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CO-MOVEMENT OF BITCOIN, GOLD, USD, OIL AND VIX: EVIDENCE OF WAVELET COHERENCE AND DCC-GARCH FROM THE PANDEMIC PERIOD

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Abstract

This study examines the relations of Bitcoin (BTC) prices and fluctuations with gold, USD, oil, VIX index, hedging, and diversification features in Turkiye. For this purpose, wavelet coherence and dynamic conditional correlations (DCCs) were used in the study. Our research explores whether the bubble behavior patterns in BTC prices during the COVID-19 pandemic can be used in the short term to protect against the bubble behavior in the markets that are the subject of this research and vice versa. However, whether other assets can be used to manage and hedge BTC's downside risk is also being explored. The aim is to understand how and at what level critical financial instruments and indicators are affected by each other in times of crisis and economic recession, such as pandemics, and to present valuable results to decision-makers. The sample for this study includes Türkiye for the period between 12/31/2019 and 13/07/2022. Wavelet Coherence and DCC-GARCH results indicate significant positive and negative movements of BTC prices with gold, oil, USD prices, and the VIX fear index during the pandemic. We find evidence of volatility persistence, causality, and phase differences between BTC and other financial instruments and indicators.

Keywords: BTC, Gold, USD, Oil, VIX, Wavelet Coherence

1. INTRODUCTION

On March 11, 2020, the World Health Organization (WHO) announced that the 2019 Coronavirus disease (COVID-19) has turned into a pandemic. There have been shocks from China, the pandemic's epicenter, to developed and developing countries and

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the economic and financial life in these countries.

The pandemic has significantly affected the economic and financial life and the health problems it has created. People worldwide have begun to get used to the harmful effects of the pandemic on economic life and to adapt their financial behaviors to the new situation. Although the pandemic has become commonplace, its eventual impact on economies and financial markets remains a cause for concern.

During this period, 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 & Lucey, 2010; Bouri et al., 2017). The price movements of Bitcoin (BTC) since its launch in 2009 have raised the issue of whether BTC exhibits safe-haven properties as an alternative to stocks (Wang et al., 2019; Shahzad et al., 2019). BTC is seen as a safe haven for several reasons, including the independence from monetary policies in a country, its role in accumulating value, and its limited relationship with traditional assets.

While many assets subject to trading in financial markets were negatively affected by the hostile atmosphere and uncertainty created by the pandemic, there were also shining financial instruments in this period. At the beginning of these are cryptocurrencies especially BTC. During the COVID-19 pandemic, cryptocurrencies have generally appreciated. The pandemic also caused significant fluctuations in energy, precious metals, foreign exchange prices, and people's confidence in the markets. In this context, analyzing and understanding the movements of the crypto money market and other financial indicators; is essential in understanding human behavior and revealing the relationships between financial instruments and indicators in crisis periods.

The term cryptocurrency is used to refer to digital currencies or assets based on blockchain technology. With the rapid development of blockchain technology, cryptocurrencies have received massive publicity in the financial markets due to some views that they can be considered a new category of investment assets. Today, the cryptocurrency market has become one of the fastest-growing markets in the world regarding trading volume and market cap (Delfabbro et al., 2021). Compared to traditional asset markets, cryptocurrency is an emerging market with a large market cap (Qiao et al., 2020). Despite the losses and fluctuations since the beginning of 2023, the cryptocurrency ecosystem continues to grow. Current research shows that Türkiye is positioned globally in the ratio of adults dealing with cryptocurrencies (Morning Consult).

On the other hand, a recent report by Bloomberg states that Türkiye ranks 7th globally in using crypto assets. Merchant Machine reveals that Türkiye ranks eighth in the world, with 25 percent, according to 2021 data, in the number of citizens of countries that own cryptocurrencies compared to the population, where Nigeria is seen as the leader. According to its growth rate, the company estimates that 45% of Türkiye's population could own cryptocurrencies by 2030. However, there was an unprecedented loss of value in the summer of 2022. BTC, the crypto ecosystem's most significant currency, lost half its record value of $ 69 thousand in

November 2021. A recent report shows that Türkiye's interest in cryptocurrencies has not decreased despite all the depreciation. In the research report prepared by the global research firm Morning Consult, Türkiye ranked second worldwide regarding the proportion of adults who trade crypto once a month. Türkiye, one step behind Nigeria with a rate of 54%, was followed by countries such as Thailand, Pakistan, Vietnam, United Arab Emirates, and Argentina. Despite the problematic processes in the crypto money market, cryptocurrencies remain popular in Türkiye. The reason is that cryptocurrencies are not seen as a game but as a necessity in Türkiye. According to a study conducted by the crypto exchange Paribu in 2022, at least 8 million people in Türkiye are investing in cryptocurrencies. Paribu's 2022 research report shows that the daily trading volume on the platform has dropped from $850 million in 2021 to $145 million.

However, despite the decrease in trade volume, the enthusiasm for digital currencies continues at full speed. Crypto money offers a kind of freedom to Turkish people. In a research report published on 26/03/2023, Morgan Stanley said that expectations for increased USD liquidity to support the banking sector after some mandatory shutdowns helped the BTC (BTC) rally, but other factors were also active. BTC (BTC) has risen about 73 percent in TRY and 72 percent in USD since the first day of 2023. Investors are taking positions, hoping the rise in the most prominent cryptocurrency, BTC, will continue in the coming months. On the other hand, the research results published by Morning Consult on January 24 reveal that US adults who participated in the study in January 2023 predict a negative future in BTC. Participants expect BTC to trade at $15,252 in six months.

Cryptocurrencies and BTC are classified as speculative investments (Vo et al., 2022). The BTC market is the most volatile (Gkillas et al., 2022). The explosive movements experienced in BTC recently show that it is not yet seen as a stable investment tool. BTC acts more like an investment tool open to speculative activities rather than a currency. Dwyer (2015) emphasized that the return volatility observed in BTC is higher than in other investment instruments, revealing this fact. Likewise, Baur & Dimpfl (2017) emphasize that BTC's highly volatile nature distracts it from the fact that it can be seen as any currency. Rapid technology development has contributed to the recent dramatic growth in the cryptocurrency market, enabling users to more easily access digital currencies and transfer money globally at a much lower cost and time than traditional money transfer methods. However, it has also led to high speculation among network users. Although rapid technology updates have brought positive effects in many ways, this fast update has caused more speculators to join the market. As a result, the cryptocurrency market has become more volatile than the stock market or other commodity markets (Hashemi Joo et al., 2020). Chaim and Laurini (2019) highlight that cryptocurrency volatility is higher than in traditional assets, indicating higher returns and risks. Therefore, an emerging and high-profile market with high recognition and income is desirable to owners, investors, and risk managers. Yu et al. (2019) discovered that the market efficiency of the BTC market is higher than that of the overall financial market due to the asymmetry of volatility.

BTC was introduced to the financial markets for the first time by Nakamoto

(2008), and although it has been about fifteen years since then, how it should be defined has not yet been fully answered. Whether BTC is a currency, a commodity, or an investment asset is still debatable—demand shock, significant price movements, etc., of cryptocurrencies, especially BTC. Exhibiting most of the commodity properties supports the idea that they are commodities (Bouri et al., 2018, Gronwald, 2019). The fact that BTC is a mining reward and its supply is limited causes BTC to be considered a digital version of commodities used for savings. When cryptocurrencies are accepted as commodities, examining price volatility and co-movement with other entities is essential. The connection between cryptocurrencies, commodities, and other traditional assets is interesting.

BTC, the first of the cryptocurrencies and the largest in total market capitalization (approx. $330.76B) and trading volumes, continues to be at the center of discussions regarding its potential role in the global financial system. In a more analytical approach, BTC's underlying technology, the blockchain, holds great promise for financial institutions. However, some other studies question the future of BTC and its prospects for mediation. In some countries, financial regulators are trying to regulate or even ban the use of BTC in their country's economies, making the financial inclusion of BTC even more challenging (Gkillas et al., 2022).

The relationship between BTC and traditional assets (e.g., stocks, bonds) and commodities (e.g., gold, crude oil) has been gaining traction in academia for some time due to its significant implications for investors, academics, and policymakers (e.g., Ji et al., 2018; Shahzad et al., 2020). Despite extreme price fluctuations (Bouri et al., 2019; Cheah and Fry, 2015), market manipulations (Gandal et al., 2018), and stock market security flaws, interest in BTC investment continues to grow.

Bouri et al. (2017b), Klein et al. (2018), and Smales (2018) find no consistent evidence that BTC acts as a safe-haven for global assets, while Selmi et al. (2018). It has been determined that it acts as a protection, safe haven, and diversifier. However, this feature seems sensitive to the different market conditions of BTC and Gold and whether the oil price is in a down, regular, or upside regime. Kurka (2019) found that the relationship between BTC and other assets depends on price shocks. In addition, Matkovskyy and Jalan (2019) found that risk-averse investors in times of crisis tend to move away from BTC with the view that it is riskier than financial markets. Baek & Elbeck (2015) argue that BTC is merely a speculative commodity rather than a currency.

The view that gold can be considered a safe-haven asset is widely accepted, especially in the depressed market environment (Beckmann et al., 2015). The traditional safe haven feature of gold emerges in short intervals, especially in crisis periods (Bredin et al., 2015). For example, Gürgün and Ünalmış (2014) documented that gold is a safe haven for domestic and foreign investors, especially when the stock market shows more severe declines. Bulut & Rizvanoghlu (2020) emphasize that while gold is generally considered a hedging tool, it is a strong safe haven in only 9 countries in their sample. BTC, the most popular and valuable among existing cryptocurrencies, has limited stock and short-term elasticity of supply (Dwyer, 2015). BTC is also called synthetic commodity money due to its scarcity and lack of fiat money (Selgin, 2015). BTC and gold have many similar features, such as being apolitical, safe-haven, and inflation-free (Shahzad et al., 2019

For this reason, BTC is also called digital Gold (Popper, 2015; Rogojanu and Badea, 2014; Selmi et al., 2018). BTC also has advantages differentiating it from gold, such as being independent of a country's politics and economy and relying on suitable algorithms and sophisticated protocols. Therefore, it is stated that BTC will not be affected by the co-movement and financialization of commodities such as gold. Such features make it meaningful to compare the safe haven features between BTC and Gold. Especially in the context of the COVID-19 outbreak, the comparison of this feature has become more attractive (Wen et al., 2022). Gold and BTC are similar regarding being a value protection tool and not being controlled by states. The fact that BTC can be used as a general payment method, such as cash or gold, due to its convertibility advantage makes it attractive to investigate hedge properties (Dyhrberg, 2016a; Bouri et al., 2017a; Selmi et al., 2018; Li et al. 2022; Al-Nassar et al, 2023). However, Wu (2021) investigated the relationship between BTC and traditional financial instruments regarding the asset quality and hedge effect of BTC and found that BTC has a unique risk-return feature and volatility clustering performance, and its high volatility persistence is similar to gold. At the same time, it was argued that while BTC exhibits a significant one-way spillover effect with other variables, BTC is much more affected by different market shocks than other markets are affected by BTC shocks. Therefore, BTC cannot be a safe haven.

Since crude oil occupies a dominant position in the global energy market (Zhang & Ji, 2019), the interaction of oil and BTC markets is another essential issue for policymakers and investors. This is because, according to the risk premium channel (Bruno & Shin, 2015), a crude oil shock can significantly affect investors' willingness to take the risk of BTC. Therefore, it is crucial to uncover the link between crude oil and BTC to more effectively assess the potential risks of cryptocurrencies and thus increase earnings (Li et al. 2022). Selmi et al. (2018) claim that BTC plays a diversified role in hedging from oil price changes and is seen as a private safe haven. However, this relationship is variable in different market conditions. Kurka (2019) pointed out that the unconditional link between cryptocurrency and crude oil can be ignored. However, recent studies have empirically confirmed the severe impact of financial shocks from extreme events (e.g., terrorist attacks, political events, and economic crises) on crude oil and BTC prices (Luo et al., 2020; Zhang et al., 2020, Li et al., 2022).

In particular, studies examine the relationship between BTC and strategic commodities such as gold and crude oil and suggest that BTC is a hybrid commodity and will be affected by crude oil prices are noteworthy (Bouri et al., 2018; Gkillas and Longin, 2019; Ji et al., 2018). Kwon (2020) examines whether BTC can be classified as a currency, commodity, or investment asset. The author found a similarity between BTC and USD. In addition, he discovered that the tail of the stock market return is associated with the risk premium in BTC's return. The bottom line shows that BTC is traded as an alternative to a medium of exchange and investment rather than a commodity. On the other hand, supply-demand factors dominate the price behavior in the BTC market (Ciaian et al., 2016). Thus, unlike standard currencies in circulation, BTC's liquidity and volatility are not influenced by a centralized system of financial institutions (e.g., central banks) or other major macroeconomic factors (Ciaian et al., 2016; Baur et al., 2018). Therefore, the price of BTC could potentially be separate from the economic and trade cycles that result from monetary policy and the central bank's money supply management (Kang et al., 2019). This latter feature suggests that BTC can serve as a dynamic diversification and hedging tool, thus managing volatility risks in the markets (Feng et al., 2018; Kang et al., 2019). On the other hand, Baur et al. (2018) suggest that BTC's extreme returns and volatility are more like a highly speculative asset than gold or the USD.

Studies investigating the relationships of cryptocurrencies with other investment alternatives state that they can provide hedging in crude oil (Selmi et al., 2018) and Gold (Pal and Mitra, 2019) prices. Another topic frequently emphasized in the literature is the co-movement of cryptocurrencies (Qiao et al. 2020; Abdul-Rahim et al., 2022; Disli et al., 2022). However, it is noteworthy that the relationship between cryptocurrencies and energy commodities is also included in the literature (Rehman & Kang, 2021). Mensi et al. (2020) focused on BTC's relationship with Islamic financial assets and stock markets and its co-movement and risk spillover. In another study by Mensi et al. (2019), the effects of structural breaks (SB) on BTC and Ethereum price returns on long binary memory levels were investigated. Also, the relationship between cryptocurrencies and especially BTC prices with the number of COVID-19 cases (Goodell & Goutte, 2021) has been closely examined recently.

One of the most critical indicators that investors pay attention to when making investment decisions is the volatility of financial instruments. The high volatility in financial markets may cause different choices for investors. Investors follow the volatility in the international market and the volatility in the national market. With the acceleration of globalization, volatility occurring in one of the financial markets with each other affects the others. Therefore, investors consider the volatility in international markets when making decisions. In this context, the VIX fear index is a volatility index considered by investors. The Volatility Index, known as the VIX Fear Index, is an index that expresses fear and anxiety about the markets. Shahzad et al. (2022) compared the weak/strong hedging capabilities of BTC, gold, and US VIX futures with the downward movements of stock market indices in BRICS countries. The results showed that BTC and Gold are weak hedging instruments. BTC has demonstrated that gold and VIX futures have a time-varying hedging role in some BRICS countries shaped by the COVID-19 pandemic. Hernandez et al. (2022) investigated US economic policy uncertainty's short- and long-term effects on BTC, Gold, and VIX. According to their results, policy uncertainty significantly affects BTC negatively (positively) on short (long) horizons.

Contrary to the existing literature, the impact of policy uncertainty on BTC returns weakens over longer horizons. Bao et al. (2022) tried to create a regional monthly joint action indicator between BTC and MSCI indices and showed a strong link between BTC and local exchanges. Al-Yahyaee et al. (2019) examined the joint movements between the Volatility Uncertainty Index (VIX) and BTC (BTC) using bivariate and multivariate wavelet approaches. According to the results of their studies, it can be said that the BTC-VIX relationship changes over time and at high and low frequencies. They also detected negative (out-of-phase) and positive (in-phase) joint movements at high and low frequencies. VIX news has predictive power on BTC price returns over different frequencies. Another study on the relationship between economic and financial uncertainty and risk level and BTC prices are carried out by Wang et al. (2019). Their study examined the spillover effect of risk from economic policy uncertainty (EPU) to BTC using a multivariate quantitative model and the Granger causality risk test. As a result of their study, they found that the risk spillover effect from EPU to BTC is negligible in most cases. In another study, Akyildirim et al. (2020) analyzed the relationship between the price volatility of a wide range of cryptocurrencies and the implied volatility of both the United States and European financial markets as measured by the VIX and VSTOXX. Their results showed, in general, the existence of positive relationships between cryptocurrencies and financial market stress over time. They also showed that these correlations increase significantly during high financial market stress periods.

Since its emergence in 2009, BTC has been intensively studied in the academic field, especially after its rise in 2017. Recently, the panic and crisis environment created by the pandemic has increased its attractiveness, and the reasons behind the surge in price have become more common. The empirical literature on the safe-haven properties of different assets in terms of financial risks has increased (Bouoiyour et al., 2019). Dyhrberg (2016) investigated the economic asset properties of BTC with GARCH models. The author has determined that BTC exhibits hedging properties and is similar to Gold and the USD because of its advantages. The author has also shown that BTC can be helpful in risk management and is ideal for risk-averse investors regarding negative expectations about the market's future. The author also emphasized that it can be classified between Gold and the USD. Baur et al. (2018) stated that BTC displays distinctly different returns, volatility, and correlation characteristics than other assets, including Gold and the USD. Oad et al. (2022) found that BTC price has an asymmetrical and negative relationship with USD in the short and long run.

In addition to various financial and economic risks, studies have been conducted on how political risks affect the role of BTC, as revealed by Bouoiyour, Selmi and Wohar (2019). The authors explored the role of different assets (especially oil, precious metals, and BTC) as a safe haven against US equities at times of heightened uncertainty about the outcome of the 2016 US presidential election. Its results show that oil is an effective safe haven against political risks. Similarly, gold and silver are a safe haven against US stock losses in the medium and long term and BTC. Li et al. (2022) examined excessive risk transmission between BTC and the crude oil market under extreme and non-extreme shocks. They found strong evidence of excessive risk transfer between BTC and crude oil and explored the time-varying nature of the BTC-oil relationship. They found time-varying interactions in the oil-BTC relationship. Their study also shows stronger causal links during large movements in oil returns. Al-Nassar et al., (2023) explore the potential hedging and safe-haven properties of various alternative investment assets, including Gold, BTC, oil, and the oil price volatility index (OVX), against the risks of the Saudi stock market and its constituent sectors at different stages of the COVID-19 pandemic. Their findings show that all researched alternative investment assets have a time-varying hedging role in the Saudi stock market, which has become expensive in the early stages of the COVID-19 pandemic. DCCs between Saudi indices and oil and, to a lesser extent, BTC peaked during the COVID-19 crisis, highlighting oil's role in transmitting financial contagion to the Saudi stock market.

In our study, the methodologies and relationships used in previous studies (Vacha & Barunik, 2012; Dyhrberg, 2016a, 2016b; Bouri et al., 2017a; Kang et al., 2019; Goodell & Goutte, 2021) 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 a diversifier. Bouri et al. (2017b) propose the critical roles of BTC in diversifying and hedging the risk of equity markets. Kang et al. (2019) 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 wavelet consistency results show high co-movement between BTC and gold futures prices.

First, the study analyses the co-movements of BTC and gold, oil, USD, and VIX with the wavelet coherence method. Then, conditional correlations and volatility were examined with DCC-GARCH analysis. Thus, the time-frequency structure of the correlation and co-movements between BTC prices and other financial assets and indicators has been discussed. Therefore, it has been tried to contribute to the limited literature on the subject. It is the first study to use phase differences from wavelet coherence to provide information on the hedging properties of BTC and gold, foreign exchange, and oil markets, as well as the direction of joint action and causal relationships with the VIX fear index. Additionally, it is important to highlight that the study is exclusively focusing on the Turkish financial market which imposes limitations in case decided to be applied to other financial markets.

The combination of DCC-GARCH and wavelet modeling strategies, in which estimated correlations are used instead of actual correlations in the study, allows us to extract information about the correlations' time-varying and time-frequency nature co-movements between the financial assets and indicators examined. For this reason, it is preferred by many authors in the literature. Specifically, wavelet decomposition allows the assumed homogeneous relationship between returns in the time domain to be decomposed into relationships between returns on different investment timescales (Kang et al., 2019).

The study discusses BTC in the context of hedging features and volatility spillover. The gold, oil, USD, and VIX fear index are included in the scope of the study because there is no study in this context against BTC prices in the literature. Generally, BTC is considered together with one or two financial instruments, and analyses are carried out. At the same time, the BTC market is subject to intense speculation and expectations. This situation is observed intensively in Türkiye as well. Especially during the COVID-19 pandemic, speculative movements have intensified, and the combined movements of USD gold oil prices and BTC have become very interesting. For this reason, the motivation behind the period of the selected data sample is to examine the movements during the COVID-19 pandemic at a local scale, to make inferences about possible similar crises in the future, and to enable functional evaluations to be made in terms of understanding the consequences of similar problems in the past. The economic and financial uncertainty caused by the pandemic will likely increase the spillover effects between BTC prices and other investment alternatives.

When the studies on the subject are examined, it is seen that the relations between gold, stock market, oil, USD, and US VIX are examined intensively in studies on developing countries such as Türkiye (Kumar, 2014; Chkili, 2016; Sarwar & Khan, 2016; Wen & Cheng, 2018). However, the main goal of this study is to examine BTC's movements and volatility spillovers with traditional investment instruments and international financial indicators in Türkiye. The reason for taking the variables in TRY is to explore the movements in the COVID-19 period 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. This study is expected to support the body of studies to understand the economic effects of COVID-19, resulting in a rapidly growing literature. The results of this study may increase the predictability of decision-makers in similar financial market movements that are likely to occur in future crises such as COVID-19.

2. DATA AND METHODS

The data used in the study were obtained from the Refinitiv Eikon* database. In this study, the movement of daily BTC (BTC) price, spot Gold TRY/GR and ABD USD in Turkish Lira and Brent Crude Oil Future in terms of ABD USD and VIX fear index in the period 12/31/2019-13/07/2022 are examined. In the study, especially the pandemic period was taken into account. In the analysis, the logarithmic first difference values of the variables, free from the unit root, were used.

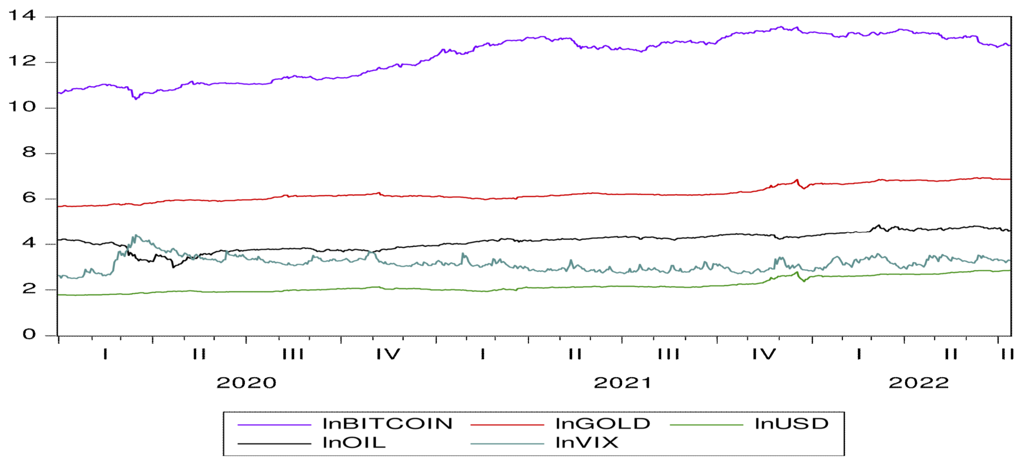
Descriptive statistics regarding the variables used in the study are given in Table 1. Table 1 presents the summary statistics of the BTC and the other related variables, including the pandemic period. The numbers in the table are statistics calculated over logarithmic values. In the whole period from December 31, 2019, to July 4, 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.

Figure 1 shows the logarithmic time series

**Refinitiv Eikon is a financial information service that provides data, analytics, trading, and collaboration tools for financial professionals. It delivers real-time and historical market data, news, and insights across various asset classes and markets.*

Table 1. Descriptive Statistics

	LNBTC	LNGOLD	LNUSD	LNOIL	LNVIX
Mean	12.28887	6.249286	2.191029	4.131062	3.154664
Median	12.68362	6.176066	2.102694	4.193964	3.131137
Maximum	13.57571	6.940316	2.858015	4.860742	4.415099
Minimum	10.37841	5.670453	1.767245	2.978077	2.493205
Std. Dev.	0.945311	0.341647	0.310753	0.389820	0.315998
Skewness	-0.429817	0.547431	0.801836	-0.338378	0.776148
Kurtosis	1.599817	2.323615	2.323144	2.565442	4.313696
Jarque-Bera	74.46074	45.68405	83.57472	17.84196	114.0687
Probability	0.000000	0.000000	0.000000	0.000134	0.000000
Sum	8135.229	4137.028	1450.461	2734.763	2088.387
Sum Sq. Dev.	590.6787	77.15375	63.83124	100.4454	66.00416
Observations	662	662	662	662	662



Note: In the graph, the horizontal axis shows the research period in days, and the vertical axis shows the logarithmic values of the variables. Accordingly, the 50th day corresponds to 2020-03-06, the 350th day to 2021-04-30, and the 650th day to 2022-06-24.

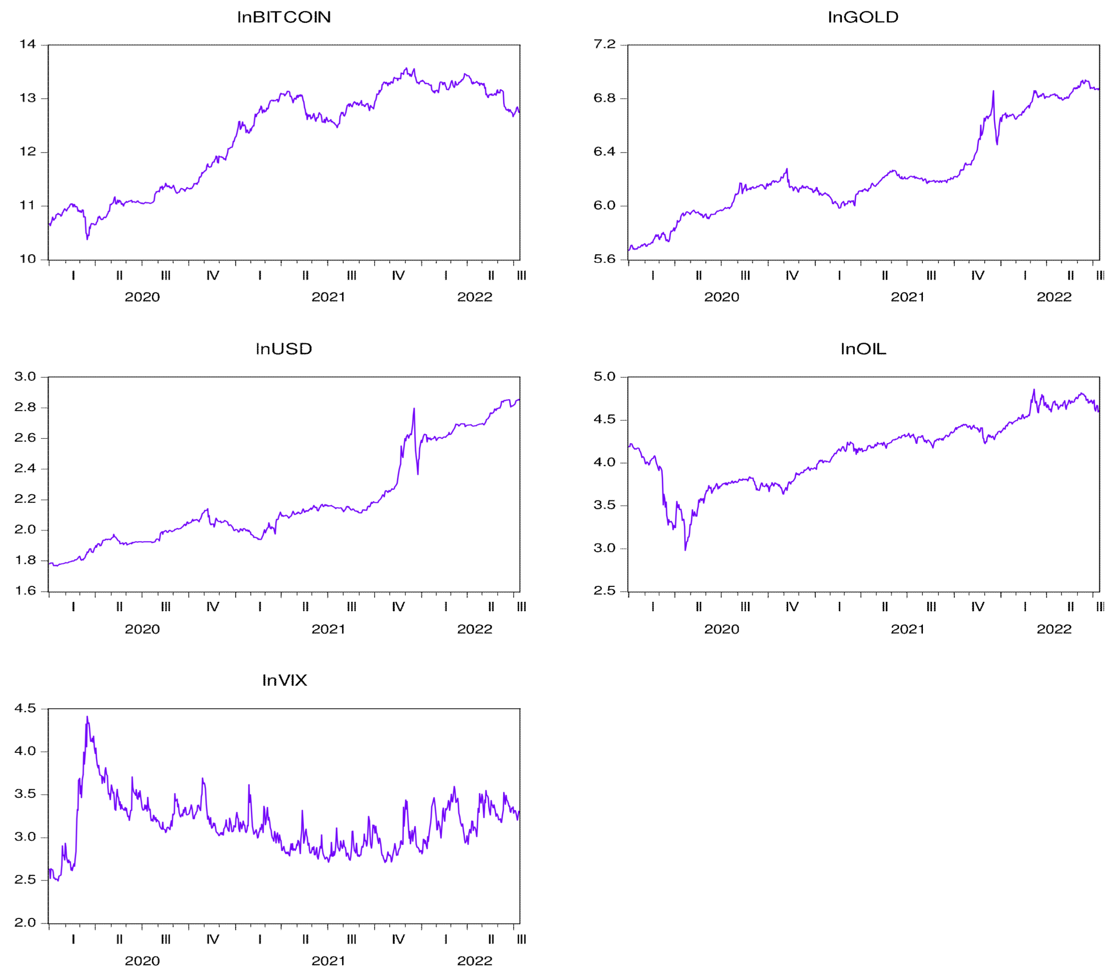
Source: Eviews 10 output.

Figure 1. Time series of logarithmic values of BTC, Gold, and USD Prices in terms of Turkish Lira and the values of Oil Barrel Prices in terms of USD and VIX after December 2019

of financial indicators and instruments within the analysis period. Since the values express logarithmic values, the fluctuations cannot be clearly understood when the changes in the variables over time are given with a single graphic. For this reason, presenting them in separate graphs will provide a clearer understanding of the changes in the values of the variables.

The graphs in Figure 2 were also created in the study. In Figure 2, BTC, GOLD, OIL, and USD prices show a severe upward trend with the pandemic. On the other hand, the VIX index showed a sudden rise at the beginning of the pandemic but then entered a downward trend. Although BTC prices exhibit similar movements with other variables in the chart, it is seen that the movements differ in some periods.

In Figure 3 below, are time series in which



Note: Day 100 corresponds to 18.05.2020, 200 to 5.10.2020, 300 to 22.02.2021, 400 to 12.07.2021, 500 to 29.11.2021 and 600 to 18.04.2022.
Source: Eviews 10 output.

Figure 2. Time Series of Variables

date information about the variables is given and raw values are used. In the charts, the vertical axis represents the values in the Turkish Lira. For example, the BTC increased to approx—800 thousand Turkish Liras in 2021.

In the following study stage, the unit root was carried out, which sometimes caused erroneous evaluations and results in a time series analysis search. We check the integration order of the time series variables to determine the stationary properties of the series. Traditional Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests were applied. The most widely used of these tests is the unit root test performed by Dickey-Fuller. The Dickey-Fuller test (1979) shows whether the autoregressive process (AR) can form time series variables. Dickey-Fuller also developed a test called Augmented Dickey-Fuller (ADF) (1981) by including the lagged values of the dependent variable in the model in case of correlation between margins of error. The models

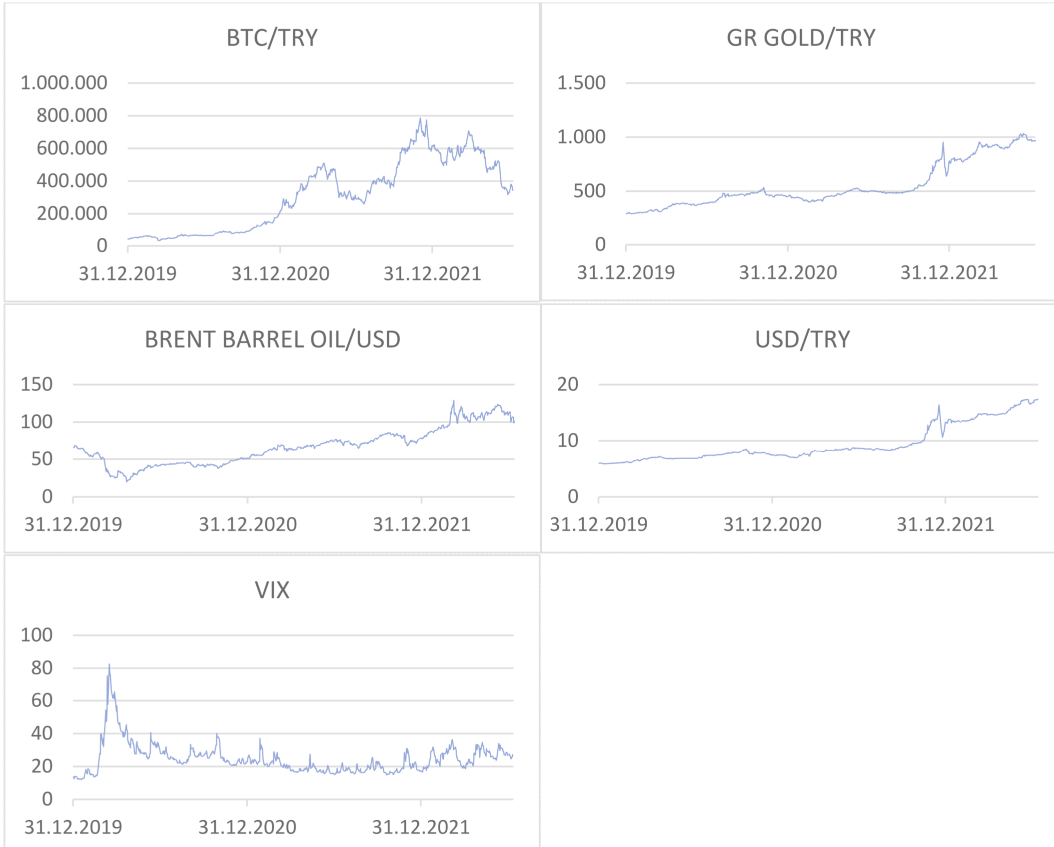


Figure 3. Time series of variables by day

suggested for this test are shown in the following equations:

$$\Delta \mathrm{Y_t} = \gamma \mathrm{Y_{t-1}} + \sum_{\mathrm{i}=2}^{\mathrm{m}} \beta_{\mathrm{i}} \Delta \mathrm{Y_{t-i+1}} + \varepsilon_{\mathrm{t}} \qquad (1)$$

$$\Delta \mathrm{Y_t} = \alpha_0 + \gamma \mathrm{Y_{t-1}} + \sum_{\mathrm{i}=2}^{\mathrm{m}} \beta_{\mathrm{i}} \Delta \mathrm{Y_{t-i+1}} + \varepsilon_{\mathrm{t}} \qquad (2)$$

$$\Delta \mathrm{Y_t} = \alpha_0 + \gamma \mathrm{Y_{t-1}} + \beta_{\mathrm{t}} \sum_{\mathrm{i}=2}^{\mathrm{m}} \beta_{\mathrm{i}} \Delta \mathrm{Y_{t-i+1}} + \varepsilon_{\mathrm{t}} \qquad (3)$$

The first equation shows the structure without coefficient and trend effect (1), the second equation shows the system with only a constant coefficient (2), and the third equation shows the structure where both constant and trend effects are observed (3). The Dickey-Fuller test is based on estimating these equations using the least squares method and finding the estimation value and standard error of γ. The t value obtained from the test is compared with the values in the Dickey-Fuller table and the γ=0 hypothesis is tested (Enders, 1995).

Phillips and Perron (1988) developed unit root tests, which are most popular in financial time series, in their article. This test differs from ADF in dealing with the problem of serial correlation and varying variance occurring in errors. The authors also rearranged the t statistics by estimating the DF equation instead of adding lagged values to avoid autocorrelation in the ADF equation. With the Dickey-Fuller approach, dividing a broken series into periods before and after the break is necessary. However, if these sub-periods do not contain enough observations, it will cause deviation due to the loss of degrees of freedom. In such cases, the loss of degrees of freedom is prevented by the PP test. This test is more potent in rejecting the H_0 hypothesis. Equations (4) and (5) show this test's hypothesis tests and statistics.

$$\Delta \mathrm{Y_t} = \beta' \mathrm{D_t} + \pi \mathrm{Y_{t-1}} + \mathrm{u_t}, \mathrm{u_t} \sim \mathrm{I}(0) \tag{4}$$

$$\mathrm{t}_\alpha = \mathrm{t}_\alpha \left(\frac{\gamma_0}{\mathrm{f_0}}\right)^{\frac{1}{2}} - \frac{\mathrm{T}(\mathrm{f_0} - \gamma_0)(\mathrm{se}(\hat{\alpha}))}{2\mathrm{f}_0^{\frac{1}{2}}\,\mathrm{s}} \tag{5}$$

α is the estimated coefficient used in the formula; s is the standard error of the equation; γ_0 is the error variance and f_0 is the zero-frequency residual spectrum estimator. In this test, the test was applied for models with constant and both constant and trend. The hypotheses and decision criteria are the same as for the DF test.

The results are seen in Table 2. In general, it is noteworthy that all series contain unit roots in their level values and become stationary in their first differences.

2.1. Wavelet coherence analysis

Wavelet coherence analysis was first used to investigate the time-frequency dependence between BTC prices and their determinants during the pandemic. Goupillaud et al. (1984) first used the wavelet method in the literature. The wavelet coherence approach is considered a suitable approach in the literature, especially since it allows the analysis of the range and correlation of the behavior of economic and financial time series (Zhang et al., 2021). Another advantage of wavelet coherence is that it considers the effect of structural reaction(s) (Adebayo, 2021). In this study, which considers time and frequency-based causality (Liu, 1994), the wavelet coherence

Table 2. ADF and PP Unit Root Test Results

	PP									
	Level					**First Differences**				
	BTC	**GOLD**	**OIL**	**USD**	**VIX**	**d(BTC)**	**d(GOLD)**	**d(OIL)**	**d(USD)**	**d(VIX)**
Constant	-1.743	-0.452	-0.842	0.517	-3.496**	-25.04***	-24.020***	-25.36***	-22.16***	-28.83***
Constant & Trend	-0.256	-1.718	-3.627**	-1.468	-3.616	-25.20***	-24.002***	-25.38***	-22.19***	-28.82***
None Constant & Trend	1.812	2.699	0.389	2.784	0.024	-24.89***	-23.815***	-25.37***	-22.01***	-28.85***
	ADF									
	Level					**First Differences**				
	BTC	**GOLD**	**OIL**	**USD**	**VIX**	**d(BTC)**	**d(GOLD)**	**d(OIL)**	**d(USD)**	**d(VIX)**
Constant	-1.768	-0.461	-0.765	0.268	-3.36**	-25.01***	-24.07***	-25.34***	-22.38***	-28.729***
Constant & Trend	-0.102	-1.684	-3.575**	-1.693	-3.79**	-25.12***	-24.05***	-25.36***	-22.40***	-28.712***
None Constant & Trend	1.812	2.655	0.415	2.385	0.009	-24.89***	-23.84***	-25.35***	-22.17***	-28.746***

Notes: (*)' Significant at 10%; (**)Significant at 5%; (***) Significant at 1%. And (no) Not Significant
Source: MacKinnon (1996) one-sided p-values

approach is the primary method to examine the causality and correlation between dependent and independent variables.

We employed wavelet analysis, whose methodology was presented in detail by Torrence & Compo (1998) and Torrence & Webster (1999), was used to detect the co-movement between BTC prices and other financial indicators. Gençay et al. (2001a, 2001b), Percival and Walden (2000), In and Kim (2013), and Yang et al. (2016) provide examples of the use of wavelet analysis in the fields of economics and finance.

Wavelet transform offers localized frequency decomposition, providing information about frequency components (Vacha & Barunik, 2012). As a result, wavelets have significant advantages over fundamental Fourier analysis when the object under investigation is not locally stationary and homogeneous (Percival and Walden, 2000; Ramsay, 2002).

Wavelet analyses offer the advantage of decomposing a time series into more basic functions containing information about a series. In the literature on the use and derivation of wavelets, it is seen that two types of wavelets are mostly mentioned, which vary according to the normalization methods. These are father ϕ and mother wavelets ψ (Aballe et al., 1999; Yousefi et al., 2005; Yang et al., 2016). $1(\int\phi(t)dt=1)$ represents the integration of the father wavelet and $0(\int\psi(t)dt=0)$ represents the integration of the mother wavelet. The detail and high-frequency components are the mother wavelet, and the flat and low-frequency parts of the signal (raw data) are the father wavelet.

By transforming any $y(t)$ function in L^2 ($\mathbb{R}$) (area for square summable functions) into different frequency components with a resolution appropriate to its scale, the wavelet function can be constructed as a series of projections on the mother and father wavelets generated from ϕ and ψ scaling and translation are as follows (Lee, 2004):

$$\phi_{j,k}(t) = 2^{-j/2}\phi\left(2^{-j}t - k\right), \qquad 6$$

$$\psi_{j,k}(t) = 2^{-j/2}\psi\left(2^{-j}t - k\right), \qquad 7$$

$j=1,2,\cdots,j$: scaling parameter in a J-level decomposition and k: translation parameter. We can express the wavelet representation of the signal $y(t)$ in L^2 ($\mathbb{R}$) as:

$$y(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \qquad 8$$

in equation 8 $s_{j,k}=\int y(t)\phi_{j,k}(t)dt$ and $d_{j,k}=\int y(t)\psi_{j,k}(t)dt$, J: the number of multi-resolution components, $s_{J,k}$: smooth coefficients, and $d_{j,k}$ illustrates the detailed coefficients. The value of coefficients $(s_{j,k}, d_{j,k})$ measures the contribution of the corresponding wavelet function relative to the total signal.

The scale factor 2^j in Eqs. (6) and (7) denote the dilation factor during the translation parameter 2^j k refers to the location parameter. The larger the index j, the larger the value of the scale factor 2^j. Thus, the function becomes more expansive and more spread out. As the functions $\phi_{J,k}(t)$ and $\psi_{J,k}(t)$ become wider, their translation parameters 2^jk also rise correspondingly.

The decomposed signals for a multi-resolution decomposition are represented as follows:

$$S_j(t) = \sum_k^5 j_{j,k}\phi_{jk}(t), \qquad 9$$

$$D_j(t) = \sum_k d_{jk}\psi_{jk}(t). \qquad 10$$

The functions $S/(t)$ and $D_j(t)$ in Eqs. (9)

and (10) are smooth and detailed signals. They constitute a decomposition of a signal into orthogonal components at different scales. Thus, a signal *y(t)* can be rewritten as:

$$y(t) = S_j(t) + D_j(t) + D_{j-1}(t) + \cdots + D_1(t) \quad 11$$

The highest-level approximation $S_J(t)$ is the smooth signal and the detail signals $D_J(t)$, $D_2(t)$, $\cdots$, $D_1(t)$ are associated with oscillations of lengths 2-4, 4-8, …, 2^J-2^{J+1}, respectively. A real-valued function *y(t)* for the discrete wavelet transform (DWT) is defined as follows:

$$\omega = Wy, \quad 12$$

Where the coefficients are ordered from coarse scales to fine scales in the vector $\propto$.W is introduced as a set of low-pass a filter and y is called by the band-pass filter. W and y are orthogonal vectors with $N\times 1$ elements. The type of the mother wavelet determines the coefficients in the filter. As n is divisible by 2^J, ω can be specified as:

$$\omega = \begin{pmatrix} s_j \\ d_j \\ d_{j-1} \\ \vdots \\ d_1 \end{pmatrix} \quad 13$$

where,

$$s_j = \left(s_{j,1}, s_{j,2}, \cdots, s_{j,2,2}\right)', \quad 14$$

$$d_j = \left(d_{l,1}, d_{j,2}, \cdots, d_{j,4/22'}\right)', \quad 15$$

$$d_{J-1} = \left(d_{j-1,1}, d_{j-1,2}, \cdots, d_{J-1,8/2}\right)', \quad 16$$

$$d_1 = \left(d_{1,1}, d_{1,2}, \cdots, d_{1,1/2i}\right)'. \quad 17$$

Each set of coefficients s_J, d_J, d_j -1, w_J, ', d_J is called a crystal in which the wavelet coefficients correspond to a set of translated wavelet functions arranged on a regular lattice.

Definition of the cross wavelet power of two-time series *x(t)* and *y(t)* is as follows (Ercan & Karahanoğlu, 2019):

$$Wxy(u,j) = Wx(u,j) \cdot Wy*(u,j). \quad 18$$

Wx(u,j) and *Wy(u,j)* represent continuous wavelet transforms of time series *x(t)* and *y(t)*. The star (*) signifies a complex conjugate, parameter u allocates a time position, and parameter j symbolizes the scale parameter. A low wavelet scale denotes the high-frequency part of the time series-a short investment horizon (Torrence & Webster, 1999).

Whenever the time series exhibit a typical high power, the cross-wavelet power reveals areas in the time-frequency space. In the co-movement analysis, we search for places where the two-time series in the time-frequency space co-movement do not necessarily have high power. A proper wavelet technique for finding these co-movements is wavelet coherence.

Torrence and Webster (1999) define the squared wavelet coherence coefficient as follows:

$$R^2(u,j) = \frac{\left|S\left[j^{-1}Wxy(u,j)\right)\right|^2}{S\left[\left[j^{-1}(Wx(u,j))^2\right]\right]S\left[j^{-1}|Wy(u,j)|^2\right]}. \quad 19$$

S represents a smoothing operator. The coefficient $R^2(u,j)$ lies in the interval [0,1]. When there is a low correlation the R^2 becomes closer to zero, whereas a stronger correlation is shown with the values more relative to one. Therefore, R^2 explains the local linear correlation between two stationary time series at each scale and is analogous to the squared correlation coefficient in linear regression. The following formula shows the phase differences according to Torrence and Webster's (1999) definition:

$$\theta_{xy}(u,j) = \tan^{-1}\left(\frac{\mathcal{F}\left\{S\left(j^{-1}W_{xy}(u,j)\right)\right\}}{\Re\left\{S\left(j^{-1}W_{xy}(u,j)\right)\right\}}\right). \quad 20$$

$\mathcal{F}$ is imaginary, and $\Re$ is a fundamental part operator in this formulation—black arrows in the wavelet coherence figures with significant coherence display the Phase differences. Once the two analyzed time series move together on a particular scale, the arrows direct to the right showing the positive correlation. On the other hand, if the correlation is negative between time series, then the arrows lead to the left. Then the arrows point to the left (Yang et al., 2016)

The result of wavelet coherence analysis is usually a shape with five main parts: eight-sided black arrows (←, →, ↑, ↓, ↘, ↗, ↙, ↖), warm and cool colors, black contours, two axes, and a cone. → (←) black arrows indicate an in-phase (out-of-phase) relationship or positive (negative) correlation, while arrows ↗ (↙) indicate the maximum effect of the first (second) series. For example, black arrows with the '↘' direction in wavelet coherence graphs show an in-phase relationship or positive co-movement between the two time series with the maximum effect of the second time series. Black arrows with the '↖' direction in wavelet coherence plots indicate an out-of-phase relationship or negative co-movement between two time series with the maximum effect of the first time series. A phase difference of zero means that both time series move together. The black curves in the graphs show regions with coherence significance at the 5% level, and the solid white bell-shaped line in the wavelet coherence graphs is the cone of influence (Rubbaniy et al., 2021).

2.2. DCC-GARCH estimations

In the second stage of the study, dynamic conditional correlation (DCC)-generalized autoregressive conditional heteroscedasticity (GARCH) was applied to estimate the level of co-movements of the variables and to reveal the dynamic correlation. The DCC-GARCH technique (Engle and Sheppard 2001; Engle 2002) helps to evaluate the traditional conditional correlation between financial time series by estimating historical correlations and conditional volatility. The time series's dynamic conditional correlation (DCC) analysis has emerged as an attractive method to reach the purpose. It decomposes the conditional covariance into two active components, a conditional standard deviation matrix and a standard deviation, as shown below (Ghosh et al., 2021; Matar et al., 2021):

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{h_{nt}} \end{bmatrix} \quad 21$$

R_t describes the time-varying conditional correlation of standardized innovations (ε_t);

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{1n,t} \\ \rho_{12,t} & 1 & \vdots \\ \vdots & \vdots & \\ \rho_{1n,t} & \cdots & 1 \end{bmatrix} \quad 22$$

DCC-GARCH model, H_t must be a positive definite matrix. Since D_t follows the structure of a positive definite matrix at its positive diagonal entries, R_t must adhere to the typical properties of a positive definite matrix with elements less than or equal to one. R_t can be parsed as follows:

$$R_t = V_t^{*-1} V_t V_t^{*-1} \quad 23$$

$$V_t = (1-\alpha-\beta)\bar{V} + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^T + \beta V_{t-1}$$

V_t^* shown below and is a diagonal matrix;

$$V_t^* = \begin{bmatrix} \sqrt{q_{11,t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{q_{nn,t}} \end{bmatrix} \quad 24$$

V_t^* transforms the elements of V_t so that the following equation holds:

$$\bar{V} = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_t\varepsilon_t^T. \quad 25$$

In the last section $\bar{V} = \mathrm{Cov}[\varepsilon_t\varepsilon_t^T] = E[\varepsilon_t\varepsilon_t^T]$ and estimates as follows;

$$|\rho_{ij}| = \left|\frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{ij,t}}}\right| \leq 1 \quad 26$$

Parameters *(α,β)* are not negative and are predicted to represent DCC. The model exhibits return to mean behavior if *α+β<1*; where α and β represent short-term and long-term persistence, respectively.

3. RESULTS

The analysis aimed to determine cryptocurrency and other financial indicators' co-movements and volatility spread to each other during the pandemic. We used daily data from December 31, 2019, to July 13, 2022.

3.1. Wavelet Coherence Results

The findings obtained from the analysis are seen in Figure 4. Figure 4 displays the analysis period on the horizontal axis daily. The vertical axis shows the frequency (the lower the frequency, the larger the scale)—regions in the time-frequency space where the two-time series change are located by wavelet coherence. Warmer colors (red) represent regions with significant correlation, while more excellent colors (blue) represent lower levels of dependency between series. The cold (blue) regions outside the areas expressing meaningful relationships represent time and frequencies that are not dependent on the series. An arrow in wavelet coherence plots represents the forward/lag phase relationships between the series under consideration. Zero phase difference means the two-time series move together on a specific scale. Arrows point right (left) when the time series is in phase (anti-phase). If the two series are in phase, they move in the same direction, while anti-phase means moving in the opposite direction. Arrows pointing right-down or left-up indicate that the first variable is leading, and arrows pointing right-up or left-down indicate that the second variable is ahead.

Figure 4 shows the Wavelet Consistency heatmaps that reflect the most important of the typical movements of BTC, the leading cryptocurrency regarding trading volume, market capitalization, and other financial indicators. Since the analysis period (two years seven months) is relatively short, the short term is defined as fluctuations in the 0–16-day frequency bands, while the long term ranges between 64–128 and > 128-day frequency bands. The wavelet coherence heatmaps in Figure 3 show that during the pandemic, especially in the long band gaps (>128-day scale), the GOLD-crypto co-movements are significant and anti-phase (reverse motion). During this period, gold prices also follow BTC prices. On the 32-64-day scale (the pandemic started to spread, and the first case was seen in Türkiye on March 11, 2020), it is seen that gold prices generally follow BTC prices, and the series are positively correlated (→↗↘). However, it is noteworthy that in band gaps of 32 days or less, BTC prices follow gold prices (↗). As seen in many countries' investors, this situation may indicate that gold lost its safe haven status in Türkiye during the pandemic period, which can be considered a current example of a crisis period at least. In short, it also gives an idea of whether each asset/commodity can be used to manage and protect the risk of the other asset/commodity due to the downside movement of the general market or sector. The obtained result also reveals the relationship between the bubbles in gold prices and the bubbles in the BTC market in the short term.

Oil prices and BTC co-movements show that BTC prices follow oil prices in 16-32 and 64-128-day band gaps at the beginning of the pandemic and there is a positive relationship between them. However, it is noteworthy that their relationship turned negative after about the 300th day and more intensely between the 350th and 550th days and on the 64-128-day scale.

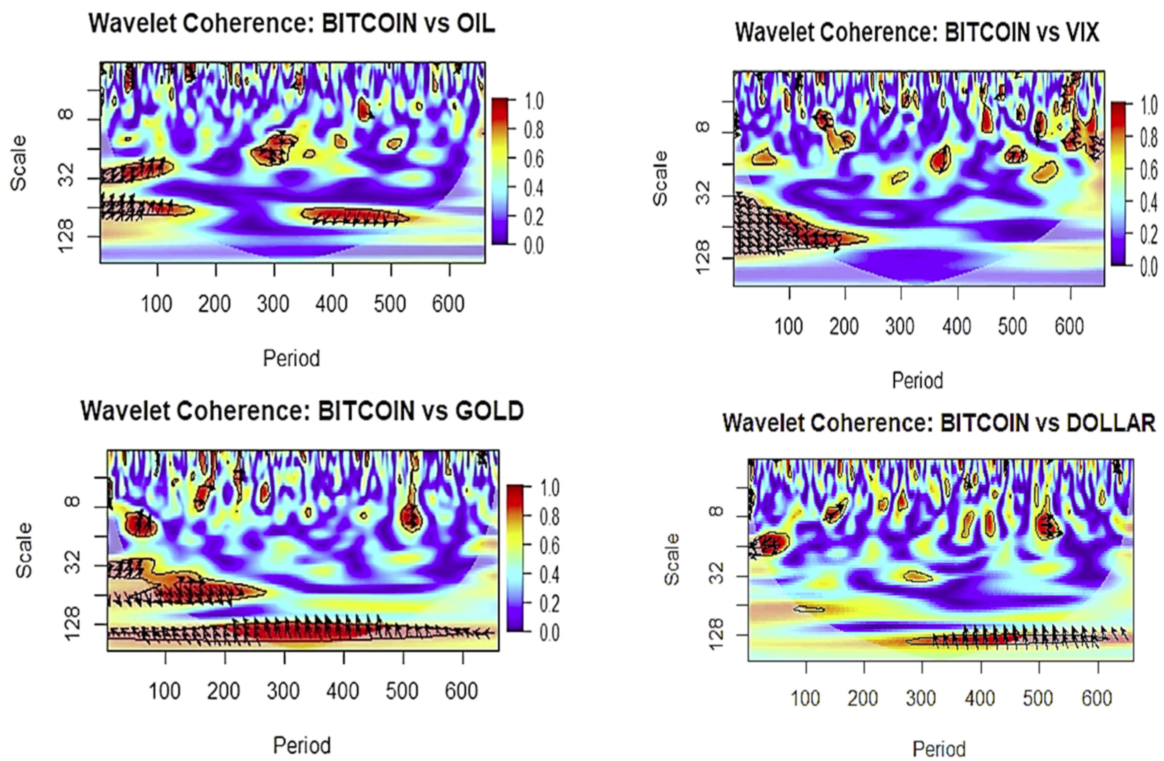
When BTC and USD movements are analyzed together, it is concluded that at the beginning of the pandemic (in the first 100-day period), BTC prices followed the USD price on a 16-32-day scale. However, the relationship between them is significant and negative. On a 128>-day scale, it is seen that the relationship is significant and negative (anti-phase) from the 300th day to the present and the USD price follows the BTC price. This may indicate that BTC was seen as a safe haven/hedging tool in Turkish markets in the Covid-19 pandemic and has begun to replace USD, previously preferred for hedging purposes. And also BTC and VIX joint movements were negative on the 32-128-day scale and at the beginning of the pandemic (200-day period), and VIX values followed BTC prices.

3.2. 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. 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 Θ_1 and Θ_2, 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 that change over the COVID-19 pandemic.

Based on these parameters, it is possible



Source: R Output
Note: Period means days

Figure 4. Wavelet Coherence Analysis

to build a model for BTC and Gold series as referred to below:

$$Q_{i,j,t} = \omega_{i,j} + 0.045212\varepsilon_{i,t-1}\varepsilon_{j,t-1} + 0.932843Q_{i,j,t-1}, \quad 27$$

The symbol Θ_1, 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 that change over the *COVID-19* period.

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

$$Q_{i,j,t} = \omega_{i,j} - 0.014650\varepsilon_{i,t-1}\varepsilon_{j,t-1} \quad 28$$

The symbols Θ_1 and Θ_2, 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 that change over *COVID-19* time.

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

$$Q_{i,j,t} = \omega_{i,j} + 0.124915\varepsilon_{i,t-1}\varepsilon_{j,t-1} + 0.683981Q_{i,j,t-1}, \quad 29$$

The symbol Θ_2 which explains the dynamic correlation relationship between BTC and VIX in Table 6, is statistically significant at the 5% significance level, respectively. Therefore, a positive and robust

Table 3. BTC and GOLD DCC GARCH Dynamic Correlations

	Coefficient	Std. Error	z-Statistic	Prob.
Θ_1	0.045212	0.015426	2.930908	0.003380
Θ_2	0.932843	0.024963	37.36861	0.0000
	t-Distribution (Degree of Freedom)			
v	4.315128	0.330931	13.03938	0.000000
Log-likelihood	3.279443	Schwarz criterion		-13.04418
Avg. log-likelihood	-13.07844	Hannan-Quinn criteria.		-13.03439
Akaike info criterion	-13.06073			

* Stability condition: theta(1) + theta(2) < 1 is met.

Table 4. BTC and OIL DCC GARCH Dynamic Correlations

	Coefficient	Std. Error	z-Statistic	Prob.
Θ_1	-0.014650	0.007886	-1.857782	0.063200
Θ_2	0.386593	0.880788	0.438918	0.6607
	t-Distribution (Degree of Freedom)			
v	4.122509	0.292315	14.10295	0.000000
Log-likelihood	2.930274	Schwarz criterion		-11.64751
Avg. log-likelihood	-11.68176	Hannan-Quinn criteria.		-11.66634
Akaike info criterion	-11.69269			

* Stability condition: theta(1) + theta(2) < 1 is met.

Table 5. BTC and USD DCC-GARCH Dynamic Correlations

	Coefficient	Std. Error	z-Statistic	Prob.
Θ_1	0.124915	0.073874	1.690912	0.090854
Θ_2	0.683981	0.212479	3.219045	0.0013
	t-Distribution (Degree of Freedom)			
v	3.310168	0.155514	21.28529	0.000000
Log-likelihood	3.469103	Schwarz criterion		-13.80282
Avg. log-likelihood	-13.83708	Hannan-Quinn criteria.		-13.81988
Akaike info criterion	-13.84622			

* Stability condition: theta(1) + theta(2) < 1 is met.

Table 6. BTC and VIX DCC GARCH Dynamic Correlations

	Coefficient	Std. Error	z-Statistic	Prob.
Θ_1	0.025036	0.017087	1.465207	0.142864
Θ_2	0.962202	0.030771	31.26969	0.0000
	t-Distribution (Degree of Freedom)			
v	4.057865	0.277297	14.63363	0.000000
Log-likelihood	2.371670	Schwarz criterion		-9.413091
Avg. log-likelihood	-9.447345	Hannan-Quinn criteria.		-9.420546
Akaike info criterion	-9.446895			

* Stability condition: theta(1) + theta(2) < 1 is met.

relationship exists between prices that change over COVID-19 time.

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

$$Q_{i,j,t} = \omega_{i,j} + 0.962202Q_{i,j,t-1}, \quad 30$$

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. In this period, the price of BTC decreased from 54.950 TRY to 32.157 TRY, and the oil price dropped from 52,63 USD to 29,62. In particular, the date of March 11 is essential because the first case was declared in Türkiye and was announced as a pandemic by the World Health Organization. This period can be evaluated as an oil price shock on the aggregate demand side.

On the Turkish Lira-denominated BTC-USD side, a significant negative correlation occurred with the detection of the first case of the Turkish leg of the pandemic, which coincided with the 52nd day of the analysis period, and a positive correlation occurred again within 10 days.

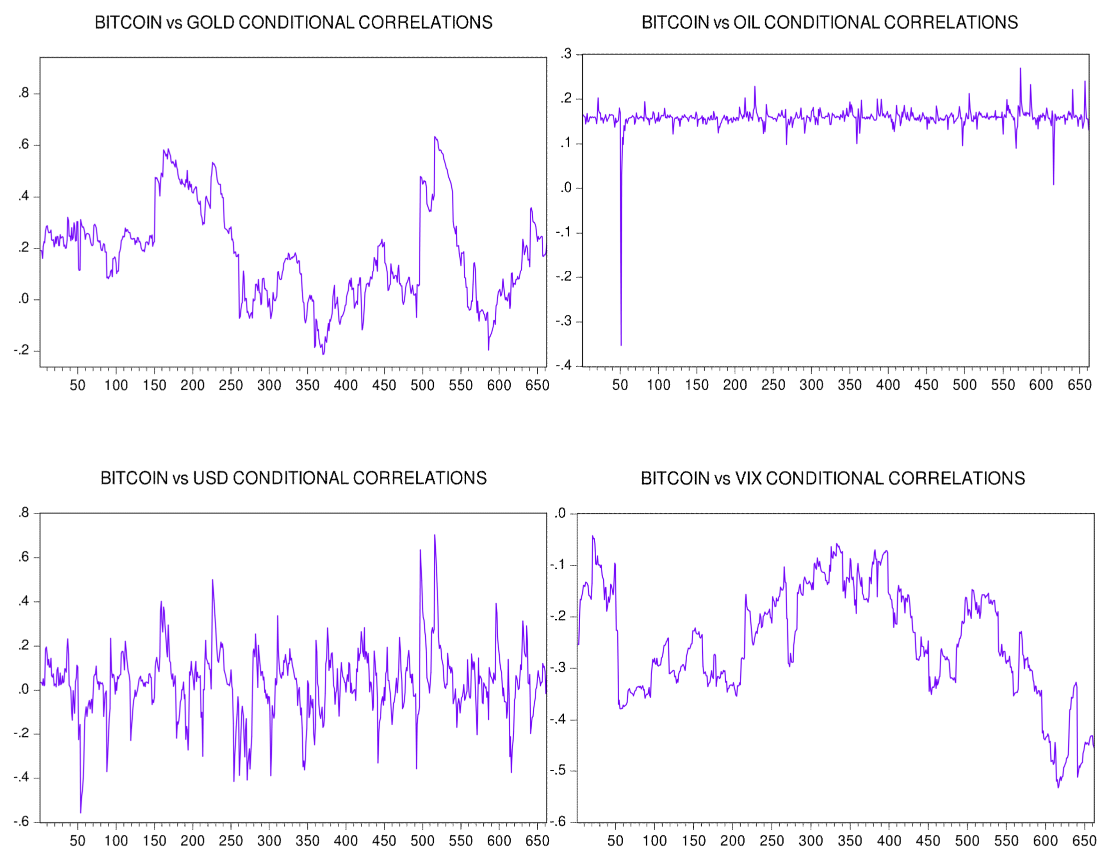


Figure 5. Dynamic Conditional Correlations

4. DISCUSSION AND CONCLUSION

The COVID-19 pandemic has not only been limited to deaths, infections, and psychological harm but also has had a significant economic impact. Due to the epidemic, which quickly became a pandemic, an atmosphere of panic has emerged worldwide. It has become a global threat with the destruction it has caused to economies. The COVID-19 pandemic has significantly affected and changed investor decisions, preferences, behaviors, and the entire financial sector, including banking, insurance, and stock markets. As a result, the share of cryptocurrencies in investor preferences has increased considerably. Cryptocurrencies have gained more attention in this process and their relationship with various financial and economic indicators has been examined more closely.

There is already a broad body of literature on the impact of the Covid-19 pandemic on economies and financial markets. The loss of confidence in the conventional financial system and its components due to the panic caused by the pandemic has motivated research for the last few years to reveal BTC's hedging, diversification and safe-haven qualities and its relationship with other commodities and financial assets.

The importance of cryptocurrencies is increasing in terms of the number of transactions that concern international markets due to their ease of use and digital support. This study analyzed the relationship between BTC prices, USD, gold prices, oil prices and stock market volatility index (VIX) costs by Wavelet Coherence and DCC-GARCH methods for 12/31/2019-13/07/2022. It has been tried to determine the standard action points to which BTC, USD, Gold, crude oil, and VIX fear index markets can relate.

The heat maps formed due to the wavelet coherence analysis performed in the study show that gold and BTC act together in the long run (>128-day scale) during the Pandemic period, and the relationship between them is negative. In addition, the fact that gold prices follow BTC prices shows that BTC is used more for hedging purposes. Because when BTC prices rise in the long term during the pandemic period, gold prices decrease. This result is consistent with the study by Pal and Mitra (2019). Long et al. (2021) and Wen et al. (2022) contradict the studies' results. This may be because this study was carried out in Türkiye. As emphasized in the previous parts of the study, Turkish investors turned to BTC and similar cryptocurrencies rather than gold, especially during the pandemic. On the other hand, in shorter-term intervals such as 32-64 days, gold prices generally follow BTC prices and the series are positively correlated. However, it is noteworthy that BTC prices follow gold prices in band gaps of 32 days and below. These results indicate that BTC and gold are not seen as alternatives to each other in shorter maturities and that they are traded for speculative purposes. When the results of the BTC-Gold wavelet coherence analysis are evaluated in general, it shows that during the pandemic, BTC gained safe haven status against TRY in Türkiye. The obtained result also reveals the relationship between the bubbles in gold prices and the bubbles in the BTC market in the short term. Although there was a reflexive orientation to gold and USD, which functioned as a traditional safe haven in Türkiye at the beginning of the Covid-19 pandemic, this situation changed quickly. BTC became more prominent later in the pandemic. BTC's rapid recovery has been an indicator of the resilience of the cryptocurrency market. According to the results obtained from most studies examining the pre-pandemic period, gold belongs to the function of being a safe haven in terms of financial markets in Türkiye. The findings obtained in this study show that there is a positive and effective relationship between gold prices and BTC. BTC, which has increased significantly during the Covid-19 pandemic, has also been a reliable investment port like gold. This is a result in line with the current international literature. In addition, the direct proportionality of the VIX index and the BTC price supports this situation.

On the other hand, crude oil has a dominant place in the global energy market (Zhang & Ji, 2019). According to the risk premium channel (Bruno & Shin, 2015), a shock in crude oil prices can significantly affect investors' willingness to take BTC risk (Li et al., 2022). Therefore, understanding how the oil and BTC markets interact extensively interests policymakers and investors. Li et al. (2022) confirmed the existence of the oil-BTC relationship. In this study, oil prices and BTC joint movements show that BTC prices follow oil prices in 16-32 and 64-128-day bands at the beginning of the pandemic and there is a positive relationship between them. However, it is noteworthy that the relationship between them turns negative after approximately 300 days and is more intense between the 350th and 550th days and on the 64–128-day scale. On the other hand, Selmi et al. (2018) claim that BTC plays a diversified role in hedging from oil price changes and is seen as a private safe haven. It is consistent with the findings of our study.

Foreign exchange is one of the traditional investment instruments in Türkiye. It also competes with gold as a hedging instrument in TRY. When BTC and USD movements are examined together, it is concluded that at the beginning of the pandemic (in the first 100-day period), BTC prices followed the USD price on a 16-32-day scale. However, the relationship between them is significant and negative. On a 128>-day scale, the relationship appears substantial and negative (anti-phase) from Day 300 to the present. However, the USD price follows the BTC price. This may indicate that BTC is a safe-haven/hedging tool in Turkish markets and has begun to replace USD, which was previously preferred for these purposes.

BTC and VIX joint movements were negative in the 32-128-day band and at the beginning of the pandemic (200-day period), and VIX values followed BTC prices. When these results are evaluated in general, it can be said that the VIX index determines its direction according to the movements of BTC. Investors' fears and expectations about BTC are effective in the movements of the VIX index. At the same time, the increase in the value of BTC in the periods when the expectations for the market and the economy, in general, are negative (VIX low) indicates that it exhibits a safe-haven feature.

As a result of wavelet coherence analysis, co-movements and significant relations between Bitcoin and gold, USD, oil and VIX were determined. 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 (European Central Bank, 2012). The results indicate short-term co-movements of BTC and Gold, oil, USD and VIX index 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 typical action patterns in long-term BTC investments (>128 days) reveal encouraging results. BTC-other variables consistency heatmaps show that the heat sometimes turns blue or dark blue. This situation indicates that there can be no continuous joint action during the pandemic. The results show that BTC is seen as a safe haven during the pandemic, especially for investors holding cryptocurrency for a longer investment horizon. The findings of this study, in which the movements of cryptocurrencies with commodities and financial indicators were analyzed in the example of BTC during the pandemic, reveal that BTC is an essential element and indicator of the financial markets and economy in Türkiye and will act together with and affect financial and economic indicators.

Over the longer investment horizon, the joint movements of BTC, Gold and the USD better explain why the currency is considered one of the traditional safe-haven assets. The findings also support previous studies showing that an asset's safe-haven properties are time- and market-dependent (Ji et al., 2020; Conlon et al., 2020). During the pandemic, causality between cryptocurrency and financial indicators has been identified. Accordingly, crypto money markets are in a leading position excluding oil prices. This finding supports assumptions that investors flock to crypto markets to protect their investments during the pandemic.

According to DCC-GARCH results, the dynamic correlation relationship between BTC and GOLD, OIL, USD and VIX is statistically significant. During the COVID-19 pandemic, there is a positive and strong relationship between BTC and GOLD prices, a negative and weak relationship between BTC and OIL, a positive and strong relationship between BTC and USD a positive and strong relationship between BTC and VIX. The results indicate that the conditional variance of BTC is positively correlated with the conditional variance of GOLD, USD and VIX. The overall results show that the conditional variance of BTC prices is statistically significant compared to the conditional variances of gold, USD and oil prices and the value of the VIX index. This suggests that the BTC currency can be used to hedge and diversify portfolio investment strategy.

The findings of our study also support current studies in the literature. During the pandemic, BTC in the national currency was seen as a hedging tool in Türkiye and had a position between Gold and the USD. For this reason, BTC's role should be taken seriously in Türkiye, and the part of BTC should be taken into account when determining future monetary policies and financial stability targets. In addition, the findings obtained in this study provide valuable and relevant information to assist investors in their asset allocation processes and decisions in Türkiye and environments with high uncertainty. Our results are critical to portfolio and risk managers and effective policy measures. First, investors and portfolio managers should know that the relationship between crude oil and BTC returns will likely strengthen when markets face extreme shocks. This means that any shock to the crude oil and BTC markets should not be considered the best option when choosing a well-diversified portfolio in pursuit of risk minimization.

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 (Li et al., 2022). 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. These results also show whether each asset/commodity can be used to manage and hedge the risk of the other asset/commodity due to the downward movement of the general market or sector.

It would also be helpful to consider recent developments regarding the banking sector crisis and cryptocurrency exchange crashes in the United States in future studies. Once this is done, deciding whether BTC is a reliable option will be easier, enabling them to understand the issue better and make practical policy implications for investors and policymakers. Investors can gain new perspectives by using different cryptocurrencies or different country currencies. These research topics can be studied using other or new econometric methods. In the study, the relationship between BTC, USD, gold, oil prices and the VIX index was analyzed only on the Turkish economy, and it is thought that panel data analyses to be carried out on different countries or groups of countries will also make significant contributions to the literature.

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ЗАЈЕДНИЧКО КРЕТАЊЕ ЗЛАТА, АМЕРИЧКОГ ДОЛАРА, НАФТЕ, VIX ИНДЕКСА: ДОКАЗИ О ВЕЈВЛЕТ КОХЕРЕНЦИЈИ И “DCC-GARCH” У ПЕРИОДУ ПАНДЕМИЈЕ

Bilgehan Tekin, Fatma Temelli, Sadik A. Dirir

Извод

Ова студија испитује везе цена и флуктуација биткоина (BTC) са златом, америчким доларом, нафтом, VIX индексом, осигурањем и диверзификацијом у Турској. У ту сврху, у студији су коришћени вејвлет кохеренција и динамичке условне корелације (DCCs). Ово истраживање испитује да ли се обрасци понашања “мехура” у ценама BTC током пандемије COVID-19 могу користити у краткорочном периоду за заштиту од образаца понашања “мехура” на тржиштима која су предмет овог истраживања и обрнуто. Међутим, такође се истражује да ли се друга средства могу користити за управљање и осигурање негативних ризика BTC. Циљ је да се разуме како и на ком нивоу критични финансијски инструменти и индикатори утичу једни на друге у временима кризе и економске рецесије, као што је пандемија, и представити вредне резултате доносиоцима одлука. Узорак за ову студију укључује Турску за период између 31.12.2019. и 13.07.2022. Резултати вејвлет кохеренције и DCC-GARCH показују значајна позитивна и негативна повезана кретања цена BTC са златом, нафтом, ценама америчког долара и индексом страха VIX током пандемије.. Налазимо доказе о постојаној волатилности, узрочности и фазним разликама између БТЦ-а и других финансијских инструмената и индикатора.

Кључне речи: BTC, Злато, USD, Нафта, VIX, Вејвлет Кохеренција

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