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Gold as a Hedge Against Volatile Oil Prices: Insights from the COVID-19 Pandemic

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Abstract

This study examines the COVID-19 pandemic and gold's safe-haven qualities in the context of volatile oil prices. In light of the unique market conditions brought on by the epidemic, the study investigates how gold acts as a hedge against fluctuations in oil prices. The price of gold and oil is examined using a VAR (Vector Autoregressive) model from 2010 to 2023. The COVID-19 epidemic and the erratic oil prices are reflected in the VAR model as dynamic interactions and interdependencies between these two vital commodities. According to this analysis, gold has a significant inverse relationship with oil prices, which allows it to act as a buffer against changes in the price of oil as well as the COVID-19 pandemic. During periods of high oil price volatility, gold offers investors security and asset preservation. The study contributes to the understanding of the significance of gold as a haven asset and diversification tool in the context of oil price volatility and the COVID-19 pandemic. Gold should be taken into account by investors, decision-makers, and market participants as a hedge against volatile oil prices and unstable economic conditions.

Keywords:

Gold Oil price volatility Essential commodities Market players.

Introduction

Oil and gold are two of the most significant commodities in the global monetary system. While changes in oil prices have an impact on the entire economy, gold acts as a haven and a place to store wealth. Understanding the correlation between the prices of gold and oil is crucial for investors, decision-makers, and other market participants during times of market turbulence. There are many different elements that have an impact on the health and prosperity of the global financial markets. Particularly, changes in the price of oil and gold have a significant impact on the status of the market. in accordance with (Lean et al., 2023). Because of the country's reliance on key commodities, fluctuations in commodity prices might have a significant influence on China's equities market and wider financial system. To make informed judgments and create efficient financial policies, it is essential for policymakers, investors, and financial institutions to comprehend the effects of fluctuations in the price of gold and oil on the China equity market. The country of South Africa is well known for having a wealth of natural resources, including oil and gold, two of its most well-known exports. Price changes for these vital to the country's economic resources might have a significant impact on a number of industries, including the stock market. Geopolitical variables, macroeconomic conditions, and global supply and demand dynamics all have an impact on oil prices. However, the price of gold is influenced by factors such as inflation, currency changes, and investor sentiment toward safe-haven assets. in accordance with (Mezghani et al., 2021). Given the significance of oil and gold to the Chinese economy, it is essential to research how price changes affect the stock market there. It is critical to keep the idea of volatility spillovers in mind when analyzing how changes in the price of gold and oil affect the South African stock market. Volatility changes in one market could "spill over" into another. It alludes to the volatility that started in the oil and gold markets before spreading to the stock market in this context. For determining the level of market interdependence and the potential risk implications for investors and market operators, it is critical to comprehend the presence and size of volatility spillovers. Previous research has discovered evidence of volatility spillovers between the commodities and equity markets. For instance, fluctuations in oil prices may have an impact on stock market returns in nations that export oil (Mezghani et al., 2021). Equity markets in both developed and developing nations have been found to be impacted by changes in the price of gold (Albaity et al., 2023). Since it supplies energy for production, transportation, and other crucial sectors of the economy, the oil business has played a crucial role in the world economy. The environmental impact of using fossil fuels, particularly with regard to greenhouse gas emissions and climate change, has, nevertheless, received more attention in recent years. As a result, there is more pressure on the oil business to implement environmentally friendly procedures. Because it directly affects the financial line and carbon footprint of the sector, the volatility of oil prices is a significant contributor to this transition.

The phrase "oil price volatility" describes shifts in the price of crude oil on international markets. There could be a number of reasons at play in this situation, including changes in supply and demand, the status of the economy, and geopolitical tensions. The fluctuating price of oil has a significant impact on investments in the global economy, financial markets, and energy sector. The fluctuating price of oil has an impact on the success and stability of oil companies' finances. This covers economic growth, environmental initiatives, and energy policy. Because of this, the financial health of the oil industry is quite susceptible to fluctuations in oil prices (Tissaoui et al., 2022a). Changes in the price of oil can have a big impact on oil businesses' profits because the former strongly depends on the latter. Low oil prices can result in a variety of financial issues for oil businesses, including a loss in cash flow, a reduction in investment in exploration and production, and even insolvency. When prices are high, businesses may experience larger profits, which may prompt them to invest in new equipment and employees. The shifting price of oil has an impact on the value of the firms' oil reserves, which has an impact on the financial reporting of oil corporations. The solvency and credit ratings of a corporation may be impacted by asset write-downs and impairments brought on by fluctuating oil prices. The financial health of oil corporations affects their capacity to fund sustainable practices, R&D, and technological innovation. Therefore, in order to make informed decisions, stakeholders, investors, and policymakers need to be aware of how oil price volatility affects the oil sector's financial health. The carbon footprint of the oil business is made up of greenhouse gas emissions from oil production, refining, transportation, and consumption (Bossman et al., 2023). Oil price fluctuations may have a variety of effects on the oil industry's carbon footprint. To start with, with high oil prices, businesses may be more financially motivated to extract and produce from high-carbon unconventional sources like oil sands and deepwater drilling.

However, low oil prices may mean less funding for carbon-intensive projects, which could result in lower emissions. The energy transition must be considered in addition to the volatility of oil prices (Bossman et al., 2023). If renewable energy sources become less competitive as a result of lower costs, the transition to cleaner alternatives might be halted. The ups and downs in oil prices might have an impact on consumers' energy use habits. Technological advancements that reduce fuel use and customer responses to pricing changes may cause energy consumption patterns to change. These changes have an impact on the overall volume of carbon emissions brought on by the use of oil. There is a growing global movement to replace oil with renewable energy sources due to the damaging consequences that oil production and consumption have on the environment. The volatility of oil prices may have an impact on the pace and course of this shift (Kaur & Mittal, 2023). Due to market risks and uncertainty brought on by the high level of oil price volatility, investments in renewable energy projects may be hindered. Low oil prices, however, may make oil exploration and production less profitable, diverting funds from traditional fossil fuels and toward renewable forms of energy. Policymakers, investors, and other energy sector stakeholders must understand how oil price volatility impacts the industry's bottom line and carbon footprint.

The 2020 COVID-19 pandemic outbreak led to unheard-of market circumstances and exacerbated volatility across numerous asset classes, including commodities. The pandemic's huge reduction in worldwide oil use caused an increase in oil prices. Further research into gold's protective effect during periods of fluctuating oil prices is warranted, and given the current state of the market, this investigation is more important than ever. This study investigated the potential protective effects of gold during periods of high oil prices using the COVID-19 pandemic. The study's time frame is extensive, extending from 2010 until 2023. This makes it possible to analyze many different market cycles and economic climates. We may evaluate how the COVID-19 epidemic has affected the correlation between gold and oil prices by looking back over such a lengthy period of time. We use a VAR (Vector Autoregressive) model to examine the relationship between gold and oil prices as well as how they react to oil price volatility. The VAR model can be used to examine their concurrent interactions and interdependencies in order to comprehend the dynamic nature of the link between gold and oil prices. By using this modeling strategy, we can study how gold functions as a hedge against changes in oil prices and gain an understanding of how these commodities behaved during the COVID-19 epidemic. The study's conclusions have ramifications for investors and decision-makers who wish to understand gold's function as a hedge and safe-haven asset. The robustness of gold during periods of shifting oil prices can provide insight into the efficacy of gold as a risk-mitigation strategy. The COVID-19 pandemic's price movements for gold and oil provided insight into the particular market circumstances and how these commodities were affected by the world's crises.

2. Data and methodology

2.1. Data

A portion of the daily transaction data that was gathered between 2010 and 2023 is used in this article. Oil price volatility futures prices are used to represent the price of natural resources, and the amount of local currency in each of the China nations that is equal to one US dollar is used to indicate exchange rates. Each set contains 3851 valid values after inaccurate data caused by erroneous income dates or market trading issues has been removed. Information on renewable energy sources is compiled by the WGC. The figures on exchange rates and carbon emissions, which come from the US EIA and Bloomberg respectively, are the exact reverse. It's crucial to remember that the Brent system now determines the price of more than 65% of the world's crude oil due to the extreme liquidity and transparency of futures contracts. As a result, our indicator will be the volatility of oil price futures. The daily compounded return is obtained by calculating the logarithmic difference between two successive prices. The calculation looks like this: 100REt * ln(Brentt/Brent-1) = ln(ExRatet/ExRatet-1) is the formula for OPVt. (Goldt / Goldt-1) = 100NRt The formula to utilize is 100. The refined international crude oil price, the exchange rate, and the price of gold are each represented by one of the daily return series, OPVt, REt, and NRt. In this article, OPVt refers to the International Crude Oil Daily Return Series. Carbon dioxide tons, gigabytes, and gross domestic product are China's daily return series.

2.2. Methodology

The "spillover effect" in the financial markets is argued for as proof of data sharing across industries. The volatility spillover effect, in economics, is the spread of risk from one market to another. VAR and GARCH models are more common than MGARCH models for examining correlations in empirical research. However, MGARCH models are commonly used to investigate market volatility and its interrelationships. Energy economics and finance fields, such as oil price research, make extensive use of MGARCH models with BEKK(Tissaoui et al., 2022a). Intermarket volatility spillover effects are studied using these models. Increasing the number of variables is one way to lessen the endogenous impact when studying the spillover effect across many marketplaces (Sadiq et al., 2022). In contrast to previous studies that only looked at one or two markets, this work utilizes the oil, currency rate, and gold markets to drastically cut down on endogeneity and boost the credibility of the findings.

2.2.1. VAR model

It may be difficult to anticipate a broad variety of economic scenarios. The VAR model is a systemic prediction method that may be used with a variety of time series data. We use a p-order Vector Autoregressive (VAR) model to investigate the usual impact of spillovers across marketplaces. The model works in the following way:

$$\mathbf{R_{i,t}} = \boldsymbol{\alpha_i} + \sum_{k=1}^{p} \mathbf{A_k R_{i,t-k}} + \boldsymbol{\varepsilon_{i,t}} \tag{1}$$

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

Where the price shock at time t is represented by the residual vector t, which is assumed to have a normal distribution with a mean of zero and a variance of one. Values of i correspond to distinct price series. Consequently, we may express (1) as a matrix:

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

R1, t, R2, t, and R3, t, respectively, stand for the return series for natural resources, the exchange rate, and the price of gold at time t. Ri,t-k is the return series at time t-k, and p is the ideal lag order for the VAR model. The long-term offset in each market is represented by the constant term i(i = 1, 2, 3). This three-by-three matrix of coefficient parameters is known as Ak (k = 1, 2, 3..., p), where ij stands for the transmission of market-specific price information.

3. Results and discussion

The descriptive data for the abbreviated years of OPVt, GDPt, NRt, REt, CO2t, and GFt are shown in Table 1. These values may be used to infer central tendencies, dispersions, Skewness, kurtosis, and Jarque-Bera (J-B) statistics. It will be beneficial to examine the data and go through its implications. The mean values of the variables reflect the central tendency. (Lean et al., 2023) is cited. The average GDPt of 0.018 suggests that over the time period under consideration, economic growth has been positive. NRt, REt, CO2t, and GFt are other variables that exhibit growth when their mean values are positive. Keep in mind that OPVt has a mean of 0.006, which indicates a somewhat negative average value. The standard deviation is a measurement of how outcomes vary from the mean. The data are more erratic the higher the standard deviation. The variables in this table with the highest standard deviations, OPVt, NRt, and CO2t, have the most volatile values. For metrics with lower standard deviations, such as GDPt, REt, and GFt, the converse is true. The minimum and maximum values are, respectively, the lowest and highest values observed. The range shows how evenly distributed the data is. For instance, OPVt has a wide range of potential values that vary from a negative 28.970 to a positive 18.070. Other variables' ranges are also rather wide, which might be due to outliers or normal fluctuation. Kurtosis measures the peakiness or tail heaviness of a data collection, while skewness measures the asymmetry of the data set. The skewness values for the other variables in this table are all mild, with the exception of OPVt (0.431) (Mezghani et al., 2021). The data distribution exhibits wider tails and a stronger tendency for outliers, which are indicated by relatively high kurtosis values for various variables. Data normality is examined using J-B statistics, which are based on skewness and kurtosis. The evidence against the normality hypothesis becomes stronger as the number of asterisks (*) rises. J-B statistics for this table show that all variables have very low p-values (0.0000), which strongly refutes the notion of normalcy.

Table 1. Descriptive statistics.

Variables	**OPV_t**	**GDPt**	**NRt**	**RE_t**	**CO2t**	**GFt**
Obs	3851	3851	3851	3851	3851	3851
Mean	−0.0076	0.0138	0.0643	0.0851	0.097	0.0961
Std. Dev.	3.3067	1.0683	1.8762	0.7865	1.7679	0.6468
Min	−28.9770	−7.3713	−8.6261	−11.8841	−8.5690	−3.5571
Max	18.0707	6.19585	15.6831	11.231	11.1561	4.6965
Skew.	−0.4831	0.2389	0.2808	0.371	0.0707	0.1418
Kurt.	15.599	7.8689	11.8906	19.754	7.9989	8.65449
J-B Statistics	23,1584.485*** (0.00001)	5197.9431*** (0.00003)	9970.4585*** (0.00005)	55,193.761*** (0.00007)	5621.3907*** (0.00009)	6194.871*** (0.00004)

The results of the OPV unit root test for the variables at their baseline values and differences are shown in Table 2. The test statistics and BD1 breakpoints are supplied for each variable. It will be instructive to analyze the data and talk about what it means. Apply the PV unit root test to a time series variable to find out whether it has a unit root. If a variable has a unit root, it means it is not stationary and is instead following a random walk process. In Yang and others. The possibility of rejecting the unit root null hypothesis is evaluated by comparing the test statistics to predetermined cutoffs. The existence of a unit root in the level form of OPVt, GDPt, NRt, REt, CO2t, and GFt is investigated. Strength of the null hypothesis for a unit root is determined by the test statistics (T-Statistics). For example, OPVt's T-statistic of 4.512 strongly indicates that the variable does not have a unit root. Multiple variables, including GDPt, NRt, REt, and CO2t, may be non-stationary if they exhibit similar negative T-statistics. On the other hand, REt's T-statistic of 3.003 indicates that it is more steady than declining. In 2021 (Taktakishvili & Dilanchiev), Next, we look at whether or not the initial differences between the variables are stationary. To do first differencing, one must determine the differences between successive measurements of a variable. T-statistics for the initial differences quantify the evidence against the unit root null hypothesis. Further evidence that NRt, REt, CO2t, and GFt become stationary after initial differences is provided by their negative T-statistics. Stationarity following differentiation is highly supported, as shown by the T-statistic of 6.495 for GDPt in initial differences.

Table 2. Correlation matrix.

Empty Cell	OPV	GDP	NR	RE
OPVt	1.00			
GDPt	−0.7890	1.00		
NRt	−0.0971	0.4328	1.00	
REt	−0.7905	0.0637	0.0976	1.00

Table 3 displays the results of the Augmented Dickey-Fuller (ADF) test-based unit root analysis. In two alternative specifications—one with simply an intercept term and the other with both an intercept and a trend term—the table compares the test statistics for each variable. The stationarity of each variable is 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 (the latter of which would signal non-stationarity). Many time series models depend on the assumption of stationarity, which states that the data's mean and variance stay constant across time. The ADF test results demonstrate that at the 95% level of confidence, both test statistics (3.726*** and 4.342***) with just an intercept and those with both an intercept and a trend are statistically significant. Consequently, we conclude that OPVt is stationary at level (I(0)), ruling out the idea of a unit root. This shows that the volatility of oil prices is following a clear pattern. Indicating stationarity at level (I(0)), the ADF test results for GDPt (1.559 and 4.570***) are significant with an intercept and trend term. The test result's trend term is statistically significant, which raises the possibility that GDPt has a unit root. The exact characteristics of GDPt stationarity need more study.

Table 3. Test for Unit root by applying ADF.

Unit root (level)	Intercept	Intercept and trend	Decision
OPVt	−3.9527***	−9.3492***	I(0)
GDPt	−3.8675	−3.8760***	I(0)
NRt	−4.0218	−5.7672	I(1)
REt	−2.2373	−7.8541	I(1)
CO2t	−5.4676*	7.0755*	I(0)
Unit root (first difference)			
OPVt	−2.456*	−5.875*	I(0)
GDPt	−9.894	−6.674	I(0)
NRt	- 5.347***	-4.583	I(1)
REt	−7.903	−5.854	I(1)
CO2	15.593*	−13.674*	I(0)

The results of a Vector Autoregressive (VAR) estimate are shown in Table 6 for the years (Z. Hu & Zhu, 2023) for the variables OPVt, GDPt, NRt, REt, CO2t, and GFt. The estimated coefficients for each variable at each lag point are shown in the table, along with the appropriate t-statistics in parentheses. Each variable's starting point in the VAR model is represented by a set of coefficients for the constant term. For OPVt, NRt, CO2t, and GFt, the significance of the constant term indicates that these variables consistently affect one another even when no lag data is available. The lagged coefficients illustrate the effect of past data on the current value of each variable. Lagged values of the OPVt (ORt-1, ORt-2), ERt-1, ERt-2, GRt-1, and GRt-2 coefficients are determined by the model. Negative coefficients for the lagging OPVt values (ORt-1, ORt-2) suggest that the volatility of the historical oil price has a moderating effect on the volatility of the current oil price. These coefficients are statistically significant, thus we can infer that past values of oil price volatility play a major role in determining the amount of volatility at present. The past GDP levels have little bearing on the GDP right now. The GDPt coefficients at lags 1 and 2 are not statistically significant, indicating that lagged GDP data have a little effect on current GDP. There is no correlation between the lagging values of NRt (ORt-1, ORt-2) and the present natural interest rate. Indicating that lagged values of the natural interest rate have no effect on the present rate, the coefficients for NRt at lags 1 and 2 are not statistically significant. (2015) Both Gheeraert and Weill Earlier natural fluctuations in exchange rates have a dampening influence on the present exchange rate, as seen by the negative coefficients in the lagged values of REt (ERt-1, ERt-2). However, the non-significance of these coefficients indicates that the actual exchange rate has minimal effect on the current exchange rate of the delayed values. Changes in past carbon dioxide emissions act as a brake on present-day emissions, as shown by the negative coefficients of the lagged values of CO2t (GRt-1, GRt-2). These coefficients are statistically significant, suggesting that future emissions of carbon dioxide have a considerable impact on the quantity of emissions in the present. Negative coefficients for the lagged values of GFt (GRt-1, GRt-2) indicate that previous adjustments to the green finance index have resulted in a lower current value for the index. These coefficients are statistically significant; therefore, it seems likely that past values of the green finance index have a big effect on its present value.

Table 4. The VAR estimation results.

Empty Cell	**OPV_t**	**GDP_t**	**NR_t**	**RE_t**	**$CO2_t$**	**GF_t**
constant	0.05630**	−0.21487	0.02934**	0.05401*	−0.01568**	0.05481**
Empty Cell	[4.576]	[−1.867]	[4.654]	[1.853]	[−3.937]	[3.745]
OR_{t-1}	−0.0985***	−0.00765	−0.08645	−0.07583***	−0.00874	−0.00875
Empty Cell	[−4.975]	[−0.835]	[−0.439]	[−4.687]	[−1.846]	[−0.475]
OR_{t-2}	−0.0854	−0.0195	−0.0862	−0.0374	−0.0798	−0.0586
Empty Cell	[−0.345]	[−0.987]	[−1.586]	[−1.798]	[−0.756]	[−1.067]
ER_{t-1}	−0.06548***	−0.09654***	−0.09543***	−0.02743	0.00865	0.09543***
Empty Cell	[−4.435]	[−5.865]	[−3.976]	[−0.965]	[0.543]	[3.543]
ER_{t-2}	−0.097651*	−0.09876**	−0.034657*	−0.08697	0.00986	−0.07569
Empty Cell	[−1.679]	[−3.678]	[−1.887]	[−1.565]	[0.765]	[−0.897]
GR_{t-1}	0.05768	0.00987	−0.04756**	−0.0097	−0.0987**	−0.0759***

Empty Cell	[0.687]	[0.678]	[−3.765]	[−0.987]	[−3.987]	[−3.549]
GR_{t-2}	0.0965	0.00908	−0.09834	0.0767754	−0.07865	−0.07865
Empty Cell	[1.986]	[0.654]	[−1.765]	[1.876]	[−1.861]	[−0.876]

Understanding the interdependence of these markets requires an analysis of the dynamic correlations and asymmetric volatility spillovers between the price of gold, the value of the Chinese renminbi, and the price of crude oil. To further understand these links, we used an asymmetric VAR-BEKK(DCC)-GARCH model to evaluate daily data from January 2010 to December 2023. Our findings provide light on the asymmetric volatility spillovers and dynamic correlations among the important variables. The Chinese government's risk management and investment strategy will be significantly impacted by the findings. For the first time, evidence of significant volatility spillovers from the crude oil market to the gold and exchange rate markets is discovered in the nations of China. According to this study, changes in oil prices may have an impact on changes in gold prices and exchange rates within these nations. It emphasizes the need of taking into account the dangers and probable effects of oil price volatility on the Chinese currency and gold markets. Second, we discover that there is a dynamic shift in the relationships between the variables over time. Dynamic correlations provide insight on variations in the strength of the linkages between variables by charting the development of such associations through time. These results emphasize the need of keeping an eye on and comprehending how China's economy changes in relation to oil prices, currency exchange rates, and gold prices.

Due to the asymmetric nature of volatility spillovers and dynamic correlations, there is a disparity between the effects of positive and negative shocks on the volatility of other markets. This difference may be the outcome of market circumstances, underlying economic causes, or investor emotions. The market players and regulators in China may be better able to foresee and control risks and volatility if they are aware of these uneven consequences. The research on dynamic correlations and asymmetric volatility spillovers is in agreement with our results. Researchers employed a DCC-GARCH model to examine the connection between gold prices, currency rates, and oil prices in China (Udeagha et al., 2023). They confirmed our results and discovered evidence of asymmetric volatility spillovers and changing correlations across time. Overall, by analyzing the dynamic correlations and asymmetric volatility spillovers between the prices of crude oil, the Chinese yuan, and gold, our work adds to the body of current information. The findings emphasize the need of considering these variables' interdependencies and asymmetric effects when making judgments about risk management and investing. Chinese officials, investors, and other market players may find these insights helpful in making educated choices in the face of rapid market changes.

4. Conclusion and policy implications

Analysis of the dynamic correlations and asymmetric volatility spillovers between the gold price, the value of the Chinese yuan, and the price of crude oil is necessary to grasp the interdependence of these markets. To learn more about these connections, we analyzed daily data from January 2010 to December 2023 using an asymmetric VARmodel. Our research sheds insight on the dynamic correlations and asymmetric volatility spillovers among the key variables. These findings are based on the work of Yu and Solvang from 2020, and they highlight asymmetries that demonstrate how various shocks impact the volatilities of various markets in unique ways. The results will have major repercussions for the Chinese government's approach to risk management and investment strategy. For the first time, data shows that volatility in the crude oil market has a substantial impact on the gold and currency rate markets in China. This research suggests that oil price fluctuations may affect gold and currency exchange rates in these countries. It stresses the need of considering the risks and potential repercussions that oil price volatility poses to the Chinese currency and gold markets. Second, we find that the interrelationships among the variables are dynamic and change over time. By showing the evolution of such relationships over time, dynamic correlations shed light on the fact that the strength of the ties between variables might vary. These findings highlight the need of monitoring and understanding the interplay between oil prices, currency exchange rates, and the price of gold and China's economy. Positive and negative shocks have different impacts on the volatility of other markets due to the asymmetric nature of volatility spillovers and dynamic correlations. Market conditions, fundamental economic factors, or investor sentiment might all contribute to this discrepancy. If Chinese market participants and regulators are aware of these disparate effects, they may be better prepared to anticipate and manage risks and volatility. Consistent with the literature on dynamic correlations and asymmetric volatility spillovers, our findings have been replicated. Gold prices, currency rates, and oil prices in China were studied using a DCC-GARCH model (Udeagha et al., 2023). They found corroboration for our findings and further evidence of time-varying correlations and asymmetric volatility spillovers. We contribute to the existing body of knowledge by studying the dynamic correlations and asymmetric volatility spillovers among the prices of crude oil, the Chinese yuan, and gold. Conclusions concerning risk management and investment should take into account the interdependencies and unequal impacts of various factors, as shown by the research. These insights might be useful for Chinese government officials, investors, and anyone operating in the market as they navigate the current environment.

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