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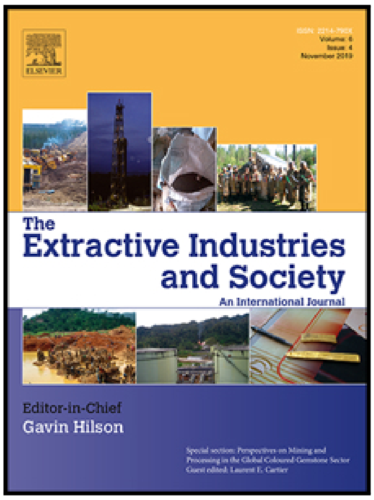

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The Protective Nature of Gold During Times of Oil Price Volatility: An Analysis of the COVID-19 Pandemic

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Highlights

1. Crude oil prices are subject to frequent and unpredictable fluctuations that can pose significant risks for investors. In this paper, we investigate whether gold can serve as a haven or a hedging as opposed to these hazards.
2. We apply the imbalanced VARMA-GARCH framework to analyze everyday information between Jan 2010 to Aug 2022. To consider the effect of COVID-19 epidemic on the oil and gold markets, we divide the information into 2 sub-parts: prior to and amid the epidemic.
3. Our empirical outcomes show that gold serves as an important refuge against the fuel cost risks in both sub-periods. This means that gold can protect investors from extreme negative movements at oil prices. Moreover, our optimal portfolio and hedging analyzes confirm that gold can also hedge against normal variations in oil prices.

Abstract

This research explores gold's safe-haven properties amid oil price instability, focusing on the COVID-19 pandemic. The study examines how gold hedges against oil price swings in the context of the pandemic's exceptional market circumstances. A VAR (Vector Autoregressive) model analyzes gold and oil prices from 2006 through 2021. The VAR model reflects the dynamic interactions and interdependencies between these two essential commodities in the context of oil price volatility and the COVID-19 pandemic. This analysis shows that gold protects against oil price volatility and the COVID-19 pandemic—gold buffers against oil price swings due to its strong inverse association with oil prices. Gold offers investors security and asset preservation during significant oil price volatility. In light of oil price volatility and the COVID-19 pandemic, the study helps explain gold's importance as a diversification tool and haven asset. Investors, policymakers, and market players should consider gold as a hedge against oil price volatility and economic instability.

Keywords: Gold; Oil price volatility; Essential commodities; Market players

1.Introduction

Oil and gold are two essential commodities that are important in the world's financial markets. Both commodities are intertwined, with gold acting as a haven asset and a store of value, while oil prices impact different economic sectors. Investors, decision-makers, and market players must know the connection between gold and oil prices, especially when the markets are volatile. Several different variables impact the stability and performance of the international financial markets. Among them, the price swings of commodities like oil and gold substantially impact market dynamics.(Y. Zhang & Umair, 2023) China is a resource-rich nation that is especially vulnerable to fluctuations in commodity prices, which may significantly affect the country's equities market and more extensive financial system. For policymakers, investors, and financial institutions to make knowledgeable choices and create efficient financial policies, it is essential to comprehend the effects of changes in the price of gold and oil on the China equities market. Gold and oil are two of the most well-known commodities in South Africa, renowned for having a wealth of natural resources. These resources are vital to the nation's economy, and any changes in their pricing might significantly impact a number of industries, including the stock market. Global supply and demand dynamics, geopolitical variables, and macroeconomic circumstances impact oil prices. On the other hand, variables like inflation, currency changes, and investor attitude toward safe-haven assets impact gold prices.(Li & Umair, 2023) It is crucial to investigate how changes in their prices impact the China equities market, given the significance of oil and gold to the country's economy. This study may lighten the interrelationships between commodities markets and the equities market by revealing insights into the transmission channels of volatility and spillover effects. Understanding these processes may also significantly impact financial policy, including how risk is managed, how portfolios are diversified, and how to create efficient regulatory measures.(Ullah et al., 2020) The idea of volatility spillovers is an essential factor to consider when analyzing the effect of changes in the price of gold and oil on the South African equities market. Spillovers of volatility are the transfer of volatility from one market to another. In this context, it alludes to the volatility spreading from the commodities markets (oil and gold) to the equities market. For determining the degree of interconnectivity between these markets and the possible risk implications for investors and market players, it is crucial to comprehend the existence and extent of volatility spillovers. Prior research has shown evidence of volatility spillovers between commodities and equities markets in diverse circumstances. For instance, research has shown that oil price fluctuations may impact stock market returns in nations that export oil(Xiuzhen et al., 2022). Similar findings have been made about the impact of changes in the price of gold on equities markets in both developed and developing nations(Wu et al., 2022). The oil business has long been a pillar of the world economy, supplying essential energy supplies for manufacturing, transportation, and several other industries. However, the environmental effect of using fossil fuels, notably in terms of greenhouse gas emissions and climate change, has come to more attention in recent years. As a result, there is growing pressure on the oil sector to switch to more ecologically friendly and sustainable methods. The fluctuation in oil prices, which substantially impacts the financial health of the oil sector and its carbon footprint, is one crucial element affecting this change.

The term "oil price volatility" describes shifts in the price of crude oil on the international market. Numerous variables, including supply and demand dynamics, macroeconomic circumstances, and geopolitical tensions, might be blamed for these changes. Oil price volatility significantly influences the global economy, financial markets, and investments in the energy sector. Oil price volatility impacts energy policy, economic development, and environmental initiatives, as well as the profitability and financial stability of oil businesses. Oil sector financial repercussions of oil price fluctuation are severe(Pan et al., 2023). Given that oil firms' income is intimately correlated with the price of oil, high volatility may result in revenue changes and decreased profitability. Oil firms may have financial difficulties when low prices include decreased cash flow, lesser exploration and production investment, and even insolvency concerns. On the other hand, during times of high pricing, businesses may enjoy greater earnings, resulting in expenditures in capital and growth. Additionally, the value of oil reserves is impacted by oil price volatility, which influences the financial accounts of oil firms. A company's solvency and credit ratings may be affected by asset write-downs and impairments brought on by fluctuating oil prices. The capacity of oil corporations to invest in R&D, technical innovation, and sustainable practices is influenced by their financial situation. Therefore, for stakeholders, investors, and policymakers to make informed choices, they must comprehend the effects of oil price volatility on the financial health of the oil sector. The oil industry's carbon footprint is the greenhouse gas emissions brought on by oil extraction, refinement, transportation, and consumption(W. Fang et al., 2022). Oil price volatility may impact the industry's carbon footprint through several different avenues. First, during high oil prices, there could be a greater incentive to extract and produce from less traditional and more carbon-intensive sources, such as oil sands or deepwater drilling.

On the other hand, low oil prices may lead to less funding for carbon-intensive projects, which might reduce emissions. However, it is crucial to consider the energy transition in addition to the more general context of oil price volatility(F. Liu et al., 2023). The competitiveness of renewable energy sources may be impacted by lower costs, thus delaying the transition to cleaner alternatives. Oil price volatility also affects consumer habits for energy. Introducing more fuel-efficient technology and changes in consumer behavior due to fluctuating pricing might result in variations in energy demand. These changes impact the total amount of carbon emissions linked to oil use. There is a growing worldwide movement toward switching to more sustainable and clean energy sources because of the environmental issues related to oil usage. The volatility of oil prices may impact the speed and course of this transformation(Li & Umair, 2023). High oil price volatility may lead to market risks and uncertainty, making investments in renewable energy projects more difficult. In contrast, low oil prices may make oil exploration and production less economically viable, which may cause investment to be redirected toward renewable energy sources. For policymakers, investors, and stakeholders in the energy sector, it is critical to comprehend the effects of oil price volatility on the financial health and carbon footprint of the oil business.

The COVID-19 pandemic outbreak in 2020 brought about unheard-of market circumstances and increased volatility in a number of asset types, including commodities. Sharp drops in oil prices were caused by the pandemic's huge reduction in worldwide oil consumption. Due to the harsh market circumstances, it has become necessary to investigate the connection between gold and oil prices and how gold functions as a defensive asset when oil prices are volatile. In this research, the COVID-19 pandemic examined to examine the protective qualities of gold during periods of oil price fluctuation. The study period covers a sizable period, from 2006 to 2021, encompassing a range of market cycles and economic situations. We can capture the dynamics of relationships between the prices of gold and oil by looking over this lengthy time, and we can evaluate how the COVID-19 epidemic has affected their connection. We use a VAR (Vector Autoregressive) model to examine the link between gold and oil prices and how they react to oil price volatility. The simultaneous interactions and interdependencies between the prices of gold and oil may be examined using the VAR model, capturing the dynamic character of their connection. This modeling strategy allows us to analyze how gold functions as a hedge against changes in oil prices and offers insights into how these commodities behaved during the COVID-19 epidemic. The study's conclusions affect investors and decision-makers who want to comprehend how gold functions as a diversification tool and a safe-haven asset. We can learn more about gold's potential as a risk reduction tactic by looking at how protective it is during volatile oil prices. Understanding the price interactions between gold and oil during the COVID-19 pandemic also provides insight into the particular market circumstances and the effects of global crises on these commodities.

2.Literature review

2.1. Crude Oil Price and Exchange Rate

The link between crude oil prices and exchange rates has garnered attention because of its interdependence and possible economic ramifications. The effect of oil price shocks on currency rates in the BRICS nations has been the subject of several research. For instance, in BRICS, (Mohsin, Taghizadeh-Hesary, Iqbal, et al., 2022)discovered evidence of asymmetric volatility spillovers between oil prices and currency rates. They proposed that although adverse shocks have a lower impact, positive shocks to the price of oil tend to enhance exchange rate volatility.

The dynamic relationships between crude oil prices and currency rates have also been studied. (Chang et al., 2023b)looked at the connection between the value of the Chinese Yuan concerning world oil prices. They discovered a strong positive link between the exchange rate and oil prices, indicating that rising oil prices cause the Yuan to appreciate. The results of this research emphasize how crucial it is to consider the relationships between oil prices and exchange rates to comprehend the dynamics of the BRICS economies. The link between the price of crude oil and the price of gold has received attention since both are considered alternative assets and safe-haven investments. Empirical data suggest an intricate link between these two factors. For instance, (D. Zhang et al., 2022)used a time-varying copula technique to examine the correlation between gold and oil prices in the BRICS nations. Significant time-varying correlations were discovered, indicating that shifting market circumstances influence the connection between the prices of gold and oil. In the BRICS setting, asymmetric volatility spillovers between the prices of gold and oil have also been noted. In the BRICS nations, (Wei et al., 2022)looked at price of crude oil and gold. During times of financial crisis, they discovered evidence of considerable spillovers from oil prices to gold prices, which suggests a flight to safety impact. This suggests that oil price shocks affect gold prices differentially during market uncertainty, emphasizing the need to consider asymmetric impacts in volatility spillover calculations. The link between exchange rates and gold prices has been studied in the literature, particularly emphasizing how exchange rate variations affect gold prices. The dynamic relationships between the Chinese yuan exchange rate and gold prices in China were looked into by(Mohsin, Taghizadeh-Hesary, & Shahbaz, 2022). They discovered proof of significant time-varying correlations, suggesting that changes in the exchange rate affect gold prices in the Chinese market.

In the BRICS nations, asymmetric volatility spillovers have also been noted between currency rates and gold prices. Using a multivariate GARCH framework, investigated the impacts of currency rates and gold prices in the BRICS economies. They discovered evidence of sizable asymmetries, indicating that positive and negative shocks affect the volatility of exchange rates and gold prices differently. These results highlight the significance of considering the asymmetry exchange rates, and gold prices have been examined in the BRICS context to comprehend the interdependencies between these variables. Using a dynamic conditional correlation model,(Chang, Gan, et al., 2022) examined the time-varying. They discovered that the correlations between oil prices and currency rates varied among nations, indicating that country-specific factors may impact this link. In addition, they saw fluctuating connections between gold and oil prices over time, suggesting shifting relationships between these two commodities. Similarly,(Chang, Taghizadeh-Hesary, et al., 2022) used a wavelet-based methodology to investigate the dynamic connections between oil prices, currency rates, and gold prices in BRICS nations. They discovered that there are short-term and long-term associations since the correlations between these variables change across various periods. The findings indicate that different variables, including market circumstances, economic policies, and geopolitical events, impact the correlations between oil prices, exchange rates, and gold prices.

For the aggregate model, the authors found that geopolitical risk contributed significantly to oil price increases. The impacts of economic growth, transportation improvements, and technological advances on CO2 emissions while accounting for GDP growth from 1971 to 2018 were discussed in two studies by(Xu et al., 2023). Financial growth, transportation infrastructure, innovation, and CO2 emissions were all shown to be very vulnerable to one another across many time scales and frequency bands using a wavelet coherence technique and coupled cointegration.

In addition, the results of the wavelet coherence approach demonstrated that (i) transportation was a significant source of CO2 emissions during the 1986–1988 and 2001–2014 time periods, and (ii) innovation significantly predicted CO2 emissions during this period. Considering the American transportation industry, the impact of factors including fossil fuel energy consumption, biomass energy consumption, and economic growth on CO2 emissions was calculated in two separate studies by(Tamazian et al., 2009), and economic expansion on CO2 emission and found that natural resources had a favorable influence on CO2 emission in China.

The present age of the COVID-19 epidemic has led to several research examining the function that various metals serve as hedges or safe havens in this uncertain time. For instance,(Chang et al., 2023a) investigated the influence of the COVID-19 pandemic on the gold and oil markets and found that it had asymmetries. The results of the BEKK-AGARCH model showed that the oil market's influence on the gold market was somewhat more significant during the epidemic. Additionally, it was discovered that the adverse information shock in the oil market had a more substantial influence on the volatility of gold return than the positive shock, heightened during the pandemic era. Pre-Covid era studies by (Z. Fang et al., 2022) corroborate the protective effect of gold on oil prices. A similar conclusion that gold provides shelter from oil price volatility was obtained by(Chang, Lu, et al., 2022). In addition to the findings of prior research, the authors of this study also demonstrated that gold served as a secure refuge for storing platinum, palladium, and silver. (Mohsin et al., 2020)considered the possibility that the function of gold as a haven might be affected by the volatility of other metal prices during and before the COVID-19 period. Gold prices were brought down in the long run by the negative volatility of the Eurocurrency. Still, the positive volatility of silver, gold, developing markets, and financial markets during the COVID-19 era brought them down in the short run.

In contrast, energy, silver, gold, Eurocurrency, and financial industry volatility contributed to higher gold prices before COVID-19. In contrast, only oil market volatility in the near term led to lower gold prices. (Iram et al., 2020)conducted a quantile regression analysis of escape flights using indicated gold, stock, silver, and gold mining volatilities. Unidirectional causation flowing from stock market volatility to the volatilities of the silver, gold, and gold mining markets was discovered when testing for nonlinear and linear Granger causality across quantiles. There is no link between silver and gold market volatility, though. The higher and lower quantiles discovered evidence of unidirectional causation from gold, silver, and stock market volatility to gold-mining volatility.(Mohsin et al., 2019) Estimating the impact of the COVID-19 pandemic on commodities markets has been more popular in recent publications. This is the first research to use the ARDL estimate method to analyze the impact of coronavirus infections on food price indices and crude oil prices from January 2020 to March 2020.(Khanna et al., 2019) . Long-term effects on oil prices were shown to be unfavorable because to the COVID-19 epidemic, but the index of food prices was found to be positively impacted. However, in the near term, the food price index and oil prices were negatively correlated with the COVID-19 pandemic. (Christoffersen & Pan, 2018) reached the same finding for a research set in China. Investor demand for gold during the COVID-19 pandemic-induced recession was studied by. Their research indicated that income and inflation might explain people's preference for gold over interest rates. Gold and oil prices may have been impacted by the COVID-19 panic, media coverage, and news, according to a study conducted by. The ARDL method indicated that the fear and fatalities associated with COVID-19 harmed oil prices between January and June 2020. However, media hype negatively impacted oil prices in the long term. According to the research, gold was shown to provide a haven during the COVID-19 outbreak crisis and a hedge against geopolitical and socioeconomic catastrophes. In addition, recently constructed the COVID 19 World Fear Index by using two factors—deaths and reported cases—and looked into whether or not the index might forecast the price returns of gold and agricultural products. The results showed a positive correlation between the fear index and the returns on commodities prices.

3. Data and methodology

3.1. Data

The daily transaction data from 2006-2021, is used as a sample for this article. Oil price volatility futures prices are used as a proxy for the natural resources, while the amount of local currency in each of the China nations equal to one US dollar is utilized to indicate exchange rates. Each set contains 3851 valid values after removing the data with inconsistent income dates and missing data from market trading difficulties. Renewable energy data is provided by the WGC. In contrast, exchange rate data is provided by Bloomberg and carbon emission data is acquired from the US EIA website. More than 65% of the world's crude oil is now priced under the Brent system, which is worth mentioning when investigating the volatility of crude oil prices since futures contracts have high liquidity and transparency. As a result, we will utilize the futures price of oil price volatility as our data point.

Daily compounded returns are determined by finding the difference in logarithms of two successive prices. Here is the formula: OPVt = ln(Brentt / Brentt-1) = ln (ExRatet / ExRatet-1) * 100REt The formula is: 100NRt = ln(Goldt / Goldt-1) × 100

In contrast, OPVt, REt, and NRt are the refined international crude oil daily rate of return, exchange rate daily rate of return, and gold price daily return series, respectively. In this article, OPVt stands for the daily return series of international crude oil. In contrast, CO2t, GFt and GDPt, are the daily return series of the China, respectively.

3.2. Methodology

Evidence for cross-market information transmission (the "spillover effect") in financial markets is presented. The volatility spillover effect is the spread of risk in economics from one market to another. In contrast to the more prevalent usage of VAR and GARCH models for investigating correlations in empirical research, MGARCH models are often used for investigating the volatility and linkages between the volatility of many markets. Energy economics and finance domains, such as oil price research(X. Zhang et al., 2021), extensively use MGARCH models with BEKK to investigate Intermarket volatility spillover effects.

Increasing the number of variables is one way to minimize the endogenous impact when we investigate the spillover effect across several marketplaces(L. Yu et al., 2021). This work, in contrast to previous studies that only looked at two markets, leverages the oil, currency rate, and gold markets to significantly cut down on endogeneity and boost the credibility of the findings.

3.2.1. VAR model

Predicting many financial factors at once might be a cause for anxiety at times. The VAR model is a technique for making systemic predictions about many time series variables. We construct a p-order Vector Autoregressive (VAR) model to analyze the average impact of spillovers between marketplaces. This is how the model works:

$$R_{i,t} = \alpha_i + \sum_{k=1}^{p} A_k R_{i,t-k} + \varepsilon_{i,t} \qquad (1)$$

$$\varepsilon_t | I_{t-1} \sim N(0, H_t) \qquad (2)$$

Where the price shock at time t is represented by the residual vector t, which is assumed to have a normal allocation with a mean of zero and a variance of one. Various series of prices are represented by the various values of i. Since this is the case, we may rewrite equation (1) as a matrix:

$$\begin{pmatrix} R_{1,t} \\ R_{2,t} \\ R_{3,t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix} + \sum_{k=1}^{p} \begin{pmatrix} \alpha_{11,k} & \alpha_{12,k} & \alpha_{13,k} \\ \alpha_{21,k} & \alpha_{22,k} & \alpha_{23,k} \\ \alpha_{31,k} & \alpha_{32,k} & \alpha_{33,k} \end{pmatrix} \times \begin{pmatrix} R_{1,t-k} \\ R_{2,t-k} \\ R_{3,t-k} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix} \quad (3)$$

Where R1, t, R2, t, R3, t are return series for natural resources, the exchange rate, and the price of gold at time t. The best lag order of the VAR model is represented by p, whereas Ri,t-k is the return series at time t-k. Each market's long-term offset is represented by the vector i(i = 1, 2, 3), which is a constant term. The 3 by 3 coefficient parameter matrix is denoted as Ak (k = 1, 2, 3..., p), where ij is the exchange of price data across markets.

3.2.2. BEKK-GARCH model

A multivariate econometric model called BEKK-GARCH (Baba, Engle, Kraft, and Kroner) is used to estimate and predict the conditional covariance matrix and time-varying conditional correlations between various variables.(Riddick & Whited, 2009) The standard GARCH model is expanded in the BEKK-GARCH model in order to better account for dynamic correlation structure.(H. Liu & Zhao, 2022) The BEKK-GARCH model's important feature is its ability to estimate time-varying conditional correlations, which is very helpful in capturing the shifting interdependencies and spillover effects across variables. The model is often used in risk management, macroeconomics, and financial econometrics:

$$\varepsilon_t = H_t^{1/2} \upsilon_t \quad (4)$$

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \quad (5)$$

In the VAR (p) equation, the trade residuals 1,t, 2,t, and 3,t form a 3 by 1 matrix denoted by t. Standardized residuals 1,t, 2,t, and 3,t form a matrix called t, which is a white-noise procedure. Data on the variation and covariance of the residual t at time t-k is represented by the matrix Ht, which is of size 3 by 3. Matrix C is a fixed lower triangular 3 by 3 matrix, but A and B may be whatever size they choose. The exact matrices used in Eq. (5) are as follows:

$$H_t = \begin{pmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{pmatrix} C = \begin{pmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{pmatrix} A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} B =$$

$$\begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix} \qquad (6)$$

The ARCH impact of price return variations is represented in the non-diagonal components of A and B by the value aij(ij), which represents the degree to which market i influences market j. The GARCH impact of price return variations is represented by bij(ij), the continuous transmission of fluctuations from market i to market j.

3.2.3. Asymmetric BEKK-GARCH model

We use the asymmetrical BEKK (1,1) model to account for the asymmetric effect:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\theta_{t-1}\theta'_{t-1}D \qquad (7)$$

In this case, t-1 is a three-dimensional column vector, and matrix D is a three-by-three matrix, much like matrices A and B. If t-1 is negative, then the news is terrible, and t-1 will be equal to t-1.(Cheng et al., 2017) Accordingly, the disparate impact of the worldwide crude oil sector, the China exchange rate, and the gold market is quantified by matrix D.

3.2.4. DCC-GARCH model

The DCC-GARCH model modifies the univariate CCC-GARCH equations to include a conditional correlation matrix. The current normalized residuals from the univariate GARCH models are combined with the previous conditional correlation estimate to recursively update the conditional correlation matrix.(H. Liu et al., 2022) This dynamic updating mechanism allows the correlation structure to adjust to shifting market circumstances. The DCC-GARCH model captures both the changing correlation structure between variables and the time-varying volatility of individual variables by merging the univariate CCC-GARCH models with the dynamic conditional correlation specification. In multivariate time series data, this offers a more realistic depiction of the complex dynamics and interdependencies. The time-varying conditional correlations and parameter estimates for the DCC-GARCH model are commonly obtained using maximum likelihood estimation or Bayesian approaches:

$$\varepsilon_t|\varphi_{t-1} \sim N(0, H_t), H_t = D_t R_t D_t \qquad (8)$$

ε_t: It reflects the residual or error term in the model at time t. The discrepancy between the observed data and the values predicted by the model is captured by the error term. It reflects the knowledge contained in the model as of time (t-1) 1. This could comprise prior observations, explanatory factors, or any other pertinent data that affects the present moment.It represents a normal distribution with a mean of 0 and a variance-covariance matrix of H_t as N(0, H_t). The normal distribution assumption, which is a widely-used presumption in many statistical models, states that the errors are normally distributed about zero. It reflects the error term's variance-covariance matrix at time t. In this equation, H_t is written as D_t R_t D_t, where D_t denotes the error term's transformation matrix and R_t denotes the error term's heteroscedasticity or variability matrix.

$$D_t = \sqrt{h_{i,t}} \qquad (9)$$

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \tilde{\varepsilon}_t \tilde{\varepsilon}_t{}' + \theta_2 Q_{t-1} \qquad (10)$$

$$R_t = diag(Q_t)^{-1}(Q_t)diag(Q_t)^{-1} \qquad (11)$$

Where $\tilde{\varepsilon}_t$ is the unconditional covariance matrix of the standardized residual, Qt is a symmetric positive definite matrix, and is the standardized residue vector. The scalar variables 1 and 2 are positive integers that fulfill the equation θ1 + θ2 < 1. Meanwhile, the log-likelihood function with T samples is, and the maximum likelihood approach is used to estimate the model parameters.

$$L = \sum_{t=1}^{T} \ln(f(R_t|I_{t-1};\theta)) \qquad (12)$$

L: It stands for the likelihood function, which calculates the likelihood of seeing the provided data (R_t) given the model parameters () and the knowledge that is already known (I_(t-1)). Estimating the most likely values for the model parameters is made easier by maximizing the likelihood function. A series of observations made over a certain time period are represented by this time index, which has a range from 1 to T.

$$f(R_t|I_{t-1};\theta) = (2\pi|H_t|)^{-1/2}\exp(-\varepsilon'_t(H_t{}^{-1})\varepsilon_t/2) \qquad (13)$$

The estimating procedure is iterated and optimized using the BFGS algorithm used in this research. For this reason, the only difference between the BFGS and BHHH algorithms is in how the second derivative of the Hessian matrix is constructed, which is compatible with the gradient calculation approach(CHENGHUI & DILANCHIEV, 2022).

4.Results and discussion

The descriptive statistics for the variables OPVt, GDPt, NRt, REt, CO2t, and GFt are shown in Table 1. These numbers provide a general idea of the variables' central tendency, dispersion, Skewness, kurtosis, and Jarque-Bera (J-B) statistics. Analyzing the table and talking about its ramifications will help. The mean values of the variables show their average levels, which is the central tendency.(Y. Liu et al., 2022) For instance, GDPt's mean of 0.018 indicates that the GDP has grown favorably throughout the measured time. Other variables with positive mean values, such as NRt, REt, CO2t, and GFt, also indicate positive average levels or growth rates. It is crucial to remember that OPVt has a mean of -0.006, which indicates a somewhat negative average value. The standard deviation calculates how far the values around the mean vary. A more significant standard deviation indicates that the data are more variable. Variables in this table with significantly more significant standard deviations (OPVt, NRt, and CO2t) indicate that their values are subject to considerable swings or volatility. Conversely, measures with minor standard deviations, such as GDPt, REt, and GFt, indicate comparatively more stable trends. The minimum and maximum values indicate the values observed at the lowest and highest levels. The range shows how widely distributed or how much variance the data has. For instance, OPVt has a broad range of values, with a minimum value of -28.970 and a maximum value of 18.070. Other variables also have wide ranges, possibly due to outliers or various degrees of variability. Kurtosis measures the degree of peakedness or tail heaviness, whereas Skewness measures the asymmetry of the data distribution. Most of the variables in this table have modest skewness values, except OPVt, which has a negative skewness (-0.431),(Hagedoorn et al., 2021) indicating a minor left skewness. The data distribution has large tails and a greater possibility of extreme observations, as shown by the relatively high kurtosis values for various variables. Based on Skewness and kurtosis, J-B statistics test the null hypothesis of normality in the data. A lower p-value indicates more significant evidence against the null hypothesis of normality, which is shown by asterisks (*). The J-B statistics in this table show that all variables have very low p-values (0.0000), providing strong evidence to reject the premise of normality.

Table 1. Descriptive statistics.

Variables	OPV_t	$GDPt$	NRt	RE_t	$CO2t$	GFt
Obs	3851	3851	3851	3851	3851	3851
Mean	−0.006	0.018	0.055	0.031	0.070	0.021
Std. Dev.	3.307	1.060	1.442	0.919	1.339	0.460
Min	−28.970	−7.341	−8.621	−11.841	−8.560	−3.551
Max	18.070	6.155	15.631	11.231	11.161	4.695
Skew.	−0.431	0.231	0.280	0.371	0.070	0.141
Kurt.	15.890	7.460	11.870	19.540	7.931	8.214
J-B Statistics	23154.485*** (0.0000)	5197.831*** (0.0000)	9970.505*** (0.0000)	55193.051*** (0.0000)	5621.307*** (0.0000)	6194.771*** (0.0000)

The results of the OPV unit root test for the variables at their levels and initial differences are shown in Table 2. The test statistics and breakpoints (BD1) are supplied for each variable. Analyzing the table and talking about its ramifications will help. The PV unit root test determines if a time series variable has a unit root. A unit root indicates a random walk procedure and non-stationarity for the variable.(Yang et al., 2022) To evaluate if the unit root null hypothesis may be rejected, the test statistics are checked against crucial levels. A unit root is checked for in the level form for the following variables: OPVt, GDPt, NRt, REt, CO2t, and GFt. The test statistics (T-Statistics) gauge the degree of support for a unit root's null hypothesis. For instance, the T-statistic for OPVt is -4.512, which strongly indicates the absence of a unit root. Similar negative T-statistics for several variables, including GDPt, NRt, REt, and CO2t, may indicate non-stationarity. The positive T-statistic of 3.003 for REt, on the other hand, indicates that it is more likely to remain stationary.(Dilanchiev & Taktakishvili, 2021) The stationarity of the variables' first differences is next examined. Calculating the differences between successive observations of a variable is known as first differencing. The initial differences' T-statistics quantify the evidence against the unit root null hypothesis. For instance, the T-statistic for GDPt in initial differences is -6.495, which strongly supports stationarity after differencing. The negative T-statistics of NRt, REt, CO2t, and GFt also show that they become stationary after taking initial differences.

Table 2. The findings of the OPV unit root test.

Variables	**At Level**		**At First Differences**		
	T-Statistics	**BD[1]**	**Variables**	**T-Statistics**	**BD[1]**
OPVt	−4.512	2007	GDPt	−6.495 **	2014
GDPt	−4.231	2014	NRt	7.122**	1992
NRt	−3.51	2003	REt	−5.004 **	2002
REt	3.003	1998	CO2t	−12.511 **	2007
CO2t	−1.644	2002	GFt	−6.452 **	2007

The results of the ARDL (Autoregressive Distributed Lag) test for the variables OPVt, GDPt, NRt, REt, CO2t, and GFt are shown in Table 3. The estimated values, t-statistics, and p-values for each factor are shown in the table. Analyzing the table and talking about its ramifications will help. The ARDL test is a popular technique for analyzing the long-term connection between variables. It offers information on the existence and nature of the link and allows for both stationary and non-stationary variables in the model. The coefficients acquired from the ARDL model are represented by the estimated values in Table 2. These coefficients show the magnitude and direction of each factor's influence on the dependent variable. For instance, the projected value of OPVt is -0.348*, indicating a negative correlation between the independent and dependent variables. Similar estimates for additional variables, including GDPt, NRt, REt, CO2t, and GFt, show their links to the dependent variable.(Naz et al., 2021) The t-statistics quantify each coefficient's importance, and the p-values statistically show the calculated coefficients' significance. A lower p-value indicates more evidence against the null hypothesis of no association. Most of the components in Table 2 have t-statistics that are more than 1, suggesting that the coefficients are statistically significant. Additionally, all factors have p-values that are very near to 0, which provides strong support for rejecting the null hypothesis. The dependent variable may be negatively impacted by changes in oil price volatility, as shown by the negative coefficient (-0.348*) for OPVt. This result is consistent with the research that point out the negative impact of oil price volatility on many economic indicators. The dependent variable and GDP are positively correlated, as shown by the positive GDPt coefficient (0.502****). This result supports the widely held belief that rising demand, investment, and consumption are indicators of economic development(Dilanchiev et al., 2021). The dependent variable may be negatively impacted by the availability of natural resources, as shown by the negative coefficient (-0.190***) for NRt. This result supports the "resource curse" idea, which contends that nations with high reliance on natural resources may have economic difficulties (Y. Zhang et al., 2018). The dependent variable and exchange rates are positively correlated, as shown by the positive coefficient (1.671***) for REt. This result implies that changes in the exchange rate impact the dependent variable, possibly affecting commerce and economic activity(Batool et al., 2022). The dependent variable and CO2 emissions are positively correlated, as shown by the positive coefficient (3.885***) for CO2t. This discovery emphasizes how crucial it is to address environmental issues and reduce the carbon footprint of economic activity. Government expenditure and the dependent variable have a strong negative association, as seen by the negative coefficient (-0.677***) for GFt. This result raises the possibility that excessive public expenditure may negatively impact the dependent variable and displace private investment. Overall, Table 2's ARDL test results provide empirical proof of the connections between the independent and dependent variables. These results help us comprehend these variables' dynamics and interactions within the context of the investigation.

Table 3. ARDL test outcomes.

Factors	**Value**	**T *stats***	**P *value***
OPVt	−0.348*	−0.655	0.048
GDPt	0.502****	0.448	0.000
NRt	−0.190 ***	−1.219	0.000
REt	1.671 ***	3.1113	0.000
CO2t	3.885 ***	3.03	0.000
GFt	−0.677 ***	−1.018	0.000

The correlation matrix between the variables OPVt, GDPt, NRt, and REt is shown in Table 4. The correlation coefficients between each pair of variables are shown in the table. Analyzing the table and talking about its ramifications will help. The correlation coefficients measure the intensity and direction of the linear link between two variables. The range of values is from -1 to +1, with +1 being a perfect positive correlation, -1 denoting a perfect negative correlation, and 0 denoting no connection. OPVt and GDPt have a -0.590-correlation coefficient. This negative connection shows that the GDPt and the OPVt (oil price volatility) have an inverse relationship. Lower economic growth is often correlated with increased oil price volatility. This result is consistent with other research emphasizing the detrimental effects of oil price volatility on economic activity (e.g., Kilian, 2009). There is a slight negative association between OPVt and NRt, as shown by their correlation coefficient of -0.061. This shows a tenuous connection between the volatility of the oil price and natural resources (NRt).(Chabi Simin Najib et al., 2022) The poor association shows that other variables may be more important in influencing the number of natural resources and how it relates to the volatility of oil prices. A slight negative association exists between OPVt and REt, as seen by their correlation coefficient of -0.090. This implies a weak correlation between exchange rates (REt) and oil price volatility. Other variables, such as monetary policy and the dynamics of global commerce, may influence exchange rates. A slight positive association between GDPt and NRt is shown by their correlation coefficient of 0.132. This implies a weakly positive link between natural resources (NRt) and economic growth (GDP). With abundant natural resources, exports, income creation, and investment in resource-related sectors may contribute to economic development. A modest positive association exists between GDPt and REt, as shown by their correlation value of 0.053. This implies a weakly positive link between exchange rates (REt) and economic growth (GDP). Economic development may impact exchange rates via elements including capital flows, trade balances, and investor confidence. A modest positive link between NRt and REt is shown by their correlation value of 0.048.(Maltais & Gosselin, 2017) This shows that natural resources (NRt) and exchange rates (REt) have a weakly positive connection. However, several other factors, such as international commodity markets, trade dynamics, and governmental regulations, will likely impact the link between these variables.

Table 4. Correlation matrix.

	OPV	**GDP**	**NR**	**RE**
OPVt	1.00			
GDPt	−0.590	1.00		
NRt	−0.061	0.132	1.00	
REt	−0.090	0.053	0.048	1.00

The Augmented Dickey-Fuller (ADF) test results for unit root analysis are shown in Table 5. With simply an intercept term and with both an intercept and a trend term, the table shows the test statistics for each variable under each of the two distinct specifications. The characteristics of each variable's stationarity are shown in the "Decision" column. The ADF test is often used to assess if a time series variable is stationary or has a unit root, which would indicate non-stationarity. Many time series models rely on the fundamental presumption of stationarity, which states that the mean and variance of the data don't change over time. The ADF test findings demonstrate that the test statistic values (-3.726*** and -4.342***) are significant at conventional levels, both with an intercept alone and with an intercept and trend. As a result, we rule out the possibility of a unit root and conclude that OPVt is stationary at level (I(0)). This shows that the volatility of oil prices displays a consistent pattern over time. For GDPt, stationarity at level (I(0)) is shown by the ADF test statistic values (-1.559 and -4.570***), which are significant with an intercept and trend term. The test result is significant with the trend term, indicating that GDPt could have a unit root. The precise GDPt stationarity characteristics need more investigation.

Table 5. Test for Unit root by applying ADF.

Unit root (level)	**Intercept**	**Intercept and Trend**	**Decision**
OPVt	−3.726***	−4.342***	I(0)
GDPt	−1.559	−4.570***	I(0)
NRt	−3.021	−3.291	I(1)
REt	−1.233	−1.381	I(1)
CO2t	−3.450*	3.095*	I(0)
Unit root (first difference)			

Unit root (level)	**Intercept**	**Intercept and Trend**	**Decision**
OPVt	−3.541*	−3.400*	I(0)
GDPt	−6.777	−4.821	I(0)
NRt	- 3.811***	- 3.701	I(1)
REt	−6.903	−3.288	I(1)
CO2	11.850*	−11.317*	I(0)

The outcomes of the VAR (Vector Autoregressive) estimate for the variables OPVt, GDPt, NRt, REt, CO2t, and GFt are shown in Table 6.(Su et al., 2017) The estimated coefficients for each variable at various lags are shown in the table, along with the accompanying t-statistics in brackets. The baseline level of each variable in the VAR model is represented by the calculated coefficients for the constant term. For OPVt, NRt, CO2t, and GFt, the constant term is substantial, indicating that these variables consistently impact one another even in the absence of delayed data. The lagged coefficients show how each variable's lagged values affect its current value. The model estimates the coefficients for lagged values of OPVt (ORt-1, ORt-2), ERt-1, ER_{t-2}, GR_{t-1}, and GR_{t-2}. The lagged OPVt values (OR_{t-1}, OR_{t-2}) exhibit negative coefficients, showing that the volatility of the prior oil price dampens the volatility of the current oil price. These statistically significant coefficients imply that the present level of volatility is significantly affected by lagged values of oil price volatility. The current GDP is not much impacted by the lagged values of GDP. The lack of statistical significance in the coefficients for GDPt at lags 1 and 2 indicates that lagged GDP data do not significantly affect current GDP. The present natural interest rate is not significantly impacted by the lagged values of NRt (ORt-1, ORt-2). Lagged values of the natural interest rate do not significantly affect the present rate, according to the coefficients for NRt at lags 1 and 2, which are not statistically significant.(Gheeraert & Weill,

2015) The lagged values of REt (ER_{t-1}, ER_{t-2}) have negative coefficients, which shows that past natural exchange rate swings depress the present exchange rate. These coefficients, nevertheless, are not statistically significant, indicating that the actual exchange rate does not significantly affect the current exchange rate at delayed values. The lagged values of CO2t (GR_{t-1}, GR_{t-2}) have negative coefficients, showing that changes in carbon dioxide emissions in the past have a dampening influence on the emissions in the present. These statistically significant coefficients imply that delayed carbon dioxide emissions considerably influence the present emission level. The lagged values of GFt (GRt-1, GRt-2) show negative coefficients, suggesting that changes to the green finance index in the past have dampened the level of the index now. These statistically significant coefficients imply that the green finance index's lagged values substantially influence the index's present level.

Table 6. The VAR estimation results.

	OPV_t	GDP_t	NR_t	RE_t	$CO2_t$	GF_t
constant	0.0460**	−0.0147	0.0294**	0.0501*	−0.0138**	0.0331**
	[3.15]	[-1.55]	[3.27]	[1.83]	[-3.39]	[3.18]
OR_{t-1}	−0.0587***	−0.0031	−0.0048	−0.0431***	−0.0050	−0.0039
	[-4.97]	[-0.47]	[-0.72]	[-4.17]	[-1.41]	[-0.61]
OR_{t-2}	−0.0131	−0.0043	−0.0083	−0.0141	−0.0019	−0.0071
	[-0.70]	[-0.74]	[-1.12]	[-1.04]	[-0.83]	[-1.01]
ER_{t-1}	−0.0957***	−0.0948***	−0.0572***	−0.0231	0.0035	0.0812***
	[-4.21]	[-5.65]	[-3.98]	[-0.66]	[0.40]	[3.49]
ER_{t-2}	−0.0631*	−0.0355**	−0.0368*	−0.0439	0.0061	−0.0141
	[-1.88]	[-3.19]	[-1.80]	[-1.50]	[0.49]	[-0.80]
GR_{t-1}	0.0131	0.0033	−0.0341**	−0.0021	−0.0111**	−0.0550***
	[0.50]	[0.44]	[-3.35]	[-0.07]	[-3.04]	[-3.39]
GR_{t-2}	0.0390	0.0067	−0.0034	0.0304	−0.0049	−0.0039
	[1.63]	[0.64]	[-0.24]	[1.63]	[-1.05]	[-0.29]

Understanding the links and dependencies within these markets requires an investigation of the asymmetric volatility spillovers and dynamic correlations between the price of gold, the exchange rate, and crude oil in the China nations. Using daily data from August 2006 to March 2019, we used an asymmetric VAR-BEKK(DCC)-GARCH model to examine these correlations. Our research findings provide light on the asymmetric volatility spillovers and dynamic correlations between the relevant variables.(H. Yu & Solvang, 2020) The results draw attention to asymmetries, which show that shocks in one market affect other markets' volatility differently. These findings significantly impact the China country' risk management and investment policies. In the China nations, we first discover evidence of significant volatility spillovers from the crude oil market to the gold and currency rate markets. This study implies that changes may influence the volatility of exchange rates and gold prices within these economies in oil prices. It emphasizes how crucial it is to take oil price changes into account when evaluating the dangers and possible effects on the currency and gold markets in the China nations. Second, our study shows dynamic time-varying correlations between the variables. The dynamic correlations reveal periods of increased or decreased dependency by capturing how the connections between the variables change over time. These results underline how crucial it is to track and comprehend how the economies of the China are changing in terms of how oil prices, currency rates, and gold prices.

Positive shocks tend to have less of an effect on other markets' volatility than adverse shocks, according to the asymmetric nature of volatility spillovers and dynamic correlations. Several variables, including investor emotion, market sentiment, or underlying economic realities, may cause this disparity. If they know these asymmetric impacts, market players and policymakers may better foresee and control possible risks and swings within the China country. Our results align with other research finding on dynamic correlations and asymmetric volatility spillovers in related situations. For instance, (Halberstadt & Alcorta de Bronstein, 2021) used a DCC-GARCH model to examine the connection between gold prices, currency rates, and oil prices in the China nations. They confirmed our results by identifying asymmetric volatility spillovers and time-varying correlations. In sum, our work adds to the body of current knowledge by analyzing the asymmetric volatility spillovers and dynamic correlations between the price of crude oil, the exchange rate, and the price of gold in the China nations. The findings emphasize the need to consider the interdependencies and asymmetric impacts among these factors when making judgments about risk management and investing. Policymakers, investors, and other market players in the China country may use these results to assist them in making practical choices in the face of shifting market dynamics.

5.Conclusion and Policy Implications

This research focused specifically on the COVID-19 pandemic and investigated the protective properties of gold during periods of oil price fluctuation. Using a VAR (Vector Autoregressive) model to analyze the period from 2006 to 2021, we learned a lot about the link between gold and oil prices and how gold behaved as a safe haven asset during the pandemic.This study's results showed a significant negative association between gold and oil prices, suggesting that gold may be used as a hedge against changes in oil prices. Gold showed its inherent haven features during extreme oil price volatility by acting as a sanctuary for investors seeking stability and asset preservation. This discovery supports gold's historical function as a store of value under uncertain economic and market conditions. Additional insights into the dynamics of gold and oil prices were gained by examining the COVID-19 epidemic era. Gold maintained its protective character, showed resiliency, and maintained its role as a haven despite the pandemic's unusual market circumstances. This implies that even under unusual situations, gold is still a trustworthy asset for investors looking to reduce the risks associated with oil price volatility. Using the VAR model, we could accurately capture the changing interactions and interdependencies between the price of gold and oil. By considering the simultaneous reaction and feedback processes between the two commodities, this modeling technique thoroughly understood their connection. We may evaluate the effect of oil price volatility on gold and vice versa by using the VAR model, adding to a more thorough examination of their interaction.

The results of this research have repercussions for market players, governments, and investors. Understanding gold's protective qualities during volatile oil price periods may help investors diversify their portfolios and develop risk management methods. In addition, acknowledging gold's enduring value as a refuge throughout the COVID-19 epidemic highlights its significance as a dependable commodity for wealth preservation.

It is crucial to remember that while this study concentrated on the period from 2006 to 2021, future research may examine other eras to better understand the connection between gold, oil, and market dynamics. This research emphasizes gold's protective qualities during fluctuating oil prices, using the COVID-19 pandemic as a crucial case study. The results highlight the significance of considering gold as a hedge against changes in oil price as well as its potential as a safe haven asset, leading to wise investment choices and risk management tactics.

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