using daily closing prices of MCB stocks showed that GARCH(1,1) models are particularly effective at capturing volatility clustering among various ARCH-type models. These studies not only confirmed GARCH(1,1) as a best-fit model but also applied ARIMA-GARCH frameworks to estimate both mean and variance components. This dual modeling approach offered a deeper understanding of the volatility structure, especially by analyzing residuals from well-fitted mean models based on daily stock price movements. Collectively, these studies highlight the value of sophisticated volatility modeling techniques in decoding market behavior and supporting strategic investment decisions (Chand et al.,

The effectiveness of different time-series models in capturing stock market behavior has been widely explored in various markets. For instance, in the Malaysian context, the Box-Jenkins ARIMA model was found to outperform the GARCH model when it came to modeling and forecasting the Kuala Lumpur Stock Exchange Properties Index and the Kuala Lumpur Composite Index (KLCI). Using monthly data from July 1997 to July 2012, the study concluded that ARIMA offered more accurate results for this particular dataset and market environment (Miswan et al., 2014).

In contrast, a study on the Nigerian Stock Exchange (NSE) All-Share Index analyzed 324 monthly observations from January 1985 to December 2011 using both symmetric and asymmetric GARCH models. The results highlighted strong volatility persistence in the market, although there was no significant evidence of asymmetric shock effects—commonly referred to as leverage effects—in the return series (Adesina, 2013). Similarly, in the case of the Karachi Stock Exchange (KSE), significant volatility patterns were detected using ARCH and GARCH models, reinforcing their utility in effectively capturing and measuring stock market fluctuations (Ali et al., 2009).

To estimate conditional market volatility, Tripathy and Rahman (2013) analyzed 23 years of daily closing data from both the Bombay Stock Exchange (BSE) and the Shanghai Stock Exchange (SSE), averaging around 5,605 observations per market. Their findings revealed strong ARCH effects in both indices, confirming that the GARCH model is well-suited for capturing stock market volatility in these contexts. Further studies exploring volatility transmission across global markets have uncovered notable spillover effects. Sakthivel et al. (2012) identified bidirectional volatility spillovers between the U.S. and Indian markets, reflecting deep economic ties through trade and investment. They also reported unidirectional spillovers from Japan and the U.K. to India, underscoring the increasingly interconnected nature of global financial markets. Collectively, these studies highlight the complexity of modeling stock market volatility and the importance of choosing appropriate models tailored to the specific behavior of each market. Al-Najjar (2016), for example, found no evidence of a leverage effect in ASE stock returns using the EGARCH model, emphasizing the need to consider market-specific nuances. Similarly, Patjoshi and Nandini (2020) combined parametric statistical tools—such as mean, standard deviation, and t-tests—with the GARCH model to investigate the "day of the week" effect. Their analysis revealed distinct patterns in daily returns, demonstrating how integrating traditional statistical techniques with volatility models can uncover seasonal trends in financial markets.

A comparative analysis of three advanced heteroscedasticity models—GARCH(1,1), EGARCH(1,1), and GJR-GARCH—demonstrated the value of applying multiple modeling approaches to capture the complexities of market volatility. Each model brought unique strengths, helping to ensure that the distinctive features of the data were accurately represented (Onwukwe et al., 2011). Together, these studies reinforce the importance of carefully selecting appropriate models and methodologies to effectively interpret the nuanced dynamics of stock market behavior. Beyond technical modeling, Shawkatul et al. (2014) highlighted the broader need for strong regulatory oversight in capital markets. While volatility is an inherent characteristic of financial markets, the study emphasized the importance of monitoring corporate insider activity, ensuring fair and equal access to information for all investors, and increasing stock availability through proactive involvement from governments and major national and multinational corporations. These insights stress the role of policy and governance in maintaining market integrity and investor confidence.

The global financial crisis underscored how information—particularly from the U.S. stock market—can significantly influence stock market returns in East and South Asia. Roy et al. (2019) observed that information spillovers from the U.S. played a crucial role in shaping market behavior in these regions. Their findings are particularly relevant for both domestic institutional investors (DIIs) and foreign institutional investors (FIIs) who seek portfolio diversification, as they highlight the importance of global market signals.

In a related study, Duran et al. (2024) examined volatility spillovers from the S&P 500 to precious metals such as gold, silver, and platinum. While gold displayed extreme volatility, there was no clear evidence linking this behavior to specific crisis periods. However, silver and platinum showed stronger correlations with the S&P 500 during times of global economic turbulence, suggesting their closer alignment with equity market stress.

Focusing on the Indonesian stock market (IHSG), Endri et al. (2020) explored the effects of various macroeconomic variables—interest rates, inflation, exchange rates—and international indices including the STI, SSE, N225, DJIA, and FTSE100. The results revealed that the BI rate, inflation, and SSE had a significant negative impact on IHSG, whereas the exchange rate, STI, and DJIA had significant positive effects. Although FTSE100 had a positive impact, it was not statistically significant, and the N225 showed a minor negative influence.

Karolyi (1996) took a deeper look into cross-border return correlations, particularly between U.S. and Japanese stocks. Interestingly, the study found that U.S. macroeconomic announcements, yen/dollar exchange rate movements, Treasury bill returns, and industry-specific factors did not significantly influence return correlations. Instead, major shocks to broad market indices—like the Nikkei Stock Average and the S&P 500—were shown to amplify both the strength and persistence of these correlations, highlighting the dominance of overall market movements over isolated economic indicators.

3.2 Gold & Silver:

A comparative study on forecasting methods for Malaysian gold bullion evaluated the performance of the Box-Jenkins ARIMA model and the GARCH(1,1) model. The results indicated that GARCH(1,1) was more accurate, with a lower Mean Absolute Percentage Error (MAPE) than ARIMA(1,1,1), making it the more reliable model for predicting gold bullion prices (Yean Ping et al., 2013). Building on this, another study used the GARCH model to examine the time-varying volatility relationships between international gold markets, Malaysia's Kijang Emas (KE) gold bullion coins, and the U.S. gold index. The findings provided critical insights for investors, commercial banks, and policymakers, highlighting the importance of developing strategies to manage and cushion the impact of gold price fluctuations (Ping et al., 2016). Further expanding the scope, Ding et al. (2024) analyzed data from eight commodity futures markets in the U.S. and China, including carbon, copper, gold, and oil futures. Their research emphasized the strong connection between oil market stability and firm behavior, showing that companies often increase their oil inventories to hedge against market volatility. Beyond corporate strategy, the study also pointed to broader implications—underscoring how oil price stability can influence sustainable development, green asset market performance, and the effectiveness of carbon emission management.

3.3 FII & DII

Foreign Institutional Investor (FII) activity is closely linked to domestic trading volume. When domestic investors actively participate in national markets, it boosts foreign investor confidence, encouraging greater FII inflows. Bodla and Kumar (2009) found a strong positive relationship between trading volume and FII purchases, suggesting that higher trading volumes in host markets make them more attractive to foreign investors. In the Chinese capital market, Zhao et al. (2024) analyzed data from all non-financial firms between 2004 and 2021 and discovered a significant positive correlation between the proportion of institutional investor holdings and the risk of future stock price crashes. This suggests that while institutional presence may signal confidence, it can also heighten crash risk due to herding behavior or strategic trading.

Looking at Latin America, Husnain et al. (2024) found that economic growth is strongly influenced by institutional quality, foreign direct investment (FDI), and domestic investment, whereas inflation has a detrimental effect. Employing advanced panel cointegration and PARDL techniques, the study shed light on the structural factors that drive regional economic performance. QFII (Qualified Foreign Institutional Investor) participation has also been shown to improve market functioning. Research by Lai et al. (2024) and Wang & Zhang (2015) found that QFII involvement enhances stock liquidity by reducing information asymmetry, increasing trading volume, attracting market attention, and improving corporate disclosure quality.

In the Indian context, Sett (2023) examined the role of industrial production growth and FII net inflows on stock returns during both pre-pandemic and pandemic periods. While industrial production showed no significant impact, FII inflows were a major driver of returns on the BSE 500 index across both periods. However, the influence of FII investments declined during the pandemic—except for a sharp surge between January and March 2020. The broader effects of stock market liberalization have also been examined. Meng et al. (2023) concluded that liberalization enhances market efficiency by boosting informational transparency, strengthening corporate governance, increasing firm value, and lowering the risk of stock price crashes. These findings support liberalization as a tool for long-term market development. Finally, Maharana (2024) analyzed the impact of the COVID-19 pandemic on stock market volatility and global interconnectedness, particularly with respect to India. The study reported a notable increase in volatility post-pandemic and highlighted shifting influences in global financial markets. While India continued to impact markets in Brazil, China, and Mexico, the influence of the U.S. market diminished. Interestingly, Russia emerged as a significant contributor to India's market volatility only after the pandemic, emphasizing the need for investors and policymakers to adapt to evolving global dynamics.

3.3 CRUDE:

A study examining the relationships between Islamic stock indices, crude oil, and natural gas prices across Middle Eastern and North African (MENA) countries (excluding Turkey) from August 2007 to September 2020 found both bidirectional and unidirectional volatility and shock spillovers among these variables. This suggests a strong flow of information across markets in the region. Interestingly, the study observed no significant spillover effect between Turkey's MSCI Islamic index and Brent crude oil, indicating a degree of market segmentation in that case (Bilgin et al., 2024). In the field of financial forecasting, Horák and Jannová (2023) assessed the predictive power of neural networks and found exceptionally high correlation coefficients—above 0.973—across all neural structures and datasets. Among the models tested, the 10 MLP 1-18-1 network stood out as the most effective for forecasting the next 20 trading days. The authors recommended further training with additional data to enhance its predictive accuracy. Jia et al. (2022) explored how crude oil market risks interact with broader macroeconomic conditions. They concluded that commodity and financial markets act as intermediaries in transmitting oil market shocks to the macroeconomy. Furthermore, the effectiveness of these markets in absorbing oil shocks varies depending on the prevailing economic environment.

In a related study, Fanelli (2024) examined long-term pricing relationships among crude oil benchmarks using cointegration techniques. The analysis confirmed a stable equilibrium between West Texas Intermediate (WTI) crude oil futures and a statistical portfolio composed of Brent and Dubai crude oils. Deviations from this equilibrium were shown to revert predictably, allowing for the application of equity-market-style trading strategies within the crude oil market. Sehgal and Kapur (2012) analyzed how oil price shocks influenced stock markets in 15 countries from January 1993 to March 2009. By categorizing countries based on their economic strength and whether they were oil-exporting or importing economies, the study revealed distinct patterns of market responses shaped by each country's economic and trade structure. A comprehensive review by Bagirov and Mateus (2024) surveyed over 190 studies on the relationship between petroleum prices and equity markets. Their findings emphasized that the effects of oil price changes are often sector- and country-specific, depending on methodological approaches and time periods analyzed. Countries with higher petroleum dependency or exporter status exhibited more direct effects, and volatility was shown to flow bidirectionally between petroleum and equity markets. The authors highlighted the need for further research to unpack these complex relationships.

Lastly, Meng et al. (2023) analyzed risk spillovers among crude oil, gold, economic policy uncertainty, and four key Chinese financial sectors using multiple risk proxies from January 2008 to June 2020. The study found that extreme quantiles—representing tail risks—exhibited significantly higher levels of spillover compared to average market conditions. Term and credit spreads were also found to be strong predictors of total returns and volatility spillovers, offering valuable insights into how systemic shocks propagate through financial markets.

3.4 COMMODITY:

Huang et al. (2023) analyzed volatility spillovers among various futures markets, including COMEX gold, soybeans, S&P 500, the dollar index, U.S. 10-year T-notes, and CME Bitcoin. Their study revealed that these spillovers are largely driven by long-term factors and exhibit time-varying behavior. A sharp but brief spike in volatility was observed during the onset of the COVID-19 pandemic, indicating a temporary market shock. Pinto-Ávalos et al. (2024) explored the relationship between international commodity markets and domestic equity returns in nine commodity-exporting countries using a multivariate DCC-GARCH model. Their findings showed no evidence of contagion between these markets, suggesting that correlations between international commodity prices and domestic stock markets have remained limited over time.

Rossi (2012) examined how commodity prices interact with equity markets and found a positive correlation between global commodity prices and lagged equity values. However, since the early 2000s, commodity prices have demonstrated changing time-series behavior and a growing correlation with equity markets—indicating a shift from their traditionally independent roles. Lu et al. (2023) investigated the impact of the COVID-19 pandemic on the interconnectedness between the Indian equity market and six major global commodity markets. Using a time-varying parameters vector autoregression (TVP-VAR) model alongside a wavelet coherence approach, they found that volatility correlations and spillovers increased significantly during the pandemic. Following the outbreak, commodity market volatility rapidly spilled over into the Indian equity market, signaling deeper integration between these markets during times of crisis. Aziz et al. (2020) evaluated volatility and mean spillovers between commodity and equity markets, focusing on gold, oil, gas, and rice. Their results indicated minimal spillover effects from commodity markets to equity markets, with a few exceptions such as oil to rice and gas. Importantly, no significant interaction was found between gold and equity markets, reinforcing the notion that gold and equities can serve as complementary assets for portfolio diversification.

A central topic in recent research has been whether the increasing financialization of commodity markets has altered risk premiums, which were traditionally influenced by the concept of normal backwardation. Carter and Revoredo-Giha (2023) examined eleven commodities and found that risk premiums have notably declined since 2007, a period that coincides with growing financialization in the sector. This shift raises important questions about how market fundamentals and investor behavior have evolved over time. Further exploring market behavior, Xiao et al. (2023) investigated the role of herding and leverage effects in commodity futures markets. Their study highlighted how these behavioral patterns contribute to market inefficiencies. By employing an ARMA-GARCH R-vine copula model, capable of capturing intricate dependencies and asymmetries in high-dimensional datasets, the researchers provided deeper insights that are especially relevant for hedgers, traders, and regulators concerned with maintaining efficient and stable markets. Building on this, Billah et al. (2024) introduced an innovative approach using a time-varying parameter vector autoregression (TVP-VAR) model combined with extended joint connectedness analysis. Their findings revealed that the relationships between Sukuks (Islamic financial instruments) and commodity markets are not only dynamic but also sensitive to financial events. This nuanced understanding offers valuable implications for both financial policy and risk management in Islamic finance and commodity-linked investments. Similarly, Fry-McKibbin and McKinnon (2023) examined the growing interdependence between commodity, equity, and currency markets—particularly in major commodity-exporting countries. Using a latent factor model, their research showed how financialization is deepening these linkages, especially for nations with so-called "commodity currencies." The study emphasized the need for such economies to consider financialization's impact in their policy and investment strategies.

On the pricing front, Sehgal and Pandey (2012) suggested that the Capital Asset Pricing Model (CAPM) can more accurately represent asset pricing in commodity markets when a commodity index is used in place of a traditional stock market index in the portfolio. However, they also noted a key limitation: unlike equities, commodities tend to lack consistent short-term return patterns, which makes them less predictable and more challenging for developing short-term trading strategies. Basak (2016) added to the discussion by comparing the behavior of commodity futures prices with commodity indices. The study found that financialization tends to raise futures prices, increase volatility, and heighten correlations—particularly among index futures compared to non-index futures. Additionally, the rise in correlations between equity and commodity markets reflects how financial shocks now influence not just futures prices but also spot prices and inventory decisions. Interestingly, spot prices of storable commodities tend to rise with financialization, and price shocks from any index commodity often ripple through the entire market.

Finally, Goldstein (2022) developed a model to examine how financialization affects various aspects of commodity futures markets. By distinguishing between financial speculators—who trade to profit from price movements—and financial hedgers—who trade to manage risk—the study evaluated their separate and combined influence on futures market outcomes. These include the informativeness of prices, biases in pricing, cross-market correlations, and the predictability of trading behavior. The findings offer a detailed perspective on how different market participants shape the broader dynamics of commodity futures under increasing financialization. Jain et al (2025).

4. Research Methodology:

4.1 Data Collection:

Data on Stock Market (NSE) has been collected from the official website (www.nseindia.com), data of Gold price was collected from The World Gold Council website (www.gold.org). Data on FII and DII have been collected from 25 year old finance portal i.e. moneycob-trol.com. Crude oil and Silver price data collected through www.investing.com that is a reliable source for these data. The table 1 below shows the variable-wise list of data collection sources.

Table 1: Data Sources

Variable	Source
Crude Oil Prices	www.investing.com
Silver Prices	www.investing.com
DII	https://www.moneycontrol.com/stocks/marketstats/fii_dii_activity/index.php#fidifisb
FII	https://www.moneycontrol.com/stocks/marketstats/fii_dii_activity/index.php#fidifisb
Gold Prices	www.gold.org
NSE	www.nseindia.com

The data collected for monthly intervals from April 2012 to August 2024.

5. Data Analysis:

Many different methods have been suggested in previous literature for testing the presence of long-run equilibrium relations among time-series variables. The majorly recommended methods consist Engle and Granger (1987) test, fully modified OLS procedure of Phillips and Hansen's (1990), maximum likelihood-based Johansen (1988, 1991) and Johansen- Juselius (1990) tests. These methods require that the variables in the system are integrated of order one i.e. I(1). In addition, these methods suffer from low power and do not have good small sample properties.

The Autoregressive Distributed Lag (ARDL) approach, while versatile, has notable limitations. It may face challenges with spurious regressions and cross-sectional dependencies in panel data (Ghouse et al., 2018; Menegaki, 2019). Context-specific outcomes, difficulties in interpreting cointegration, and limitations in handling structural breaks further constrain its application (Bist & Bista, 2018; Nkoro & Uko, 2016). Additionally, structural breaks and model specification issues can lead to misleading conclusions, necessitating careful application (Chandio et al., 2022; Sehrawat & Giri, 2015). Due to these problems, a newly developed autoregressive moving average (ARMA) approach to cointegration has become popular in recent years.

The ARMA (Autoregressive Moving Average) model is widely recognized as a powerful tool for modelling and forecasting time series data, with extensive support from academic research. It has been effectively applied in various domains, such as meteorological predictions using the MODWT-ARMA model, which demonstrates its versatility in handling different types of data (Zhu et al., 2014). Additionally, combining ARMA models with nonlinear techniques has been highlighted for capturing complex patterns in time series forecasting (Rojas et al., 2008). In operational research, ARMA models are regarded as effective "black box" methods for capturing time series dynamics, showcasing their broad applicability (Cortez et al., 2004). The foundational Box-Jenkins methodology underscores the ARMA model's central role in statistical time series analysis (Chujai et al., 2013). Furthermore, ARMA models have been applied to ecological and hydrological data, demonstrating their adaptability to diverse scientific fields and their capacity to extract valuable insights from complex datasets (Ives et al., 2010); Salas & Obeysekera, 1982). These studies collectively highlight the ARMA model's enduring significance in capturing the intricacies of time series data across a wide range of applications.

First data checked for stationarity using ADF test. FII and DII data was stationary at level whereas Crude, Gold, Silver & NSE were stationarity at first difference. Crude at first diff

Stationarity results:

- **DII at level**
- **FII at level**
- **Gold at first diff (DGOLD)**
- **NSE at first diff (DNSE)**
- **Silver at First Diff (DSILVER)**

The ARMA (Autoregressive Moving Average) model is a popular statistical method used for modelling and forecasting time series data. It combines two components:

1. **Autoregressive (AR) part**: This component uses the relationship between an observation and a specified number of lagged observations (previous values) to predict future values. It essentially captures the momentum in the series.
2. **Moving Average (MA) part**: This component models the relationship between an observation and a residual error from a moving average model applied to lagged observations. It helps account for the random shocks or noise in the data.

An ARMA model is typically denoted as ARMA(p, q), where:

- **p** is the order of the AR part (number of lagged observations).
- **q** is the order of the MA part (number of lagged forecast errors).

ARMA Test was applied on the data and the ARMA(4,4) model was selected.

ARMA (4,4) Model Equation

The general equation for an ARMA(4, 4) model is:

$$yt=c+\phi 1yt-1+\phi 2yt-2+\phi 3yt-3+\phi 4yt-4+\theta 1\epsilon t-1+\theta 2\epsilon t-2+\theta 3\epsilon t-3+\theta 4\epsilon t-4+\epsilon tyt \quad (1)$$

5.1 Breakdown of the Components

- **yt: The NSE index value at time tt.**
- **c: A constant term (optional, often included).**

5.2 Autoregressive Part (AR):

- **ϕ1,ϕ2,ϕ3,ϕ4: Coefficients for the lagged values of y**
  - *yt*−1: The value at time t−1
  - *yt*−2: The value at time t−2
  - *yt*−3: The value at time t−3
  - *yt*−4: The value at time t−4

5.3 Moving Average Part (MA):

- **θ1,θ2,θ3,θ4: Coefficients for the lagged forecast errors.**
  - ϵt: The white noise (error term) at time t
  - ϵt−1: The error term at time t−1
  - ϵt−2: The error term at time t−2
  - ϵt−3: The error term at time t−3
  - ϵt−4: The error term at time t−4

The next step was the application of VAR model. The VAR (Vector Autoregression) model is a statistical model used to capture the linear interdependencies among multiple time series. Unlike univariate models like ARMA, which focus on a single time series, VAR allows for the analysis of systems where multiple variables influence each other over time (Andersson et al. 2022; Kang & Yoon 2020). To represent a VAR (Vector Autoregression) model for the variables DNSE, DCRUDE, DSILVER, DGOLD, FII,and DII with 4 lags, we can formulate the equations by expressing each variable as a function of its past values and the past values of all other variables in the system.

$$Y_t = [DNSE_t\ DCRUDE_t\ DSLIVER_t\ DGOLD_t\ FII_t\ DII_t\ ],$$

$$the\ VAR(4)model\ can\ be\ written\ as\ follows$$

$$Y_t = C + A_1Y_{t-1} + A_2Y_{t-2} + A_3Y_{t-3} + A_4Y_{t-4} + \varepsilon_t \tag{2}$$

Where:

- C us the vector of constants (intercepts).
- A1, A2, A3, A4 are the coefficient matrices for lagged values.
- εt is the vector of error terms, which are assumed to be white noise i.e. εt ~iid(0,Σ)

BVAR was also calculated BVAR, it is an extension of the traditional Vector Autoregression (VAR) model that incorporates Bayesian statistics to improve estimations and predictions, especially in contexts where the number of parameters is large relative to the number of observations. It's particularly useful for small sample sizes and can handle multicollinearity issue among the variables effectively. By integrating prior information into the model, BVAR addresses overfitting issues common in high-dimensional data and provides better forecasts compared to traditional VAR models. BVAR is particularly effective in scenarios with limited data, as it allows for the incorporation of subjective beliefs or previous knowledge to stabilize estimates (Artis & Zhang, 1990; Todd, 1990).

The roots of the characteristic polynomial calculated, basically, they are critical in assessing the stability of the VAR model. The stability condition requires that all roots must lie inside the unit circle (i.e., their modulus must be less than 1).

Also, Variance decomposition was calculated which shows the percentage of the error made forecasting a variable over time due to specific shock. In other words, how much of the variability in the dependent variable is explained by its own shock vs the shock in the other variable in the system?

The last step was model estimation with the help of the ARMA forecasting method after checking for the stability of the model.

6. Result & Analysis:

6.1 Analysis of DNSE Volatility and Causality: Summary of Results

A. **Volatility of DNSE (Figure 1)**

DNSE (India's stock market returns) has shown significant volatility, particularly after 2020, with extreme spikes visible in the data. This indicates sensitivity to global shocks and domestic factors. Graphical and statistical evidence confirm a volatile regime for DNSE.

B. ARMA Model Findings (Table 2) Constant term

is significant, implying a reliable baseline value in DNSE returns. AR terms (lags 1-4) and MA terms (lags 1-4) are all significant, indicative of a complex, self-reinforcing dynamic where both past returns and past shocks matter. (Table 3). Durbin-Watson statistic ≈ 2.07: Confirms there's no autocorrelation in model residuals, so predictions are not biased by serial dependence. Model selection (AIC): Minimum at (4,4) lag—the chosen ARMA model is statistically optimal.

C. VAR Model Insights (Table 4)

- **DNSE(-1):** Negative and weakly significant—recent stock moves tend to mean-revert a little.

- **DCRUDE:** Past oil prices (lags 1 and 2) strongly and positively affect both current DCRUDE and other commodities, showing oil's influence on markets.
- **DGOLD:** Past gold returns strongly forecast negative current returns in gold and FII.
- **DSILVER:** Silver's past values have **very strong, positive effects** on its own future returns and impact several other variables.
- **FII & DII:** Institutional investor flows show persistent but modest self-influence (especially DII on FII), with DII displaying a complex, time-varying impact.

Indian stock returns are not isolated—they react strongly to crude oil and precious metals (especially silver), and respond to institutional investor behavior. Most shocks (especially to DCRUDE and FII/DII) have both immediate and lingering effects.

D. Model Stability & Serial Correlation

- **Root analysis (Table 5) (Inverse roots of the characteristic polynomial):** All lie inside the unit circle—VAR system is stationary. This means **mean and variance remain constant over time** and shocks do not destabilize the system.
- **Serial correlation tests:** No serial correlation at lags 1 and 2; present at lags 3 and 4—may prompt model refinement. **(Figure 4 and Table 6)**

E. Impulse Response and Variance Decomposition Insights (Figure 3)

One standard deviation shocks (oil, gold, silver, FII/DII) impact DNSE both quickly and, in some cases, persistently. The market's response magnitude allows variables to be ranked by their importance, with DCRUDE and FII/DII often dominating. Variance Decomposition: (Table 7) Short run: Each variable (especially DCRUDE, DGOLD, DSILVER, DII) is most influenced by its own values. Long run: Cross-influences rise. For example: DCRUDE and DSILVER eventually impact DNSE more, while DII becomes a strong driver for FII and vice versa.

Overall, the statistical models robustly reveal that India's stock market returns (DNSE) are shaped by a web of influences:

- **Commodities (Oil, Gold, Silver):** Both direct and through cross-market effects.
- **Institutional Flows (FII/DII):** Affect and are affected by market trends, sometimes amplifying shocks.
- **Past Behavior:** History matters—lagged values are consistently significant in determining current outcomes.
- **Stability:** The VAR system is stable, and most relationships uncovered are data-driven and robust over time.

6.2 Variance Decomposition Results shows that:

- **Crude Oil's Own Volatility Dominates Initially:** Most of the fluctuations in crude oil prices are explained by changes in crude oil prices themselves — especially in the short term (about 87-100% in early periods). This means crude oil prices are largely influenced by their own market dynamics.
- **Gold and Silver Partially Affect Crude Oil Prices:** Over time, small but growing portions of crude oil price fluctuations can be attributed to movements in gold and silver prices. This shows some interdependence, albeit modest, between these commodity prices.
- **Stock Market (NSE) and Institutional Investors Impact Crude Oil:** The decomposition shows that equity market trends (NSE) and institutional investor activities (DIIs and FIIs) have a small but noticeable role in explaining volatility in crude oil prices over longer periods.
- **Gold Price Volatility Is Mainly Driven by Gold Itself:** Similar to crude oil, gold price changes are mostly due to factors within the gold market. However, it is somewhat influenced by crude oil prices and DII flows, indicating connections between commodities and investor behavior.
- **Silver Price Fluctuations Are More Mixed:** Silver's volatility is influenced by a combination of its own market shocks and external factors including crude oil, gold, and investor activities, reflecting silver's dual role as both a precious metal and an industrial commodity.

6.3 Impulse Response Results found that:

- **Stock Market Reaction to Crude Oil Shock:** The NSE tends to respond positively but modestly to sudden changes in crude oil prices. This means a sharp change in oil prices can trigger some movement in the stock market, but the effect is not extreme or immediate.
- **Gold's Response to Oil and Equity Shocks:** Gold's price tends to react with a delay and generally in the opposite direction to oil and stock market shocks, reinforcing its role as a "safe haven"—investors move to gold when other markets are unstable.
- **Silver's Reaction Is More Volatile:** Silver shows more sensitivity and varied responses to shocks from crude oil, gold, and equity markets, reflecting its mixed investment-industrial nature.
- **Institutional Investment Flows and Commodities:** Fluctuations in investor flows (DII and FII) have measurable impacts on commodity prices and vice versa, suggesting that large investors' trading decisions respond to and influence commodity market shocks.

The commodity markets (crude oil, gold, silver) and the stock market are interconnected, but each has its own main drivers of volatility. Sudden shocks in one market create ripples affecting other markets, but these effects vary in size and timing. Institutional investors play an important role in transmitting shocks between commodities and stocks. Gold acts as a protective asset during market turbulence, while silver is influenced by both market and real economic factors. Policymakers and investors should understand these interactions to better anticipate market movements and manage risks.

7. Discussion:

DNSE Equation: Negative Coefficients for DNSE(-1) and DNSE(-2) suggest that increases in the NSE index from the previous two periods lead to decreases in the current index. This indicates a potential mean-reversion characteristic in the index. DCRUDE(-1) and DCRUDE(-2) have notably positive coefficients, indicating that increases in crude oil prices from previous periods positively influence the current index significantly. Strong positive influences from DSILVER and significant influence from DII as well. In a contrasting study, Adesina (2013) analyzed 324 monthly data points for the Nigerian Stock Exchange (NSE) All-Share Index, covering the period from January 1985 to December 2011. Utilizing both symmetric and asymmetric GARCH models, Adesina assessed stock return volatility and the persistence of shocks to that volatility. The results indicated a high degree of volatility persistence but found no evidence of asymmetric shock effects, commonly known as leverage effects, in the return series. While volatility is a typical feature of capital markets, Shawkatul et al. (2014) highlight the critical need for regulatory authorities to remain vigilant. They emphasize the importance of monitoring corporate insider activities, ensuring equitable access to information for all investors, and promoting stock availability through proactive engagement from both the government and key national and multinational corporations.

DCRUDE Equation for Negative Impact from DNSE: The coefficients relating to DNSE are negative, particularly DNSE(-1). This suggests that a rise in the NSE index may lead to a decrease in crude oil prices in the following period. DSILVER has a strong positive impact on DCRUDE, indicating that rising silver prices positively affect crude oil. Sehgal and Kapur (2012) investigated the impact of oil price shocks on stock markets across 15 countries from January 1993 to March 2009. They categorized these countries based on their economic strength and whether they were oil exporters or importers, exploring how oil price fluctuations affected stock market dynamics in various economic and trade contexts. Similarly, Bilgin et al. (2024) studied the relationships among Islamic stock indexes, crude oil, and natural gas prices in Middle Eastern and North African countries (excluding Turkey) from August 2007 to September 2020. Their findings revealed both bidirectional and unidirectional volatility and shock spillovers among the variables, indicating significant information transfer. However, they observed no spillover effects between Turkey's MSCI Islamic index and Brent crude oil. These results are non-confirmatory to Li et al. (2024). They investigated the spillover relationships between international crude oil markets and global energy stock markets, highlighting the influence of geopolitical risks. It finds that energy stock markets in developed countries primarily transmit systemic shocks to crude oil markets, while geopolitical risks have intensified the spillover from crude oil to energy stocks since 2015, with minimal impact in the opposite direction. Also, the study conducted by Choi (2024) found the dependence and risk spillovers between natural gas, crude oil, and stock markets in major energy producer and consumer countries from 2006 to 2022. It finds a long-term dependence of natural gas on stock markets, with natural gas acting as a hedge asset and oil serving as a diversifier in the long term. The research highlights significant bidirectional and asymmetric spillovers, particularly noting that natural gas transmits more risk to stock markets than oil, especially in Russia.

DGOLD Equation - DNSE has negative coefficients, suggesting a trend where increases in the NSE index might lead to a decline in gold prices. The results align with the findings of Aziz et al. (2020), who examined volatility and mean spillovers between commodity and equity markets, specifically focusing on gold, oil, gas, and rice. Their study revealed that there were no significant volatility spillovers from commodity markets to equity markets, with exceptions occurring only in specific cases, such as from oil to rice and gas. Additionally, they noted a lack of meaningful interaction between gold and equity markets, implying that investors might consider using gold and equities as complementary assets to mitigate portfolio risk. While crude oil shows a positive link to the gold prices, albeit weaker. Ding et al. (2024) conducted an analysis of data from eight commodity futures markets in the U.S. and China, including futures for carbon, copper, gold, and oil. Their research emphasized the vital connection between oil market stability and corporate behavior, showing that firms are likely to boost oil inventories to protect themselves against market volatility. Furthermore, the study illuminated the wider implications of oil market stability for sustainable development, the performance of green asset markets, and effective carbon emission management efforts.

DSILVER Equation: The coefficients for DNSE(-1) and DNSE(-2) are minimal, indicating a negligible impact. However, it has significant negative coefficients for its own lags, suggesting corrections or mean-reversion in silver's behavior. Opposite results were obtained from Rossi (2012), who investigated the relationship between commodity prices and equity markets, finding a positive correlation between global commodity prices and lagged equity values. However, since the 2000s, commodity prices have exhibited unique time-series characteristics and a heightened correlation with equity markets, suggesting a shift in their traditional dynamics. In a more recent study, Lu et al. (2023) analyzed the effects of COVID-19 on the interconnectedness between the Indian equity market and six major commodity markets. Utilizing a time-varying parameters vector Autoregression model and a wavelet coherence approach, their findings revealed a significant increase in volatility correlations and spillovers during the pandemic. Following the outbreak, volatility in the commodity markets rapidly spilled over into the Indian equity market, indicating a greater degree of market integration.

FII Equation: Significant negative impacts from DGOLD indicate a strong inverse relationship whereby rising gold prices correlate with falling foreign institutional investments. This might suggest a reallocation effect where funds are shifted away from equities towards gold. The findings align with the research by Bodla and Kumar (2009), who noted that Foreign Institutional Investor (FII) investments significantly influenced by trading volume. Their study indicated that active investment by domestic investors enhances the confidence of foreign investors, thereby encouraging them to participate in the market. They discovered a strong positive relationship between trading volume and foreign institutional purchases, suggesting that higher trading volumes in host markets attract more foreign investors and boost FII activity. In a more recent analysis, Sett (2023) similarly explored the effects of industrial production growth and FII net inflows on returns in the Indian market. While industrial production did not demonstrate a significant impact during the pre-pandemic and pandemic periods, FII inflows found to be significantly affecting returns on the BSE 500 index in both periods. Notably, the influence of FII investments on returns diminished during the pandemic, with the exception of a spike observed between January and March 2020.

DII Equation: The coefficients for DNSE suggest that increases in the index lead to increases in domestic investments, reflecting investor confidence when the market is performing well. Husnain et al. (2024) also confirmed the results in their study of economic growth in Latin America, emphasizing that institutional quality, Foreign Direct Investment (FDI), and local investment play crucial roles in promoting economic growth, whereas inflation has a detrimental effect. The study employed advanced methods, including panel cointegration tests and the PARDL approach, to offer valuable insights into the economic dynamics of the region.

The model indicates strong interdependencies between the assets as changes in crude oil, gold, and silver prices significantly affect the NSE index. Recent research has focused on the debate surrounding the impact of the increasing financialization of commodity markets on risk premiums, which traditionally influenced by normal backwardation. A study examining eleven commodities found that risk premiums have decreased since 2007, aligning with heightened financialization (Carter & Revoredo-Giha, 2023). This research analyzed weekly data from 11 commodity futures contracts covering the period from January 1986 to July 2019, offering strong support for this hypothesis.

The exhibited relationships might reflect general market sentiments linking institutional investments to market movements. For instance, increases in commodity prices such as crude oil and silver could reflect investor sentiment that may lead to adjustments in stock investments. The VAR model reflects feedback mechanisms where past values influence current and future values, indicating dependencies that could be crucial for forecasting.

8. Conclusion

This study has explored the intricate relationships and synergies between commodities, institutional investments, and the stock market using advanced econometric models such as ARMA, VAR, and BVAR. The findings reveal several key insights:

1. **Dynamic Interactions:** Commodities such as crude oil, gold, and silver demonstrate significant interplay with institutional investments (FII and DII) and stock market indices (NSE). Variance decomposition and impulse response analyses highlight the evolving impact of these variables over time, underscoring the interconnected nature of global financial markets.

2. **Volatility and Stability:** The ARMA and VAR models confirm the presence of volatility in the NSE, with lagged effects from commodities and institutional flows playing pivotal roles. The stability of the system, validated by the roots of the characteristic polynomial, suggests that while markets react to shocks, they tend to revert to equilibrium.
3. **Institutional Influence:** Foreign and domestic institutional investments significantly influence market dynamics, with their impacts varying across timeframes and in response to commodity price changes. This highlights the critical role of institutional actors in shaping market behaviors.
4. **Policy and Strategy Implications:** Policymakers and investors can leverage these insights to better navigate market uncertainties, optimize portfolio allocations, and design strategies that mitigate risk during periods of heightened volatility. For instance, the study underscores the utility of commodities as hedging instruments and the necessity for robust regulatory frameworks to manage spillover effects.
5. **Broader Economic Indicators:** The study reinforces the importance of commodities as leading indicators of economic health and their role in influencing investor sentiment. Shocks in commodity prices, particularly crude oil and gold, have cascading effects on institutional strategies and stock market trends.

In conclusion, the research underscores the complex yet vital synergies between commodities, institutional investments, and stock markets. As global markets become increasingly interlinked, understanding these dynamics will remain crucial for fostering market stability and achieving sustainable economic growth.

9. Suggestion:

For Policymakers: Regulatory Measures to Stabilize Markets

- **Enhance Market Surveillance and Transparency**
  Strengthen real-time monitoring of commodity and financial markets, particularly for crude oil, gold, and silver. Implement stricter disclosure requirements for institutional investors (DIIs/FIIs) during heightened volatility. Increased transparency can reduce information asymmetrical and panic-driven trading.
- **Establish and Utilize Strategic Reserves**
  Maintain adequate reserves of crude oil and other critical commodities. Strategic reserves can be released during supply shocks, muting the inflationary pass-through and stabilizing broader market conditions.
- **Implement Circuit Breakers and Price Bands**
  Apply circuit breakers or price limits in both commodity and equity markets to contain excessive price movements caused by speculative trades or external shocks. This mechanism is especially effective during events such as supply disruptions in oil markets or global financial turmoil.
- **Promote Cross-Market Coordination**
  Foster better coordination between financial and commodity market regulators. Joint policy actions can address systemic risks arising from volatility transmission across asset classes, especially when spillover effects are evident from VAR and impulse response analyses.
- **Support Hedging and Risk Management Instruments**
  Encourage the development and adoption of hedging tools (e.g., commodity futures, options, ETFs) for investors and firms exposed to commodity price risk. Regulatory facilitation of such instruments enables more efficient risk sharing and reduces the likelihood of market contagion.
- **Monitor and Address Financialization Risks**
  Scrutinize the activities of large financial speculators in commodity markets, as increased financialization may amplify volatility and reduce price discovery efficiency. Adaptive margin requirements and transaction taxes could be considered during periods of excessive leverage or herding behavior.

For Investors: Portfolio Strategies Amid Commodity Price Shocks

- **Diversification Across Asset Classes**
  Maintain diversified portfolios including equities, commodities (crude oil, gold, silver), and fixed-income instruments. Diversification mitigates the risk of sharp declines in any single asset class during commodity-led market stress.
- **Strategic Hedging**
  Use available hedging instruments such as commodity futures or gold ETFs to protect against adverse price swings. For example, holding gold during equity market downturns or oil price shocks has historically provided downside protection.
- **Dynamic Asset Allocation**
  Rebalance portfolios in response to changing volatility regimes indicated by GARCH or VAR analyses. During periods of high commodity volatility, consider increasing allocation to assets less correlated with commodities (e.g., defensive stocks, certain bonds).
- **Monitor Institutional Flows**
  Pay attention to DII and FII activity as they can signal risk-on or risk-off sentiment in both commodity and equity markets. Large and sudden institutional inflows or outflows often precede changes in market direction and volatility.
- **Scenario and Stress Testing**
  Conduct scenario analysis and stress tests reflecting commodity price shocks (e.g., sudden oil price spikes or gold rallies) to assess portfolio vulnerabilities and develop contingency plans for rapid market movements.

10. Future Suggestion for Research:

- Model Refinement and Expansion: The VAR model revealed serial correlation at higher lags (3 and 4), indicating scope for further refinement. Consider increasing lag length or integrating alternative models (e.g., VECM for co-integrated series or non-linear models) to improve forecasting accuracy, especially in turbulent periods.

Volatility remains a persistent feature of the DNSE, especially during macroeconomic or global shocks. Establish dedicated market surveillance systems that use real-time analytics, including ARMA/VAR-type models, to detect abnormal volatility or spillovers as early warning mechanism

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Appendices:

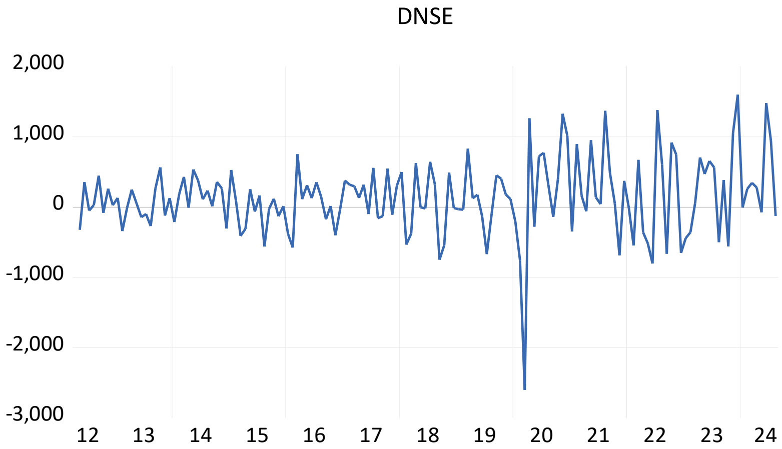

Fig 1: Volatility of DNSE

Table 2: ARMA estimation

Dependent Variable: DNSE				
Method: ARMA Maximum Likelihood (BFGS)				
Date: 12/15/24 Time: 15:34				
Sample: 2012M05 2024M08				
Included observations: 148				
Convergence achieved after 66 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	130.5231	47.86177	2.727085	0.0072
AR(1)	0.663570	0.072211	9.189278	0.0000
AR(2)	-1.242449	0.078372	-15.85318	0.0000
AR(3)	0.654518	0.081469	8.033979	0.0000
AR(4)	-0.964961	0.070314	-13.72352	0.0000
MA(1)	-0.618064	0.108102	-5.717410	0.0000
MA(2)	1.166469	0.138407	8.427816	0.0000
MA(3)	-0.560728	0.144630	-3.876972	0.0002
MA(4)	0.852525	0.133147	6.402889	0.0000
SIGMASQ	236038.9	18399.76	12.82837	0.0000
R-squared	0.156423	Mean dependent var		132.2635
Adjusted R-squared	0.101407	S.D. dependent var		530.7642
S.E. of regression	503.1334	Akaike info criterion		15.36010
Sum squared resid	34933764	Schwarz criterion		15.56262
Log likelihood	-1126.648	Hannan-Quinn criter.		15.44238
F-statistic	2.843232	Durbin-Watson stat		2.070525
Prob(F-statistic)	0.004211			
Inverted AR Roots	.62+.77i	.62-.77i	-.29+.95i	-.29-.95i
Inverted MA Roots	.59+.76i	.59-.76i	-.29+.91i	-.29-.91i

Table 3: Model Lag selection Criteria

Model Selection Criteria Table
Dependent Variable: DNSE
Date: 12/15/24 Time: 15:34
Sample: 2012M04 2024M08
Included observations: 148

Model	LogL	AIC*	BIC	HQ
(4,4)(0,0)	-1126.647564	15.360102	15.562617	15.442383
(2,2)(0,0)	-1131.011472	15.365020	15.486528	15.414389
(3,2)(0,0)	-1130.997257	15.378341	15.520101	15.435938
(2,3)(0,0)	-1131.004117	15.378434	15.520194	15.436031
(3,3)(0,0)	-1131.010741	15.392037	15.554049	15.457862
(3,4)(0,0)	-1131.003818	15.405457	15.587720	15.479510
(0,0)(0,0)	-1138.100256	15.406760	15.447263	15.423216
(0,2)(0,0)	-1137.079807	15.419997	15.501003	15.452910
(0,1)(0,0)	-1138.083763	15.420051	15.480805	15.444735
(1,0)(0,0)	-1138.087306	15.420099	15.480853	15.444783
(2,0)(0,0)	-1137.240039	15.422163	15.503168	15.455075
(1,1)(0,0)	-1137.341444	15.423533	15.504539	15.456445
(2,1)(0,0)	-1136.711222	15.428530	15.529787	15.469671
(3,0)(0,0)	-1136.756542	15.429142	15.530400	15.470283
(1,2)(0,0)	-1136.767270	15.429287	15.530545	15.470428
(0,3)(0,0)	-1136.794541	15.429656	15.530913	15.470797
(2,4)(0,0)	-1133.845155	15.430340	15.592351	15.496165
(4,2)(0,0)	-1133.891179	15.430962	15.592973	15.496787
(4,0)(0,0)	-1136.419345	15.438099	15.559608	15.487468
(0,4)(0,0)	-1136.543272	15.439774	15.561283	15.489143
(3,1)(0,0)	-1136.632750	15.440983	15.562492	15.490352
(1,3)(0,0)	-1136.722340	15.442194	15.563702	15.491562
(4,3)(0,0)	-1133.884419	15.444384	15.626647	15.518437
(4,1)(0,0)	-1136.321866	15.450295	15.592056	15.507892
(1,4)(0,0)	-1136.441637	15.451914	15.593674	15.509511

Table 4: BVAR Analysis

Vector Autoregression Estimates
Date: 12/15/24 Time: 15:54
Sample (adjusted): 2012M08 2024M07
Included observations: 144 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DNSE	DCRUDE	DGOLD	DSILVER	FII	DII
DNSE(-1)	-0.019697	-0.125276	-0.018338	-0.000608	-2.823720	1.296823
	(0.13652)	(0.04388)	(0.01161)	(0.00046)	(4.13778)	(3.05675)
	[-0.14428]	[-2.85497]	[-1.57920]	[-1.32547]	[-0.68242]	[0.42425]
DNSE(-2)	-0.156330	-0.023352	0.007358	0.000390	-13.56799	10.27967
	(0.13707)	(0.04406)	(0.01166)	(0.00046)	(4.15448)	(3.06909)
	[-1.14049]	[-0.53003]	[0.63109]	[0.84534]	[-3.26587]	[3.34942]
DNSE(-3)	0.178310	0.013394	0.014702	-1.73E-06	-0.403123	2.589805
	(0.11412)	(0.03668)	(0.00971)	(0.00038)	(3.45889)	(2.55523)
	[1.56244]	[0.36516]	[1.51456]	[-0.00451]	[-0.11655]	[1.01353]
DCRUDE(-1)	0.338696	-0.033864	0.079514	0.001451	14.15989	-12.04009
	(0.29013)	(0.09325)	(0.02468)	(0.00098)	(8.79353)	(6.49614)
	[1.16738]	[-0.36314]	[3.22196]	[1.48756]	[1.61026]	[-1.85342]
DCRUDE(-2)	0.858385	-0.068162	0.033817	0.000648	19.29831	-12.69068
	(0.30305)	(0.09740)	(0.02578)	(0.00102)	(9.18502)	(6.78535)
	[2.83248]	[-0.69978]	[1.31190]	[0.63556]	[2.10106]	[-1.87030]
DCRUDE(-3)	-0.693307	0.001030	0.083415	0.000975	-17.73075	12.22060
	(0.29942)	(0.09624)	(0.02547)	(0.00101)	(9.07510)	(6.70416)

	[-2.31547]	[0.01070]	[3.27519]	[0.96883]	[-1.95378]	[1.82284]
DGOLD(-1)	-3.311423	-0.151964	-0.027779	0.001647	-61.46017	52.51177
	(1.36286)	(0.43804)	(0.11592)	(0.00458)	(41.3064)	(30.5147)
	[-2.42975]	[-0.34692]	[-0.23963]	[0.35943]	[-1.48791]	[1.72087]
DGOLD(-2)	0.430673	-0.139027	-0.139140	-0.002260	14.00223	22.52863
	(1.39181)	(0.44734)	(0.11839)	(0.00468)	(42.1836)	(31.1627)
	[0.30943]	[-0.31078]	[-1.17530]	[-0.48302]	[0.33194]	[0.72293]
DGOLD(-3)	2.994050	-0.278469	0.002750	0.002769	74.50393	-43.44962
	(1.12496)	(0.36158)	(0.09569)	(0.00378)	(34.0958)	(25.1880)
	[2.66148]	[-0.77015]	[0.02874]	[0.73209]	[2.18514]	[-1.72501]
DSILVER(-1)	68.71814	-5.563973	10.08679	-0.072458	966.0966	-666.3532
	(35.7581)	(11.4931)	(3.04156)	(0.12022)	(1083.77)	(800.629)
	[1.92175]	[-0.48411]	[3.31632]	[-0.60269]	[0.89142]	[-0.83229]
DSILVER(-2)	12.43526	-2.034068	0.012651	-0.064879	430.3238	-904.1685
	(38.1424)	(12.2595)	(3.24437)	(0.12824)	(1156.04)	(854.014)
	[0.32602]	[-0.16592]	[0.00390]	[-0.50592]	[0.37224]	[-1.05873]
DSILVER(-3)	-43.03268	-1.949769	-3.412292	-0.213127	-837.0198	-381.0200
	(36.8272)	(11.8368)	(3.13250)	(0.12382)	(1116.18)	(824.567)
	[-1.16850]	[-0.16472]	[-1.08932]	[-1.72127]	[-0.74990]	[-0.46208]
FII(-1)	0.005970	0.003081	0.000930	1.34E-05	0.159820	0.079962
	(0.00505)	(0.00162)	(0.00043)	(1.7E-05)	(0.15308)	(0.11309)
	[1.18197]	[1.89785]	[2.16558]	[0.78974]	[1.04400]	[0.70707]
FII(-2)	-0.000837	0.001751	-0.000244	2.22E-05	0.076210	-0.084380
	(0.00507)	(0.00163)	(0.00043)	(1.7E-05)	(0.15352)	(0.11341)
	[-0.16532]	[1.07582]	[-0.56665]	[1.30357]	[0.49643]	[-0.74403]
FII(-3)	0.001273	0.003364	-0.000485	-9.23E-06	0.345425	0.066247
	(0.00486)	(0.00156)	(0.00041)	(1.6E-05)	(0.14730)	(0.10882)
	[0.26194]	[2.15349]	[-1.17366]	[-0.56479]	[2.34505]	[0.60880]
DII(-1)	0.008263	-0.001565	0.001271	-1.54E-05	-0.602850	0.617082
	(0.00642)	(0.00206)	(0.00055)	(2.2E-05)	(0.19460)	(0.14376)
	[1.28689]	[-0.75828]	[2.32776]	[-0.71294]	[-3.09792]	[4.29252]
DII(-2)	-0.003520	0.002652	0.000825	7.48E-05	-0.132624	0.281055
	(0.00799)	(0.00257)	(0.00068)	(2.7E-05)	(0.24218)	(0.17891)
	[-0.44048]	[1.03273]	[1.21451]	[2.78350]	[-0.54763]	[1.57094]
DII(-3)	0.006875	0.005637	-0.000701	-1.94E-05	0.561107	-0.040794
	(0.00798)	(0.00256)	(0.00068)	(2.7E-05)	(0.24184)	(0.17866)
	[0.86158]	[2.19779]	[-1.03339]	[-0.72131]	[2.32018]	[-0.22834]
C	80.13043	-14.22261	-0.926967	-0.142151	2448.107	-719.2646
	(57.3867)	(18.4448)	(4.88127)	(0.19294)	(1739.30)	(1284.90)
	[1.39633]	[-0.77109]	[-0.18990]	[-0.73675]	[1.40752]	[-0.55978]
R-squared	0.231819	0.151960	0.369776	0.129665	0.481737	0.582440
Adj. R-squared	0.121200	0.029842	0.279024	0.004337	0.407108	0.522312
Sum sq. resids	31533718	3257637.	228149.7	356.4630	2.90E+10	1.58E+10
S.E. equation	502.2646	161.4345	42.72233	1.688699	15222.89	11245.78
F-statistic	2.095665	1.244369	4.074572	1.034607	6.455025	9.686576
Log likelihood	-1089.693	-926.2495	-734.8191	-269.5892	-1580.939	-1537.335
Akaike AIC	15.39852	13.12847	10.46971	4.008183	22.22138	21.61576
Schwarz SC	15.79037	13.52032	10.86156	4.400033	22.61323	22.00761
Mean dependent	136.9594	-10.64299	5.565278	0.007243	-2336.345	6871.537
S.D. dependent	535.7814	163.8985	50.31466	1.692373	19770.11	16271.11
Determinant resid covariance (dof adj.)	6.29E+28					
Determinant resid covariance	2.69E+28					
Log likelihood	-5939.270					

Akaike information criterion	84.07320
Schwarz criterion	86.42430
Number of coefficients	114

Source: Author's Calculation 2

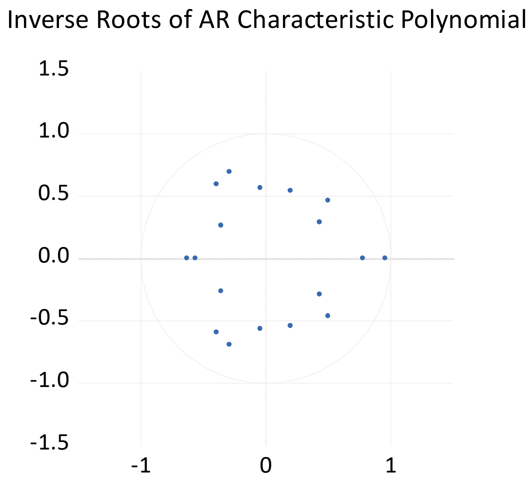

***Fig 2**: Inverse Roots of AR Characteristic Polynomial*

Table 5: Roots of Characteristic Polynomial

Roots of Characteristic Polynomial	
Endogenous variables: DNSE DCRUDE DGOLD DSILVER FII DII	
Exogenous variables: C	
Lag specification: 1 3	
Date: 12/15/24 Time: 15:55	
Root	Modulus
0.956786	0.956786
0.777330	0.777330
-0.290420 - 0.692303i	0.750751
-0.290420 + 0.692303i	0.750751
-0.394321 - 0.593492i	0.712547
-0.394321 + 0.593492i	0.712547
0.499362 + 0.462182i	0.680423
0.499362 - 0.462182i	0.680423
-0.630106	0.630106
0.198116 + 0.540914i	0.576054
0.198116 - 0.540914i	0.576054
-0.043871 + 0.565205i	0.566905
-0.043871 - 0.565205i	0.566905
-0.563148	0.563148
0.430151 - 0.289831i	0.518683
0.430151 + 0.289831i	0.518683
-0.357895 + 0.263985i	0.444722
-0.357895 - 0.263985i	0.444722
No root lies outside the unit circle.	
VAR satisfies the stability condition.	

Source: Author's Calculation

Table 6: VAR Residual Serial Correlation LM Tests

VAR Residual Serial Correlation LM Tests

Date: 12/15/24 Time: 16:03

Sample: 2012M04 2024M08

Included observations: 144

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	45.62465	36	0.1306	1.281298	(36, 503.4)	0.1310
2	32.41100	36	0.6400	0.898587	(36, 503.4)	0.6406
3	49.43183	36	0.0672	1.393382	(36, 503.4)	0.0675
4	48.10287	36	0.0856	1.354164	(36, 503.4)	0.0859

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	45.62465	36	0.1306	1.281298	(36, 503.4)	0.1310
2	90.41149	72	0.0702	1.275321	(72, 593.4)	0.0712
3	151.3382	108	0.0038	1.449566	(108, 591.7)	0.0040
4	182.0403	144	0.0175	1.300069	(144, 568.9)	0.0195

*Edgeworth expansion corrected likelihood ratio statistic.

Source: Author’s Calculation

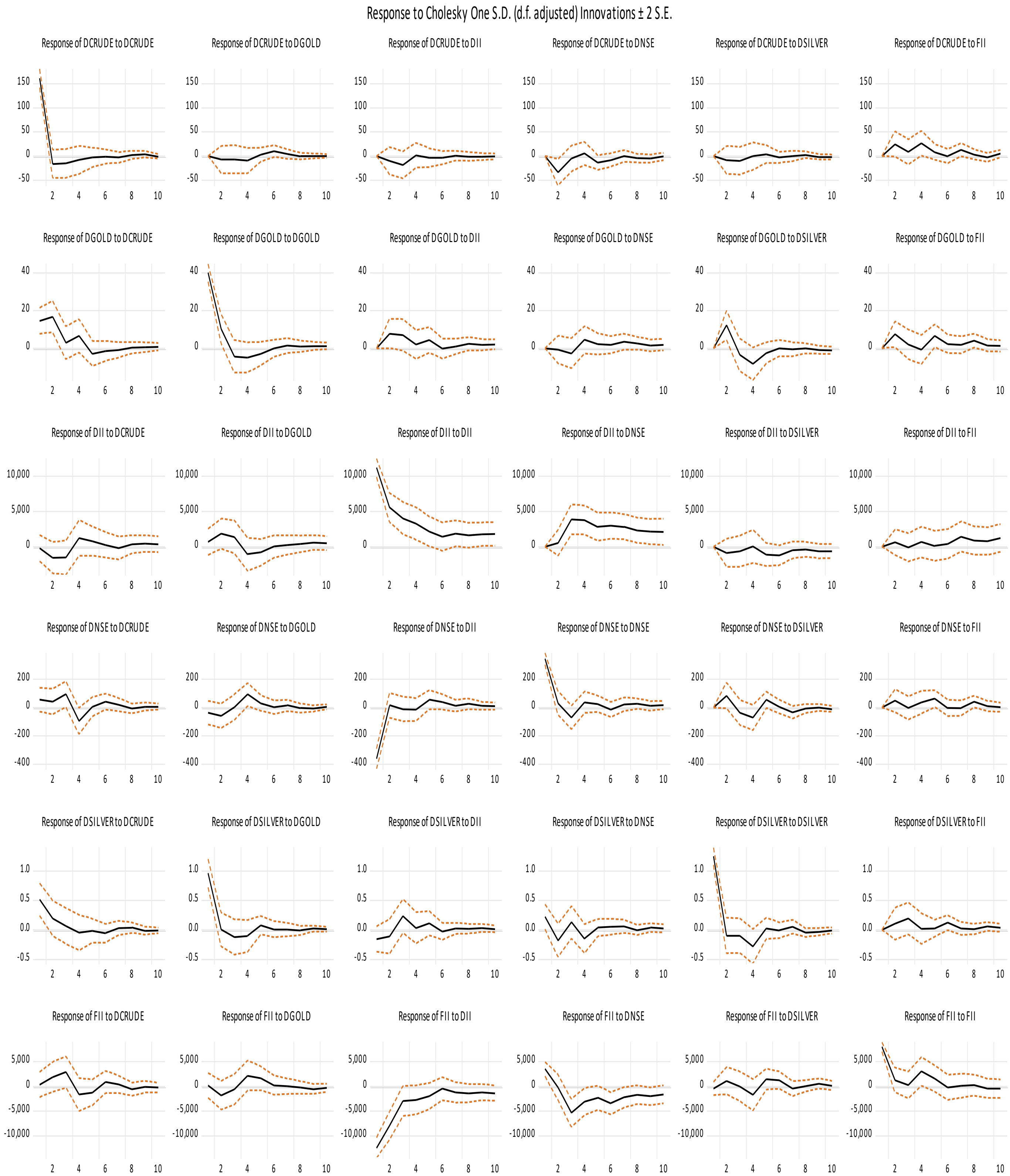

Fig 3: Impulse Response Graph

Fig: 4 Correlogram

Table 7: Variance Decomposition Chart Variance Decomposition of DCRUDE:

Period	S.E.	DCRUDE	DGOLD	DII	DNSE	DSILVER	FII
1	161.4345	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	168.1093	93.12800	0.193154	0.336701	3.934164	0.246383	2.161595
3	170.5246	91.30880	0.356743	1.489692	3.919593	0.580160	2.345016
4	173.1456	88.78427	0.645618	1.453136	3.904426	0.562846	4.649703
5	174.0001	87.94225	0.674911	1.479460	4.463980	0.605709	4.833693
6	174.5433	87.39900	1.007459	1.505355	4.658100	0.625419	4.804661
7	175.1247	86.85067	1.056792	1.497979	4.627278	0.621275	5.346010
8	175.2450	86.74588	1.055790	1.500659	4.688499	0.638074	5.371095
9	175.4057	86.63559	1.053892	1.501510	4.769925	0.647364	5.391718
10	175.4978	86.54894	1.052787	1.502476	4.767940	0.661425	5.466437

Variance Decomposition of DGOLD:

Period	S.E.	DCRUDE	DGOLD	DII	DNSE	DSILVER	FII
1	42.72233	11.63132	88.36868	0.000000	0.000000	0.000000	0.000000
2	49.79426	19.88774	69.36725	2.436945	0.020712	6.040674	2.246678
3	50.78627	19.43813	67.41446	4.252998	0.313055	6.264218	2.317138
4	52.34848	19.90310	64.34226	4.140741	1.038663	8.375938	2.199290
5	53.21171	19.54942	62.57020	4.705651	1.178804	8.326286	3.669636
6	53.31143	19.54856	62.33663	4.688849	1.295272	8.295209	3.835480
7	53.49193	19.44389	61.98614	4.687745	1.710615	8.248765	3.922850
8	53.76524	19.24953	61.39222	4.835549	1.929766	8.165269	4.427662
9	53.85788	19.19431	61.22765	4.927940	1.994466	8.160816	4.494825
10	53.97518	19.13019	61.00696	5.059068	2.106980	8.169625	4.527185

Variance Decomposition of DII:

Period	S.E.	DCRUDE	DGOLD	DII	DNSE	DSILVER	FII
1	11245.78	0.029465	0.369885	99.60065	0.000000	0.000000	0.000000
2	12836.31	1.470837	2.374682	95.24399	0.200136	0.460628	0.249726
3	14171.58	2.348523	2.900246	86.30784	7.660465	0.573659	0.209263
4	15143.95	2.749939	3.056464	80.32308	12.97800	0.503533	0.388987
5	15638.98	2.831855	3.119739	77.24238	15.44677	0.987200	0.372057
6	16044.59	2.714456	2.964788	74.17993	18.21343	1.511342	0.416056
7	16471.04	2.587132	2.835061	71.68759	20.21117	1.511968	1.167088
8	16751.59	2.542309	2.802112	70.25258	21.47240	1.507691	1.422913
9	17031.10	2.525639	2.837818	69.05539	22.39431	1.590409	1.596440
10	17326.85	2.481031	2.824897	67.82830	23.13581	1.662752	2.067210

Variance Decomposition of DNSE:

Period	S.E.	DCRUDE	DGOLD	DII	DNSE	DSILVER	FII
1	502.2646	1.192566	0.523034	51.75290	46.53150	0.000000	0.000000
2	517.5742	1.769663	1.795275	48.82102	44.15267	2.605166	0.856201
3	532.1958	4.754935	1.699450	46.22940	43.57831	2.923380	0.814524
4	555.5587	7.329760	4.247155	42.49940	40.40975	4.349307	1.164632
5	565.4864	7.079539	4.379136	41.92041	39.18893	5.085890	2.346104
6	568.4238	7.502798	4.334777	41.93777	38.85477	5.041198	2.328690
7	570.4874	7.549694	4.355936	41.67726	38.72918	5.369054	2.318876
8	573.3178	7.489029	4.320774	41.47340	38.56683	5.334823	2.815144
9	573.6806	7.489010	4.332942	41.45665	38.55892	5.328078	2.834401
10	574.1551	7.483745	4.331268	41.41592	38.57765	5.361333	2.830086

Variance Decomposition of DSILVER:

Period	S.E.	DCRUDE	DGOLD	DII	DNSE	DSILVER	FII
1	1.688699	9.487610	32.71141	0.829131	1.811251	55.16060	0.000000
2	1.718756	10.44492	31.58096	1.199106	2.817644	53.56555	0.391816
3	1.759570	10.11079	30.62503	2.980310	3.239870	51.42133	1.622672
4	1.791648	9.821845	29.85975	2.910713	3.815166	52.01228	1.580248

5	1.797894	9.758416	29.85561	3.290670	3.829137	51.67221	1.593964
6	1.804105	9.783037	29.65377	3.286002	3.903551	51.31895	2.054681
7	1.806713	9.789553	29.56985	3.298091	4.010650	51.26577	2.066087
8	1.807890	9.819304	29.53480	3.306794	4.005608	51.26251	2.070985
9	1.810098	9.800890	29.47899	3.333570	4.045388	51.16700	2.174165
10	1.810778	9.795391	29.46093	3.338661	4.062088	51.13051	2.212415

Variance Decomposition of FII:

Period	S.E.	DCRUDE	DGOLD	DII	DNSE	DSILVER	FII
1	15222.89	0.054509	0.016821	66.72993	5.343619	0.084838	27.77029
2	17429.22	1.244018	1.095348	71.35416	4.087698	0.493143	21.72564
3	18709.01	3.485752	1.045810	64.45922	11.70223	0.428037	18.87894
4	19671.04	3.848287	2.186561	60.24361	13.08261	1.141153	19.49777
5	20125.95	4.058854	2.759676	58.49887	13.83450	1.599746	19.24835
6	20480.38	4.114098	2.676206	56.54047	16.15003	1.920846	18.59835
7	20643.07	4.088185	2.634528	56.00406	17.02494	1.938834	18.30946
8	20767.63	4.108946	2.616161	55.77540	17.47730	1.917611	18.10459
9	20915.18	4.052733	2.648534	55.31060	18.13684	1.963329	17.88796
10	21031.99	4.019355	2.641251	55.12924	18.52576	1.947190	17.73720

Cholesky Ordering: DCRUDE DGOLD DII DNSE DSILVER FII

Source: Author's Calculation