Analysis of return and volatility spillover between oil-gold and oil-bitcoin during the covid-19 pandemic

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Abstract This study analyzes the return and volatility spillover between oil-gold and oil-Bitcoin pairs before and after the COVID-19 pandemic using the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model. The data used in this research consists of daily returns of oil, gold, and Bitcoin from January 2018 to December 2021 to understand volatility dynamics. The data period is divided into two phases: before and after the COVID-19 pandemic. The analysis results show no significant volatility spillover between oil and gold. The relationship between oil and Bitcoin points to volatility spillover, although not following an identical pattern. The absence of volatility spillover indicates that markets or assets are more independent of each other. This reduces the interdependence between markets, making it more challenging to predict market movements based on the behavior of other markets.

1 Introduction

The COVID-19 pandemic has significantly impacted the price dynamics of various assets, including the crude oil market. During the COVID-19 pandemic, it is crucial to examine extended data that includes the returns and volatility of assets such as crude oil. This is important because portfolio managers need to allocate assets to diversify risk, and financial policymakers need to understand how volatility and returns transfer from one asset to another. Some assets that have drawn attention during the crisis are gold (Yousaf et al., 2021) and Bitcoin (Bouri et al., 2020), which are considered safe-haven investments.

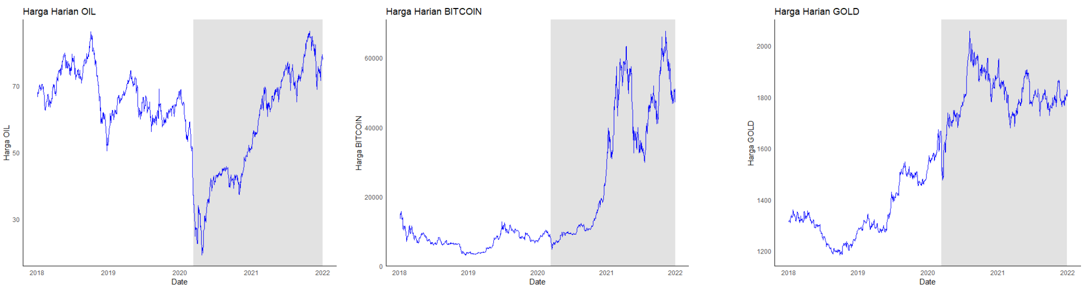

Figure 1. Daily prices of oil, bitcoin and gold

Figure 1 shows that the price of oil experienced a significant decline at the beginning of the COVID-19 pandemic. The COVID-19 pandemic period is marked in gray. During the early stages of the COVID-19 pandemic, Bitcoin prices experienced a slight drop, but after 2021, there was a significant price increase compared to the previous period, even before the pandemic. Conversely, gold prices fell at the onset of the COVID-19 pandemic but increased throughout 2020, indicating rising demand for gold. Overall, COVID-19 had a detrimental impact on the oil market but a positive effect on the gold and Bitcoin markets. Therefore, it is important to study the oil-gold and oil-Bitcoin pairs during the pre-COVID-19 and COVID-19 periods.

Dutta et al. (2019) tested the relationship between the crude oil market and metal markets (gold and silver) using ARDL and non-linear causality tests. The results showed a bidirectional and non-linear causal relationship between oil and metal markets. Gold is considered a hedge against the stock and oil markets during the pandemic (Adekoya et al., 2021). Spillovers between the gold market and oil also occurred during various crises, including in 2015 and the COVID-19 pandemic (Gharib et al., 2021). Hedging portfolio returns in many cases is largely driven by the implied volatility in gold (Yousaf et al., 2021).

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Zeng et al. (2019) stated that there is significant return transmission between Bitcoin, oil, and gold using a connectedness-based approach. Information spillovers change over time, becoming stronger between cryptocurrencies and other markets such as energy, agriculture, and metals (Jin et al., 2019). Changes in crude oil prices are expected to affect production costs and the value of Bitcoin (Das et al., 2020). Several studies have analyzed the return and volatility transmission between oil and gold, as well as oil and Bitcoin, during crisis and non-crisis periods. However, the hedging capabilities of gold and Bitcoin against crude oil risk during crisis and non-crisis periods are of particular interest. Although gold and Bitcoin are considered hedges and/or safe havens during periods of uncertainty, it is necessary to analyze the comparison between oil and gold, as well as oil and Bitcoin.

This study will use the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model (Engle, 2002) to analyze the oil-gold and oil-Bitcoin pairs during the pre- and post-COVID-19 periods. Previous research that combines crisis and non-crisis periods (Yousaf and Ali, 2020) highlights the importance of this analysis. One of the main advantages of the DCC-GARCH model is its ability to estimate covariance, volatility, and correlations between assets that change gradually and parsimoniously. Additionally, the conditional covariance matrix is positive definite. Therefore, it is essential to examine the return and volatility spillover between crude oil and gold, as well as crude oil and Bitcoin, during the pre-and post-COVID-19 periods.

2 Data and Methodology

The data used in this study is daily data sourced from Refinitiv Eikon, specifically the Bitcoin/US Dollar FX Spot Rate (BTC), Gold Spot Rate Credit Suisse Zurich Contributed Commodity Cash (XAU), and Brent Crude Oil (LCOc1). The data period encompasses both pre-COVID-19 and during COVID-19. The pre-COVID-19 data spans from January 1, 2018, to March 10, 2020, while the COVID-19 period data ranges from March 11, 2020, to December 31, 2021. The division of these periods is based on the World Health Organization's (WHO) declaration of the COVID-19 pandemic on March 11, 2020. Additionally, as weekly trading days and daily trading hours differ for the oil, gold, and Bitcoin markets, all data used for analysis is adjusted to align with working days and trading hours. All data is denominated in US Dollars.

The analysis is conducted using return data calculated from the collected price data. The return calculation formula used is as follows:

$$R_t = \frac{P_{t-}P_{t-1}}{P_{t-1}} \qquad (1)$$

where R_t is the return value, P_t is the price at time t, and P_{t-1} is the price at time t−1. After obtaining the return values for oil, Bitcoin, and gold, the next step is to compile the descriptive statistics for the data used in this study. The descriptive statistical analysis includes calculating the minimum, maximum, median, mean, standard deviation, and normality test using the Kolmogorov-Smirnov test.

Once the descriptive statistics are analyzed to provide a general overview of the data, the next step is to test the stationarity of each dataset by dividing the period into pre-COVID-19 and during COVID-19 as per the periods used in the study. The stationarity test is conducted using the Augmented Dickey-Fuller (ADF) test, which is designed to detect the presence of unit roots in time series data. The ADF model used is as follows:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha \sum_{i-1}^{m} Y_{t-1} + \varepsilon_t \qquad (2)$$

where Y_{t-1} is the variable observed at time t-1 and ΔYt is the first change of Yt. βt is the time trend, δ is the coefficient to be tested in the ADF model, $\alpha i{-}1mYt{-}1$ is the addition of lagged terms to ensure that the error term εt is not correlated. The hypothesis used is H0 states that the data is not stationary and H1 states that the data is stationary.

The data analysis employs the Dynamic Conditional Correlations-Generalised AutoRegressive Conditional Heteroskedasticity (DCC-GARCH) model to examine the returns and volatility between oil-gold and oil-Bitcoin. The DCC-GARCH model is efficient because traditional multivariate GARCH models are generally limited by dimensionality in conditional volatility and correlation analysis. Additionally, DCC-GARCH not only estimates the covariance matrix and conditional correlations but also directly estimates the correlation matrix using standardized residuals. Therefore, DCC-GARCH is highly flexible, reducing the number of parameters that need to be estimated (Laurent et al., 2012).

The DCC GARCH model was first introduced by Engle and Sheppard. The idea of this model is to look at the covariance matrix of H_t composed into a matrix of conditional standard deviations D_t and R_t. The following is a bivariate model specification of DCC GARCH using two assets as examples x and y,

$$r_t = \mu_t + \alpha_t$$
$$\alpha_t = H_t^{1/2} \alpha_t z_t \quad z_t \sim N(0,1)$$
$$H_t = D_t R_t D_t \qquad (3)$$

Where H_t represents the conditional covariance matrix; D_t= diag $\{\sqrt{h_{x,t}}, \sqrt{h_{y,t}}\}$ is the diagonal matrix of the conditional standard deviation of x and y at time t. This is obtained from the univariate GARCH model $h_t = c + ae^2 \quad + bh_{t-1}$ Where c is a constant, h_t is the conditional covariance, a and b are parameters that describe the effects of ARCH and GARCH. $R_t = [\rho_{xy,t}]$ is the matrix of time-varying conditional correlations that can be formulated $R_t = diag\,\{Q_t\}^{-1} Q_t diag\,\{Q_t\}^{-1}$ Where $Q_t = [q_{xy,t}]$ is the unconditional correlation matrix of e_t and the positive definite variance-covariance matrix. Time-varying correlation estimation performs the extraction by calculating from the equation

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha e_{t-1} e'_{t-1} + \beta Q_{t-1}. \quad (4)$$

Where $\bar{Q}$ indicates the average correlation matrix of the standardized residuals, $\bar{Q} = cov(\varepsilon_t \varepsilon_t^T) = E(\varepsilon_t \varepsilon_t^T)$. The estimator of Correlation follows the following equation:

$$\rho_{xy,t} = \frac{q_{xy,t}}{(\sqrt{q_{x,t}}\sqrt{q_{y,t}})} \quad (5)$$

Ensuring the requirements needed in using DCC-GARCH, then $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. Variable estimation in the GARCH family will use maximum log-likelihood.

3 Analysis Results Descriptive Statistics

Descriptive statistics are used to describe the characteristics of data in a study. This research utilizes daily data from the prices of OIL, BITCOIN, and GOLD, covering the period before COVID-19 from January 1, 2018, to March 10, 2020, and the period during the COVID-19 pandemic from March 11, 2020, to December 31, 2021. The price data for OIL, BITCOIN, and GOLD are converted into returns.

Table 1. Descriptive statistics of daily returns of OIL, BITCOIN and GOLD

	Before Pandemic COVID-19 (January, 1st 2018 until March, 10th 2020)			After Pandemic COVID-19 (March 11th 2020 Until December 31st 2021)		
	OIL	**BITCOIN**	***GOLD***	***OIL***	**BITCOIN**	***GOLD***
Mean	-0.000775	0.000035	0.000448	0.000529	0.0022695	0.000362
Median	0.001271	-0.001409	0.000019	0.002179	0.0002975	0.000407
Maximum	0.146131	0.297223	0.030231	0.210186	0.2972239	0.056486
Minimum	-0.240998	-0.230445	-0.037696	-0.244036	-0.2752710	-0.047138
Std. Dev	0.022447	0.045742	0.006595	0.032371	0.047193	0.010432
Observation	565	565	565	469	469	469
Normality	0.10949***	0.097639***	0.071011***	0.12939***	0.081485***	0.10429***
(Kolmogorov-Smirnov)						

*** p-*value* < 1%

Table 1 presents the descriptive statistics of daily return data, showing the mean, median, maximum, minimum, standard deviation, and the number of observations. The total number of daily return observations amounts to 1,034 over the period from January 2018 to December 2021. The normality test results in Table 1, conducted using the Kolmogorov-Smirnov test, indicate that the daily return data for the periods before and after the COVID-19 pandemic follow a normal distribution.

Based on Table 1, it can also be seen that the standard deviation values of the returns for oil, Bitcoin, and gold before and after the pandemic indicate that volatility tends to increase during theCOVID-19 pandemic.

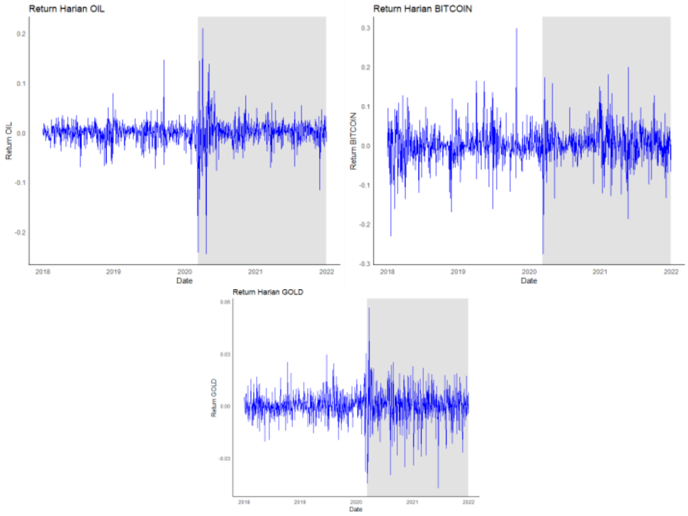

Figure 2. Daily return of oil, bitcoin and gold

Figure 2 shows the daily returns of OIL, BITCOIN, and GOLD. The shaded gray area indicates the period after the COVID-19 pandemic announcement, starting from March 11, 2020. Figure 2 illustrates that there was an increase in volatility at the time of the COVID-19 pandemic announcement.

4 Data Stationarity Test

The data used in this study are time series data, which must meet the condition of stationarity. Thestationarity of the data is tested using the Augmented Dickey-Fuller (ADF) unit root test. If the data are stationary, they are suitable for use in subsequent calculation steps or processes.

Table 2. Results of Data Stationarity Test

	T-statistics	P-*value*
Return Oil-before	-5.9847	0.01
Return BTC-before	-7.934	0.01
Return GOLD-before	-9.2351	0.01
Return Oil-after	-9.4566	0.01
Return BTC-after	-7.5648	0.01
Return GOLD-after	-9.0001	0.01

Based on Table 2, the results of the stationarity test using the ADF test are presented. The ADF testresults indicate that the time series data used in this study, which includes the returns of oil, Bitcoin,and gold divided into two periods (before and after the COVID-19 pandemic), are stationary at a 95% significance level. This is evidenced by the p-values being smaller than the alpha level (5%).

5 Paired Correlation Analysis

The correlation test is conducted to measure and analyze the strength and direction of the linear relationship between two variables. Correlation is calculated using the correlation coefficient, which ranges from -1 to 1. The most commonly used correlation coefficient is the Pearson correlation coefficient. Correlation can indicate whether two variables tend to move together (positive correlation), move in opposite directions (negative correlation), or have no linearrelationship (correlation close to zero).

Table 3. Results of pairwise correlation analysis of daily returns of OIL, BITCOIN and GOLD

Before Pandemic COVID-19 (January, 1st 2018 until March, 10th 2020)				After Pandemic COVID-19 (March 11th 2020 Until December 31st 2021)		
	OIL	**BITCOIN**	***GOLD***	***OIL***	**BITCOIN**	***GOLD***
OIL	1.000			1.000		
BITCOIN	0.04461	1.000		0.05266	1.000	
GOLD	0.02678	-0.00419	1.000	0.07589	0.03855	1.000

Based on Table 3, the analysis of paired correlations from daily returns of OIL and BITCOIN, aswell as OIL and

GOLD, shows that the correlations between OIL returns and BITCOIN returns, and between OIL returns and GOLD returns, have increased from before to after the COVID-19 pandemic. Additionally, these relationships are positively correlated. This indicates that there is a directional movement between OIL returns and BITCOIN returns, as well as between OIL returnsand GOLD returns.

6 Return and Volatility Spillover

To test the return and volatility spillover between the oil-gold and oil-Bitcoin pairs, this study employs the Dynamic Conditional Correlations-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model.

Table 4 . Volatility spillover estimates

Before Pandemic COVID-19					**After Pandemic COVID-19**			
	Oil	Bitcoin	*Oil*	*Gold*	*Oil*	Bitcoin	*Oil*	*Gold*
μ	0.00074	0.00058	0.00739	0.00027	0.00247	0.00414	0.00247	0.00027
(p-value)	0.39382	0.75773	0.39279	0.30537	**0.00215**	**0.03730**	**0.00215**	**0.00104**
ar1	0.43142	-0.56183	0.43142	-0.54738	0.74385	-0.65383	0.74385	0.98379
(p-value)	0.12493	0.05168	0.12464	**0.00409**	**0.00000**	**0.00277**	**0.00000**	**0.00000**
ma1	-0.45873	0.58218	-0.45873	0.49611	-0.77365	0.60123	-0.77365	-0.99968
(p-value)	0.09239	**0.03952**	0.09244	**0.00137**	**0.00000**	**0.00277**	**0.00000**	**0.00000**
ω	0.00002	0.00024	0.00002	0.00002	0.00002	0.60123	0.00020	0.00000
(p-value)	0.41966	0.54358	0.41963	0.30529	**0.02132**	**0.00736**	**0.02140**	0.99997
α1	0.13935	0.07392	0.13935	0.04073	0.14368	0.05556	0.14368	0.00526
(p-value)	**0.00624**	0.45135	**0.00621**	**0.00000**	**0.00013**	**0.00583**	**0.00013**	**0.00010**
β1	0.85950	0.81078	0.85950	0.92649	0.83371	0.91738	0.83371	0.99305
(p-value)	**0.00000**	**0.00192**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**	**0.00000**
dcca1	0.00000		0.07054		0.00000		0.00616	
(p-value)	0.99919		0.32650		0.99973		0.66145	
dccb1	0.92649		0.31615		0.92825		0.82114	
(p-value)	**0.00000**		0.14310		0.17589		**0.00000**	
Log-likelihood	2,361.602		3,458.617		1,878.306		2,571.20	
Akaike	-8.3066		-12.190		-7.94590		-10.901	

Table 4 shows that before the COVID-19 pandemic, the relationship between oil and Bitcoin indicates that the current volatility changes in oil were driven by previous period volatility **(**Q_1**)** by 85%, while changes in current volatility due to previous period shocks **(**a_1**)** accounted for 13%.Changes in conditional correlation were driven by past correlation **(dccb1)** by 92%. For Bitcoin, current volatility changes due to previous period volatility **(**Q_1**)** were 81%.

In the relationship between oil and gold, the changes in current volatility were driven by previous period volatility **(**Q_1**)** by 92%, while changes in current volatility due to previous periodshocks **(**a_1**)** were 0.04%.

After the COVID-19 pandemic, both the changes in volatility driven by previous period volatility and those driven by previous period shocks were significant. Additionally, the constant parameter (ω), which has a very low and significant value, indicates that even when there are no new shocks (ε_{t-1}) or past volatility (σ_{t-1}), there remains a small component of volatility.

Table 4 also shows that the Akaike values resulting from the DCC-GARCH modeling are quitelow (negative values), indicating the model's efficiency in fitting the data.

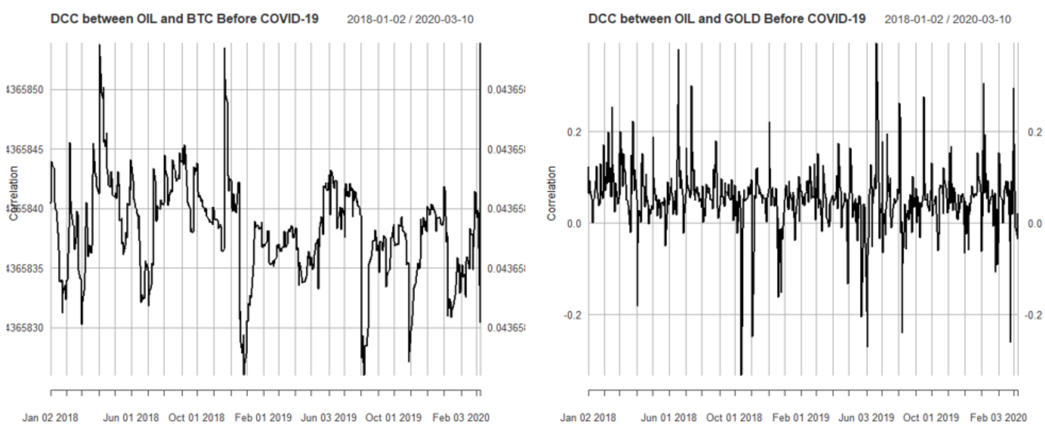

Figure 3 DCC before the COVID-19 pandemic

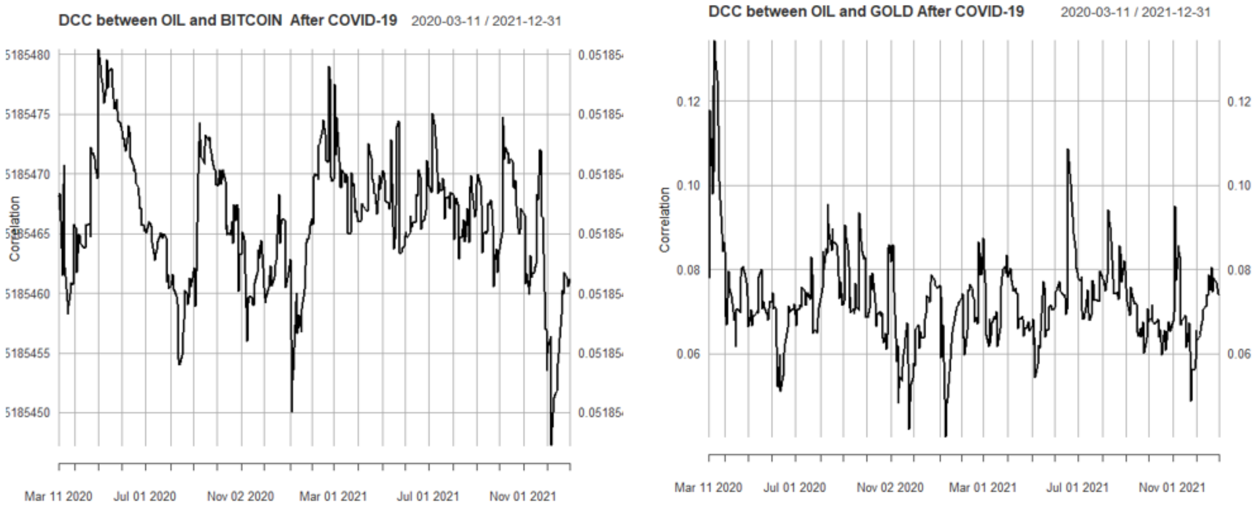

Figure 4. DCC during the COVID-19 pandemic

The results for return and volatility spillover between oil and gold before and during the COVID-19 pandemic can be seen in Figures 3 and 4. Based on the tests conducted using the DCC-GARCHanalysis technique, it is evident that there are differences in the dynamic correlation conditions between oil-Bitcoin and oil-gold during the pre-pandemic and pandemic periods.

Figure 3 illustrates that the relationship between oil and Bitcoin has a low correlation, or is close to zero, indicating a weak or non-linear relationship between the two return time series data. The relationship between oil and gold does not differ significantly, showing opposing movements. Thiscan be seen from the data range from -0.2 to 0.2, even though the correlation is not far apart. However, it indicates an inverse relationship.

Figure 4 shows the period after the COVID-19 pandemic. Similar to the pre-COVID-19 period, even with a 1% increase, the relationship between oil and Bitcoin still has a low correlation or is close to zero, indicating a weak or non-linear relationship between the two return time series data.The relationship between oil and gold after the COVID-19 pandemic shows an increase in correlation. This indicates that the two times series move together in a similar manner, although they are still not close to +1.

Table 5. Dynamic correlation

		Maximum	Minimum	Median	Mean
BEFORE COVID-19	OIL-GOLD	0.3926363271	-0.3324409353	0.0551083635	0.0544501053
	OIL-BTC	0.0436585389	0.0436582597	0.0436583832	0.0436583814
AFTER COVID-19	OIL-GOLD	0.1342821406	0.0402164150	0.0710669575	0.0724244656
	OIL-BTC	0.0518548038	0.0518544723	0.0518546605	0.0518546617

Figures 3 and 4, along with Table 4, present the results of dynamic correlations between oil-Bitcoinand oil-gold for the periods before and during the COVID-19 pandemic. Table 4 shows that the dynamic correlation between oil and gold was higher before the COVID-19 pandemic compared to during the pandemic. This is evident from the range of values between the maximum and minimum dynamic correlation values. Meanwhile, the relationship between oil and Bitcoin showsan increase in value, but the range of dynamic correlation values remains nearly the same as in thepre-pandemic period.

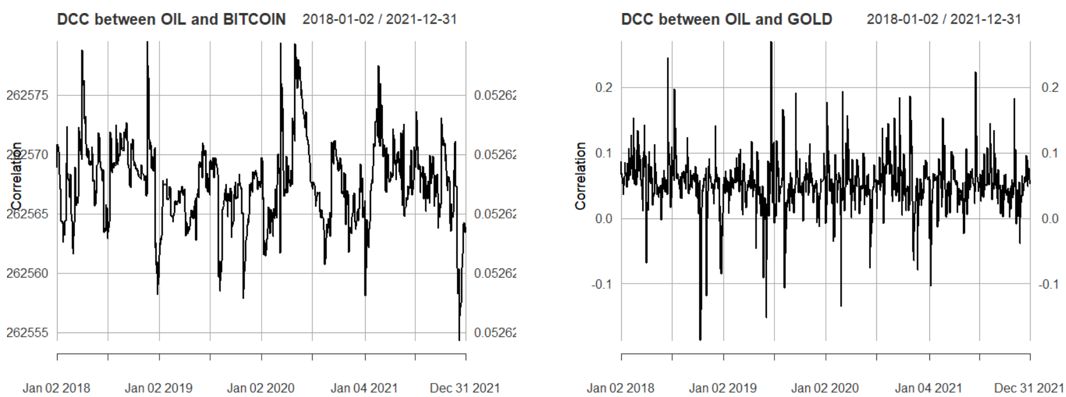

Figure 5. DCC entire period

Figure 5 shows the dynamic correlations at the onset of the COVID-19 pandemic in early 2020. Itcan be observed that there is an increase in the dynamic correlation between oil and Bitcoin duringthis period. In contrast, the relationship between oil and gold does not experience a spike during the COVID-19 pandemic. However, the dynamic correlation between oil and gold exhibits a decreasing gap in correlation values, indicating a closer relationship over time.

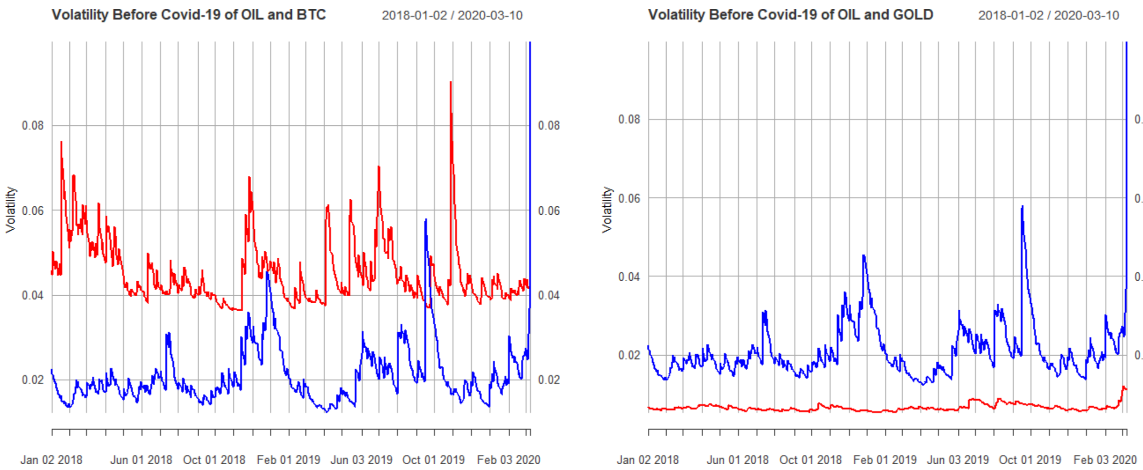

Figure 6. Volatility before COVID-19 (caption - : Oil; - : Bitcoin (left); - : Gold (right))

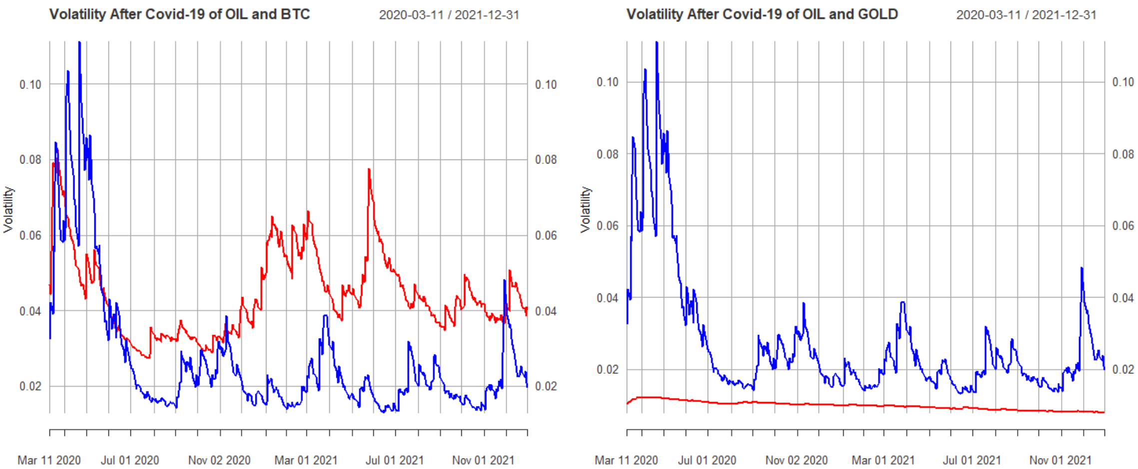

Figure 7. Volatility after COVID-19 (caption - : Oil; - : Bitcoin (left); - : Gold (right))

Based on Figures 6 and 7, which show the volatility before and after the COVID-19 pandemic, itis evident that the volatility of oil and Bitcoin exhibits slightly different movements. In contrast, the volatility relationship between oil and gold does not show similar movements. This indicates that there is no spillover relationship between oil and gold. These results suggest that fluctuationsin oil do not spread to the gold market. Without spillover volatility, portfolio managers and investors can more easily predict and manage risks. Portfolio managers can focus on the volatility of individual assets or markets without having to consider the spillover effects of volatility from other markets. The relationship between oil and Bitcoin also cannot be concluded to have volatilityspillover because their movements are not exactly the same, although they do exhibit somewhat similar patterns.

7 Conclusion

This study analyzes the return and volatility spillover between crude oil and gold, as well as crudeoil and Bitcoin pairs during the periods before and after the COVID-19 pandemic. The analysis method used is DCC-GARCH. The results reveal that the spillover transmission varied during thepre-COVID-19 and COVID-19 periods for the oil-gold and oil-Bitcoin pairs. The findings indicateno significant unidirectional volatility impact from gold to the oil market in the pre-COVID-19 period, and from oil to the oil market during the COVID-19 period. Volatility fluctuations from Bitcoin to oil during the pre- and post-COVID-19 periods also do not exhibit identical movements, though they show similar patterns. The absence of significant volatility spillover suggests that themarkets or assets are more independent of each other. This reduces intermarket correlations, making it more challenging to predict market movements based on the behavior of other markets. Future research could employ BEKK-GARCH or VAR-GARCH models to capture the temporal dynamics of interactions between the oil-Bitcoin and oil-gold pairs.

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