Relationship between financial markets with using GARCH-DCC approach

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ABSTRACT

The purpose of this article was to investigate the non-linear relationship between the price of Bitcoin, gold, oil and the USD in global markets. In this regard, the fluctuations of each of these variables were modeled using the GARCH model. Then, using a bivariate GARCH model, the relationship between the variables was investigated. In this study, the statistical data wase used for period of 2010-2022 based on the frequency of monthly data. Nowadays, with development of information system and interaction among financial markets across the world, downturn and boom transition in different markets is growing with a significant speed and with regard to economies in countries; contagion of crisis from global markets, slows down the development countries. The results indicated that the fluctuations of the financial markets had an effect on each other. It was also observed that the volatility was transferred between the dollar and bitcoin. In addition, fluctuations in the gold and dollar market have also been transferred to other markets. Also, the results indicated that any shock from any financial market had significant effects on other financial markets.

Keywords: Volatility, Bitcoin, Gold Price, USD, Spillover effect.

1. Introduction

The Spillover and connectedness between various financial assets are essential for risk management and forecasting aspects of financial markets. In the past few decades, the literature has extensively concentrated on developing methods to measure the aggregate connectedness between financial assets. However, analyzing only aggregate connectedness between assets is not adequate since different shocks to one asset may have different effects at different frequencies. On the one hand, some of the shocks may only affect the short-term; on the other hand, others may affect investor expectations and have more permanent, long-term effects. Furthermore, the effects of shocks may also be different on returns and volatilities. Therefore, investors must examine the effects of shocks on return/volatility structures and at different frequencies since they may affect investors' diversification decisions (Ozturk, 2020; Kwon, 2020, Bao et al, 2022, Asgari et al, 2024).

Recently, a growing literature has focused on the relationship between bitcoin and conventional markets, which has important implications for investors and policymakers. Bitcoin is found to be connected with commodity markets, foreign exchange markets, and stock markets. However, the relationship between bitcoin and conventional markets is not as strong as that between the conventional markets, making it possible to use bitcoin as a hedge or safe haven for investors during market turmoil. During the last years, the value of many financial assets decreased rapidly. This general risky economic environment and market decline were accompanied by some assets considered safe havens. Calling an investment a safe haven depends on whether it is uncorrelated to stocks and against stocks, maintains its price level, or exhibits upward movements (Baur et al, 2018; Sandoval and Franca, 2012; Bouri et al., 2017).

In our study, the methodologies and relationships used in previous studies (Vacha and Barunik, 2012; Dyhrberg, 2016a, 2016b; Bouri et al., 2017a; Mensi et al, 2019; Kang et al., 2019; Goodell and Goutte, 2021; Li et al, 2022; Oad Rajput et al, 2022, Khatamy et al, 2024) are included. In these studies, the hedging features of BTC are discussed in general. Dyhrberg (2016b) investigated BTC's position in stock and currency price fluctuations with the GARCH model and found that BTC's gold has some hedging behaviors. According to Bouri et al. (2017a), while BTC exhibited distinct hedging properties for investment-grade energy commodity portfolios in the pre-crisis period, post-crisis BTC only functioned as diversifiers. Bouri et al. (2017b) propose the critical roles of BTC in diversifying and hedging the risk of equity markets. Kang et al. (2017) examined the hedging and diversification properties of gold futures against BTC prices using dynamic conditional correlations (DCCs) and wavelet coherence. They find evidence of volatility persistence, causality and phase differences between BTC and gold futures prices.

The innovation of the present study was in examining the relationship between financial markets using a dynamic approach. In this study, during periods of high and low volatility, the relationship between financial markets has been evaluated and the transfer of volatility between markets has been modeled. Our paper contributes to the existing literature in three parts. First, we study the relationship between bitcoin, gold, USD and crude oil simultaneously. As far as we know, there have not been enough studies investigating the relationship between the four markets. Moreover, the existing literature usually only compares bitcoin with gold, to analyze whether bitcoin can diversify investment risks. However, few studies consider the USD and analyze the interaction between these markets. This paper studies the relationship between four markets, which is a more comprehensive analysis framework. Second, the correlations of the four markets are considered. When analyzing the bitcoin market, it is necessary to take the behavior of markets into consideration. Third, the GARCH-DCC method is used to analyze the relationship between markets.

The main goal of this study is to examine BTC's movements and volatility spillovers with traditional investment instruments and international financial indicators in Iran. The reason for taking the variables in Iran is to explore the movements in the last years locally and to obtain helpful results for local decision-makers and policymakers. In addition, it ensures that inferences are made to represent developing countries with similar economic, financial and social structures internationally. To this purpose, employing GARCH-DCC model, the current study evaluates the co-movement between bitcoin, gold, USD and oil in Iran.

The remainder of this paper is organized as follows. Section 2 describes the theoretical foundations, followed by a review of relevant studies in Section 3. Section 4 estimates and analyzes the research model, and finally Section 5 concludes the paper and gives some concluding remarks.

2. Literature Review

Aliu et al (2023) analyzed the impact of bitcoin (BTC) on gold, the volatility index (VIX) and the dollar index (USDX). The series used are weekly and cover the period from January 2016 to November 2022. To generate the results, the unrestricted vector autoregression (VAR), structural vector autoregression (SVAR) and wavelet coherence were performed. The findings are mixed as not all tests show the exact effects of BTC in the three asset classes. However, common to all the tests is the significant influence that BTC maintains on gold and vice versa. The positive shock in BTC significantly increases the gold prices, confirmed in three different tests. The effects on the VIX and USDX are still being determined, where in some tests, it appears to be influential while in others not.

Zha et al (2023) examined the relationship and risk spillover between Bitcoin, crude oil, and six traditional markets (the US stock, Chinese stock, gold, bond, currency, and real estate markets) from 2019 to 2020, during which the coronavirus disease 2019 (COVID-19) outbreak occurred as well. They first discuss the static relationship between Bitcoin and these markets using a quantile-on-quantile model and examine the dynamic relationship using a time-varying copula model. A conditional value-at-risk model is subsequently used to estimate the risk spillover between the markets studied. The empirical results reveal that the relationship between these markets is always time-varying, and the COVID-19 outbreak has revealed such changes in the relationship between Bitcoin and other traditional financial markets. The risk of all single markets has enhanced because of the pandemic. Further, the risk spillover of these markets has also changed dramatically since the COVID-19 outbreak during which the Bitcoin market has played an important role and exerted a significant impact on the crude oil market, and the four other markets (US stock, gold, Chinese stock, and real estate markets). Overall, Their findings indicate that investors and policymakers need to be made aware of the risk spillover between Bitcoin, crude oil, and other traditional markets and that flexible hedge strategies and policies should be implemented in response to the challenges and economic recession observed following the COVID-19 outbreak.

Salisu et al (2023) considered the relationship between oil price and the bitcoin market. In this study using data over the period of January 27, 2017 (coinciding with the emergence of Bitcoin bubbles) to June 3, 2022, they conduct some predictability analyses and establish the following outcomes. First, they find that higher oil prices tend to raise the cost of producing Bitcoins, therefore lowering its returns and by extension its trading and volatility. Second, they find improved forecast performance of oil price for the realized volatility of Bitcoin as our proposed model that accounts for oil price consistently outperforms the benchmark (random walk) model, regardless of the oil price variant and forecast horizon. Third, investors in the Bitcoin market that observe oil price movements when making investment decisions are more likely to derive higher economic gains than their counterparts that ignore it.

Ghorbel et al (2022) analyzed the connectedness with network among the major cryptocurrencies, the G7 stock indexes and the gold price over the coronavirus disease 2019 (COVID-19) pandemic period, in 2020. This study used a multivariate approach proposed by Diebold and Yilmaz (2009, 2012 and 2014). For a stock index portfolio, the results of static connectedness showed a higher independence between the stock markets during the COVID-19 crisis. It is worth noting that in general, cryptocurrencies are diversifiers for a stock index portfolio, which enable to reduce volatility especially in the crisis period. Dynamic connectedness results do not significantly differ from those of the static connectedness, the authors just mention that the Bitcoin Gold becomes a net receiver. The scope of connectedness was maintained after the shock for most of the cryptocurrencies, except for the Dash and the Bitcoin Gold, which joined a previous level. In fact, the Bitcoin has always been the biggest net transmitter of volatility connectedness or spillovers during the crisis period. Maker is the biggest net-receiver of volatility from the global system. As for gold, the authors notice that it has remained a net receiver with a significant increase in the network reception during the crisis period, which confirms its safe haven.

Jin et al (2022) considered the linkages between bitcoin, gold, dollar, crude oil, and stock markets. Their model the linkages between bitcoin, gold, dollar, crude oil, and stock markets using the GARCH-EVT-copula approach. The results show that the gold market is in the central position among these markets, which is consistent with the status of gold as a major safe asset. Before the outbreak of COVID-19, bitcoin and the dollar also had the ability to diversify risks, although less effective than gold. However, during the COVID-19 period, gold loses its dominant position and gold, bitcoin, and dollar can no longer act as a hedge. They measure the value at risk (VaR) and expected shortfall (ES) of simulated portfolios constructed based on these five markets and use several backtesting methods to check the validity of the risk measures. The backtesting results show that this model can provide accurate risk measures before and within the COVID-19 period, which may help investors and risk managers construct the optimal portfolios.

Ozturk (2020) analyzes the connectedness among bitcoin, gold, and crude oil between 3 January 2017 and 31 December 2019. The paper's motivation is based upon the idea that bitcoin can be similar to gold in terms of its hedging properties and can be used for hedging for different assets. Moreover, although it is more metaphorical, bitcoin is also accepted because it is mined like crude oil, namely, a commodity. These similarities can be investigated by analyzing the connectedness among these financial assets. The connectedness results derived from both total connectedness and frequency connectedness methods indicate that volatility connectedness is higher than the return connectedness among these assets. Furthermore, connectedness in volatilities is mostly driven by medium frequency, although connectedness in returns mostly exists in high frequency. Therefore, these results suggest that investors should consider these financial assets for their diversification decisions. The results suggest that although diversification among these three assets is more difficult in the short- and medium-term, investors may benefit from diversification in the long-run.

Su Li (2020) examined the sentiment spillovers among oil, gold, and Bitcoin markets by employing spillovers index methods in a time-frequency framework. They find that the total sentiment spillover among crude oil, gold and Bitcoin markets is time-varying and is greatly affected by major market events. The directional sentiment spillovers are also time-varying. On average, the Bitcoin market is the major transmitter of directional sentiment spillovers, whereas the crude oil and gold markets are the major receivers. In particular, the sentiment spillover effects are major created at high-frequency components, implying that the markets rapidly process the sentiment spillover effects and the shock is transmitted over the short-term. Moreover, They also find that the sentiment spillover effects differ significantly in term of intensity and direction when compared with return and volatility spillover effects.

3. Research Methodology

In this study, the movement of daily BTC (BTC) price, spot Gold price, USD in and Brent Crude Oil Future in terms of USD in the period 12/31/2010-12/31/2022 are examined. In the analysis, the logarithmic values of the variables were used.

Descriptive statistics regarding the variables used in the study are given in Table 1. Table 1 presents the summary statistics of the BTC and the other related variables. The numbers in the table are statistics calculated over logarithmic values. In the whole period from December 31, 2010, to December 31, 2022, the mean daily logarithmic price of BTC is 12.29. Skewness, Kurtosis, Jarque-Bera, and Probability values indicate that the data are typically not normally distributed. The number of observations included in the analysis is 662. Other statistics that can be used in the context of the structure of the data set in the table are mean, median, maximum, minimum, and standard deviation statistics. For example, standard deviation *(sd)* can evaluate every variable's volatility. BTC and oil series are skewed to the left because the skewness value is negative, while other variables are skewed to the right.

Table 1. Descriptive Statistics of variables

	LNBTC	LNGOLD	LNUSD	LNOIL
Mean	12.87	6.71	2.31	4.18
Median	12.75	6.28	2.26	4.23
Std. Dev.	0.95	0.35	0.32	0.39
Skewness	-0.43	0.62	0.92	-0.34
Kurtosis	1.62	2.57	2.44	2.57
Jarque-Bera	42.84	39.72	71.62	17.69
Probability	0.00	0.00	0.00	0.01

Source: Research finding

The graphs in Figure 1 were also created in the study. In Figure 1, BTC, GOLD, OIL and USD prices show a severe upward trend with the pandemic. Although BTC prices exhibit similar movements with other variables in the chart, it is seen that the movements differ in some periods.

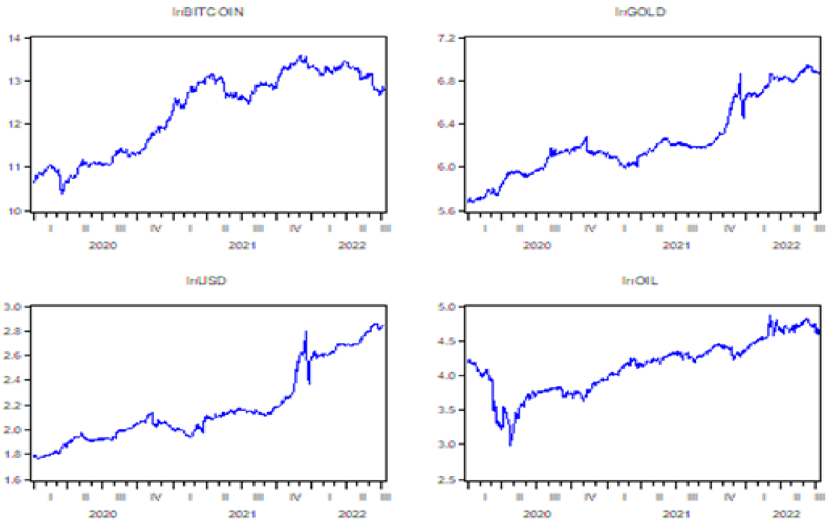

Figure 1. Time Series of Variables

Source: Research Finding

4. Model Estimation

4.1. Static Variable Testing

According to the econometric literature, before any estimation and in order to prevent the emergence of false regressions, the variables must be static. If the model's variables are static, estimates will not be subject to the issue of false regression. Using the HEGY test and ADF test, the variables were examined in terms of stationarity. The null hypothesis in these tests is that there is a unit root. The summary of test results is shown in Table 2. According to the results, all variables are within 5 percentage points of the y-intercept.

The results are seen in Table 2. In general, that all series has not contain unit roots in their level values and be stationary in level.

Table 3. Results of the unit root test

Variables	HEGY		ADF	
LNBTC	Tstatistic	-5.75	T-statistic	87.52
	P-value	0.00	P-value	0.00
LNGOLD	Tstatistic	-12.62	T-statistic	63.93
	P-value	0.00	P-value	0.00
LNUSD	Tstatistic	-6.18	T-statistic	69.11
	P-value	0.000	P-value	0.00
LNOIL	Tstatistic	-8.64	T-statistic	93.87
	P-value	0.00	P-value	0.00

Source: Research findings

4-2. Model Estimation and Outcome Interpretation

DCC-GARCH Results

The DCC-GARCH analysis is used in this study as a second method. With *DCC-GARCH* analysis, the conditional correlations between the variables were determined.

Before applying the DCC volatility matrix, first, GARCH mean and variances should be calculated (Sampid and Hasim, 2018; Feng et al, 2022). Bollerslev (1986) proposed the GARCH model that allows the dependence of the conditional variance to its previous lags. The GARCH(1,1) model has the following form:

$\zeta_{u,t} = \chi_u + a_{u,t}, a_{u,t} = \lambda_{u,t}\vartheta_{u,t}$
(1)
$\lambda_{u,t}^2 = a_u + \beta_u a_{u,t-1}^2 + \gamma_u \lambda_{t-1}^2$, $for\ u = 1,2,\dots,N\ , t = 1,2,\dots,T$

(2) where in Equation (1) $\zeta_{u,t}$ represents the log-returns of variable, χ_u represents the conditional log-return mean, $a_{u,t}$ represents the mean residuals, $\vartheta_{u,t}$ shows the white noise having variance 1 and 0 mean, and $\lambda_{u,t}$ shows the conditional volatility series; α, β, and γ in Equation (1) are described as the key parameters of GARCH(1,1) estimation, T represents the available sample size, and N represents the number of variable. Thus, the covariance matrix of DCC at time t is as follows:

$\Sigma_t = G_t P_t G_t$ (3)

And the DCC conditional correlation matrix is then P_t:

$P_t = G_t^{-1}\Sigma_t G_t^{-1}$ (4)

In Equation (3), G_t represents the diagonal matrix of the *N* conditional volatilities of the variables, that is, $G_t = diang\{\sqrt{\lambda_{11,t}},\dots,\sqrt{\lambda_{NN,t}}\}$ and $\lambda_{u,t}$ is the (*u,v*)th component of the volatility matrix. Based on the above assumptions, the DCC model can be expressed as follows:

$P_t = (1 - \Theta_1 - \Theta_2)\bar{P} + \Theta_1 P_{t-1} + \Theta_2 \phi_{t-1}$ (5)

In Equation (5), $\bar{P}$ shows the unconditional correlation matrix of ϑ_t, θ_1, and θ_2, which are positive real numbers satisfying $0 \le \Theta_1 + \Theta_2 < 1$. ϕ_{t-1} stands for the correlation matrix of return's of variables depending on $\{\vartheta_{t-1},\dots,\vartheta_{t-n}\}$ for some integer *n*.

As a result of the *DCC-GARCH* analysis, we can say that the positive correlation between *BTC* prices and other variables is characteristic for the entire period. Higher values of parameter α marked theta (1) in tables make our models more dynamic. Therefore, *DCC-GARCH* models can respond flexibly to changes in measured correlations.

Estimations of the DCC GARCH models meet the requirement that the sum of dynamic parameters *theta (1) + theta (2) <1*. It means that it fulfilled the positive definiteness of matrix Q_t. In addition, the estimated parameters of both *DCC-GARCH* models are statistically significant because of the high values of the sum of the dynamic parameters achieved; high persistence in conditional volatility can be observed. All parameters for conditional variances and correlations were also statistically significant. The estimate of the v parameter shows that the *t* distribution is correctly adjusted to the data. The symbols *Θ1* and *Θ2*, which explain the dynamic correlation relationship between *BTC* and *GOLD* prices in Table 3, are statistically significant at the 5% significance level. Therefore, a positive and influential relationship exists between prices.

Based on these parameters, it is possible to build a model for BTC and Gold series as referred to below:

$$Q_{i,j,t} = \omega_{i,j} + 0.024\varepsilon_{i,t-1}\varepsilon_{j,t-1} + 0.923Q_{i,j,t-1},$$

The symbol *Θ1*, which explains the dynamic correlation relationship between *BTC* and *OIL* in Table 4, is statistically significant at the 10% significance level. Therefore, a negative and weak relationship exists between prices.

Based on these parameters, it is possible to build a model for *BTC* and *OIL* series as referred to below:

$$Q_{i,j,t} = \omega_{i,j} - 0.016\varepsilon_{i,t-1}\varepsilon_{j,t-1} + 0.275Q_{i,j,t-1},$$

The symbols Θ1 and Θ2, which explain the dynamic correlation between BTC and USD in Table 5, are statistically significant at the 10% and 5% significance levels, respectively. Therefore, a positive and robust relationship exists between prices.

Based on these parameters, it is possible to build a model for BTC and USD series as referred to below:

$$Q_{i,j,t} = \omega_{i,j} + 0.184\varepsilon_{i,t-1}\varepsilon_{j,t-1} + 0.739Q_{i,j,t-1},$$

Figure 5 shows estimated dynamic correlations. As of December 31, 2019, it is seen that the correlation coefficients created by the DCC-GARCH models have reached positive and negative values for the examined bilateral relations. When BTC-Gold movements are concerned, positive and negative trends are observed between July and October and October-December, respectively, in 2020. Between 2021 November-2022 and February-2022 April, positive and negative movements were observed. Especially in the November-February 2022 period, significant positive and negative correlation trends were observed between February 2022 and April 2022. On the oil side, the first thing to notice is the profound negative correlation in March 2020.

Table 3. BTC and GOLD DCC GARCH Dynamic Correlations

	Coefficient	Std. Error	z-Statistic	Prob.
Θ_1	0.024	0.011	2.181	0.007
Θ_2	0.923	0.018	51.27	0.001
	t-Distribution (Degree of Freedom)			
v	4.52	0.330931	13.03938	0.000
Log-likelihood	3.34	Schwarz criterion		-12.08
Avg. log-likelihood	-12.08	Hannan-Quinn criteria.		-12.06
Akaike info criterion	-12.07			
* Stability condition: theta(1) + theta(2) < 1 is met.				

Source: Research finding

Table 4. BTC and OIL DCC GARCH Dynamic Correlations

	Coefficient	Std. Error	z-Statistic	Prob.
Θ_1	-0.016	0.009	-1.77	0.068
Θ_2	0.275	0.017	16.17	0.000
	t-Distribution (Degree of Freedom)			
v	5.18	0.292315	14.10295	0.000000
Log-likelihood	2.84	Schwarz criterion		-11.56
Avg. log-likelihood	-11.97	Hannan-Quinn criteria.		-11.68
Akaike info criterion	-11.74			
* Stability condition: theta(1) + theta(2) < 1 is met.				

Source: Research finding

Table 5. BTC and USD DCC-GARCH Dynamic Correlations

	Coefficient	Std. Error	z-Statistic	Prob.
Θ_1	0.184	0.028	6.57	0.000
Θ_2	0.739	0.215	3.43	0.001
	t-Distribution (Degree of Freedom)			
v	3.48	0.155514	21.28529	0.000000
Log-likelihood	3.56	Schwarz criterion		-14.09
Avg. log-likelihood	-14.47	Hannan-Quinn criteria.		-14.13
Akaike info criterion	-14.51			
* Stability condition: theta(1) + theta(2) < 1 is met.				

Source: Research finding

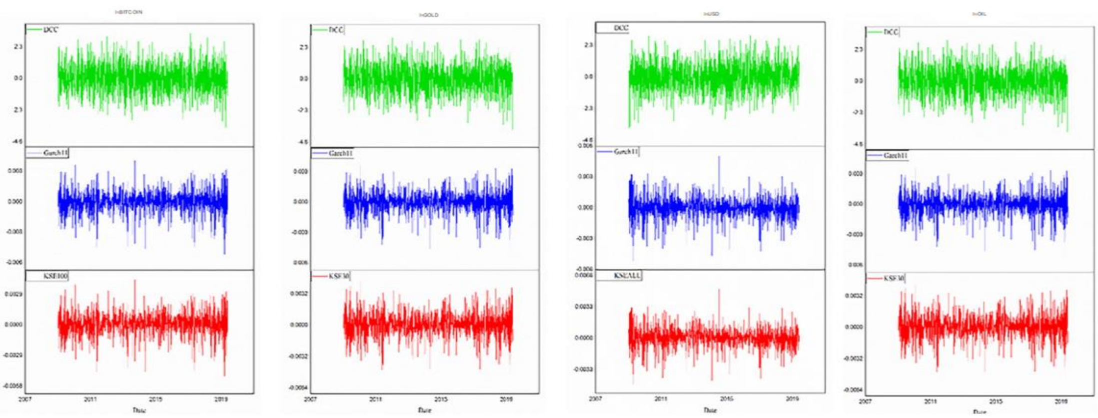

Figure 5. Dynamic Conditional Correlations

5. Conclusion

This study examines the relations of Bitcoin (BTC) prices and fluctuations with gold, USD and oil. For this purpose we used GARCG-DCC model from 2010 to 2022. The results indicated that the fluctuations of the financial markets had an effect on each other. It was also observed that the volatility was transferred between the dollar and bitcoin. In addition, fluctuations in the gold and dollar market have also been transferred to other markets. Also, the results indicated that any shock from any financial market had significant effects on other financial markets. The findings of this study show that the BTC market should be constantly monitored, given its ability to transfer volatility risk to strategic commodities (such as crude oil) and even safe havens (such as gold) that are often seen as hedging instruments. The results indicate short-term co-movements of BTC and Gold, oil, USD are challenging to predict. The results also reflect the behavior of assets that appeal to speculators and uninformed noise investors that cause significant market fluctuations with their excessive transaction volumes during crisis periods that potentially affect the entire world economy and financial markets, such as the pandemic. Considering that before the pandemic, BTC was considered a relatively weak hedging tool or diversifier, the findings from this study become more remarkable. The findings of variance decompositions between financial market variabels increase or decrease depending on market conditions throughout the scales, however, this trend will converge in the long run. The results obtained from the present study was matched with the results Su Li (2020), Ozturk (2020), Jin et al. (2022) and Salisu et al (2023).

All findings conveyed several insights regarding the policy implications of this study. First, investors can choose alternative investment horizons in different characterized products, which may offer portfolio gains. Further, this study uncovers important consequences and practical implications for the risk assessment, asset allocation, and diversification of funds in different asset lines during crisis periods. Fund managers can take appropriate steps for assessing the market movement in international avenues. Because of this, portfolio strategy and its success depend on better understanding the market correlation in dynamic ways.

Additionally, policymakers should pay close attention to the tight interconnections between crude oil, especially during a crisis, if they want to implement optimal economic and energy policies to minimize the destabilizing effects of oil/BTC return shocks and avoid contagion risks. The results of this study also serve as a cautionary note for portfolio managers and investors who include BTC in their portfolios as a hedge against uncertainty.

The most important limitations of the present study are the statistical data after the COVID19 epidemic, that in future studies, the relationship and dynamics between the financial markets before and after the COVId19 epidemic period can be investigated.

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