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ANALYSIS OF BITCOIN VOLATILITY DURING THE COVID-19 PANDEMIC: AN EXAMINATION USING ARCH AND GARCH MODELS

Bitcoin Volatilitesinin COVID-19 Pandemisi Döneminde Analizi: ARCH ve GARCH Modelleriyle Bir İnceleme

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Keywords:
Bitcoin, Volatility, Covid-19, GARCH, ARCH.

JEL Codes:
G10, G15, C22.

Abstract

The COVID-19 pandemic has had a profound effect on the global economy and financial markets, including a significant impact on the cryptocurrency markets. This study analyzes the impact of the COVID-19 process on bitcoin price movements. The study examines the daily price data of bitcoin between 01/03/2020 and 01/04/2022 and uses ARCH and GARCH models to estimate volatility. The results show that there was a significant increase in bitcoin volatility during the initial period of the pandemic. This reflects a period when the pandemic increased uncertainty in financial markets and spurred investor interest in cryptocurrencies. While the ARCH model showed limited success in analyzing the short-term dynamics of volatility, the GARCH model captured the long-term trends in volatility more effectively. However, both models were insufficient to fully predict the sudden and extreme increases in volatility observed during crisis periods such as the pandemic. In addition to analyzing the impact of the pandemic on cryptocurrency markets, the study provides important implications for investor behavior and volatility management. In this context, it highlights the importance of developing risk management and regulatory frameworks in cryptocurrency markets.

Anahtar Kelimeler:
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Öz

COVID-19 pandemi süreci küresel ekonomi ve finansal piyasalar üzerinde derin etkiler bırakmış olup bu durum kripto para piyasalarını da önemli ölçüde etkilemiştir. Bu çalışmada COVID-19 sürecinin Bitcoin fiyat hareketleri üzerindeki etkileri analiz edilmiştir. Araştırmada, Bitcoin'in 01/03/2020- 01/04/2022 tarihleri arasındaki günlük fiyat verileri incelenmiş ve ARCH ve GARCH modelleri kullanılarak volatilite tahmini yapılmıştır. Bulgular pandeminin başlangıç döneminde Bitcoin'in volatilitesinde belirgin bir artış olduğunu göstermektedir. Pandemi dönemi finansal piyasalardaki belirsizlikleri artırmakla birlikte yatırımcıların kripto paraları ilgisinin de yükseldiği bir dönemi yansıtmaktadır. Çalışmada kullanılan ARCH modeli, volatilitenin kısa vadeli dinamiklerini analiz etmede sınırlı bir başarı gösterirken, GARCH modeli sonuçları volatilitenin uzun vadeli eğilimlerini daha etkili bir şekilde yakalamıştır. Bununla birlikte her iki model de pandemi gibi kriz dönemlerinde gözlemlenen ani ve ekstrem volatilite artışlarını tam anlamıyla öngörmekte yetersiz kalmıştır. Çalışma, yalnızca pandeminin kripto para piyasalarındaki etkilerini analiz etmekle kalmayıp, yatırımcı davranışları ve volatilite yönetimi konularında da önemli çıkarımlar sağlamaktadır. Aynı zamanda kripto para piyasalarında risk yönetimi ve düzenleyici çerçevelerin geliştirilmesinin önemine işaret etmektedir.

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1. Introduction

Cryptocurrencies are virtual currencies traded in technology-based financial systems. They are typically produced digitally by individuals or institutions rather than by countries. Cryptocurrencies are generally used in the market for investment purposes rather than commercial transactions. Bitcoin is considered the first digital currency. Although thousands of cryptocurrencies have been launched over time, bitcoin is still considered to have a high transaction volume. While the strengths of cryptocurrencies include ultra-secure encryption, the inability to make the desired redirects and the inability to change the amount, the difficulty of acceptance, lack of account security, inability to be taxed and money laundering risks are the weaknesses of the system (Çetinkaya, 2018: 20). In particular, hacking of digital wallets and exchanges can lead to users losing their assets. In addition, phishing attacks and malware also pose serious threats to cryptocurrency owners. The fact that governments around the world do not have a legal infrastructure for cryptocurrencies and that cryptocurrencies are not backed by a government guarantee exacerbates the problems associated with this issue. Having a decentralized payment system is an important advantage because there is no dependency problem on institutions and individuals.

The number and usage of traded crypto assets are increasing every day. Although Bitcoin was not very popular in its early years, its popularity increased with the rapid rise in its price in later years, and it is the cryptocurrency with the most transactions (Ngunyi, 2019: 591). Initially, it was only used for investment purposes, but over time it began to be used for commercial transactions, albeit to a lesser extent (Dilek, 2018: 16). Fluctuations in the price of bitcoin bring with them the risk of large gains and losses, so examining the volatility of bitcoin can provide important data for investors.

The COVID-19 pandemic has significantly affected the use and value of cryptocurrencies. As global economic uncertainties increased during the pandemic, many investors sought safe havens. For risk-averse investors, bitcoin and other cryptocurrencies have come to the forefront as alternative investment vehicles during this period. The increased demand for digital and contactless payment methods during the pandemic has increased the adoption rate of cryptocurrencies. However, the negative impact of COVID-19 on economies has increased the volatility of cryptocurrencies and caused speculative movements in the markets. The pandemic has revealed the potential of cryptocurrencies to be used not only for investment purposes but also for everyday financial transactions. This process has strengthened the position of Bitcoin and other cryptocurrencies in the financial system. At the same time, it has caused regulators and governments to reevaluate their attitudes toward these new financial instruments. In the post-pandemic period, discussions about the legal regulations and security protocols of cryptocurrencies are expected to intensify (Yermack, 2020).

With the COVID-19 pandemic affecting the entire world, there has been an increase in the number of deaths and cases. This situation has posed a major threat to economies and has caused economies and stock markets to react quickly to risk perceptions around the world. The uncertainty experienced has led to quite sharp declines in stock markets. The pandemic period, which has even affected the growth and development indices of countries, has caused quite high losses in value. It can be said that the most curious feature of cryptocurrencies, which can be bought and sold 24/7 without any trading day limit, is the price volatility (Guizani and Nafti, 2019; Saleh, 2019). The autoregressive conditional heteroskedasticity (ARCH) model is often used in these volatility calculations. Since financial time series generally do not show a normal distribution, ARCH models and their derivatives are commonly used to solve these problems (Kahraman et al., 2019).

With the development of the ARCH model, many generalized ARCH models have emerged. The most popular are the symmetric GARCH model and the non-symmetric EARCH, PARCH, and TGARCH models. These models allow more accurate estimation of volatility and risk in financial time series. This study aims to analyze the volatility dynamics of bitcoin prices during the COVID-19 pandemic. In this context, the effects of the pandemic on the price movements of bitcoin have been comprehensively examined using the ARCH and GARCH models. A fundamental framework for examining volatility dynamics, especially in financial data, is offered by the ARCH and GARCH models. This study aims to investigate general volatility dynamics and evaluate the effects of the COVID-19 pandemic, even though EGARCH and TGARCH models are known in the literature for their better performance in modeling asymmetric effects and more accurately capturing the impact of negative shocks (Ni et al., 2022; Marisetty, 2024). Since the study's main goal is to shed light on the broader market behavior during this extraordinary global event, ARCH and GARCH models were thought to be better suited for capturing the overall volatility patterns.

The originality of the study lies in the limited number of studies examining the effects of the pandemic on volatility and investor behavior in cryptocurrency markets. In addition, a detailed examination of Bitcoin's responses to positive and negative shocks provides important insights for understanding the dynamics of these new investment instruments in the financial system. In this respect, the present study aims to contribute to the literature by providing important insights from both an academic and an investor perspective.

2. The Impact of the COVID-19 Pandemic on Financial Markets

Stock markets reflect political, cultural, social, and economic developments in prices. Information appearing on the stock exchanges receives very fast reactions. With the COVID-19 pandemic affecting the entire world, there has been an increase in the number of deaths and cases. This situation has posed a great threat to economies and has allowed economies and stock exchanges to react quickly to risk perceptions around the world. The uncertainty experienced has led to quite sharp declines in stock markets. Situations such as curfews, closures of workplaces, mandatory use of masks and health equipment, and the suspension of activities of production and service companies have increased the perception of risk and fear in global markets. Despite the declaration of a pandemic, the lack of a vaccine or medicine to treat the COVID-19 virus, the increase in deaths and severe illnesses, the rapid spread of the epidemic around the world, and the lack of information on how to take precautions against this epidemic have paved the way for sharp sell-offs on the stock markets. There have been historic declines in stock markets and cryptocurrency markets. If we look at the U.S. stock markets, the sharp declines that occurred in the second week of March reached 7%, and more daily, circuit breakers were implemented (Şenol, 2020).

Table 1 shows the declines experienced by some of the world's leading stock exchanges and Borsa Istanbul in Turkey after the global pandemic was declared by the World Health Organization on March 11, 2020. Just one day later, on March 12, 2020, it was observed that the

S&P 500 U.S. Stock Exchange lost 9.51%, the Developed Markets Index lost 9.91%, the NASDAQ lost 9.43%, the SHCOMP Stock Exchange lost 1.52%, the NIKKEI lost -4.41% and the Emerging Markets Index lost 6.71%. In addition, the BIST100 index in Turkey lost 7.25%. If we look at this table, we can see that the highest percentage loss was in the CAC40 stock exchange and the lowest decrease was in the SCHOMP stock exchange with 1.52.

Table 1. Percentage Change Between Global Pandemic and Stock Indices

Index	Index Value	Return (%)
S&P 500	2.741	-9,51
MSCI-DM	1.972	-9,51
CCO-NASDAQ	7.952	-9,43
DAX	10.439	-12,24
FTSE 100	5.877	-10,87
CAC40	4.61	-12,27
NIKKEI 225	19.416	-4,41
HANG SENG	25.232	-3,66
SHCOMP	2.969	-1,52
SENSEX	35.697	-8,18
RTSI(RUSYA)	1.086	-11,03
MSCI-EM	947	-6,71
BIST 100	1.009	-7,25

Source: Kazan (2020).

From the first day of the outbreak in Turkey, the value of the BIST100 index decreased from 1,159 to 936. If we look at these figures, there was a loss of approximately 20% (Karpuz and Koç, 2022). As can be seen in the table, the losses of approximately 30% in the world's major stock market indices during this period also increased the volatility rates in the stock markets. The return volatility levels experienced during the COVID-19 pandemic are very close to the volatility levels experienced during the 2008 global crisis. The declines experienced on some days have brought them to historical levels. For example, at the beginning of the pandemic, on March 16, 2020, the losses experienced were 11% on the U.S. stock market, 10.7% on the French stock market, 8.65% on the U.K. stock market, 11.3% on the Italian stock market, and 8.65% on the Turkish BIST 100. The losses experienced on March 12, 2020, in the table are among the historical declines in the Dow Jones Index. In addition, the 13% decline experienced on March 16, 2020, is the third-highest single-day decline in the history of the Dow Jones Index. The decline experienced during the Great Depression on October 28, 1929, is equal to the 13% decline experienced on March 16, 2020. At the same time, looking at other economic indicators, the asset with the largest decline in yield was the yield on US Treasury bonds. Immediately after that, however, the price of oil fell sharply. As the pandemic spread around the world, central banks also adopted a policy of lowering interest rates. The FED cut rates to 1.75% and then to 0%. Japan and Europe made no changes as their interest rates were negative. While the US 2-year Treasury rate was 1.5% at the beginning of the year, it fell to 0.15% in May, a total decline of 85%. The Central Bank of Turkey reduced interest rates three times during the pandemic and the last level remained at 8.25% (Şenol, 2020).

If we look at the world, there has been a decrease in the prices of materials and substances in many sectors, especially energy. The reason for this is the decrease in production and consumption levels. Historic declines have been experienced in the price of oil, one of the largest sectors. The price of a barrel of Brent oil, which was $71 on January 6, 2020, fell to $18 on April

22, 2020, a decrease of 74%. According to the International Energy Agency (IEA), oil demand in 2020 has decreased by 57% (IEA, 2020).

3. The Impact of the COVID-19 Pandemic on Cryptocurrency Markets

With many people around the world forced to stay at home, digitization has increased across all platforms, combined with the driving force of technology. In the process, consumers have experienced more digital services than ever before. In the 2020-2021 period, when the pandemic was most effective, changes in investor behavior were observed (Öztürk and Dilek, 2021). If we look at Bitcoin, which is known as the first crypto asset and still has the largest market value, it was much more affected by the Covid-19 period. As of May 11, 2024, there are 19.6 million bitcoins in circulation (Blockchain, 2024). It is estimated that the production of this encrypted coin, which is limited to a total of 21 million, will continue until 2140 (Göktaş and Aksu, 2021). Bitcoin is the crypto asset with the highest market value.

Currently, there are hundreds of active crypto assets in the market. As of July 2024, the top 10 crypto assets with the highest market value were identified as Bitcoin, 18.34% Ethereum, Tether, BNB, Solana, XRP (Ripple), USDC, Dogecoin, Toncoin, and Cardano. The total value of crypto assets, which could reach $3 trillion by 2021, has fallen to $2.5 trillion by July 2024 (https://coinmarketcap.com/charts/). The pandemic, when people were confined to their homes, combined with the impact of technology, increased activity on all digitized platforms, and consumers benefited from the service experiences they received digitally. There has also been curiosity and an increase in cryptocurrency markets and supporting platforms (Öztürk and Dilek, 2021). With the declaration of the pandemic by the World Health Organization, the prices of BTC and ETH decreased by about 50% on March 12, 2020. Later, institutional investors such as Grayscale, Square, and MicroStrategy announced large BTC purchases. Coinbase was listed on the NASDAQ under the name COIN in April 2020. According to Forbes, the global crypto ETF market grew 549% in November 2021 compared to the end of 2020. Many new business forms have emerged, namely decentralized finance (DeFi) and NFT. The DeFi market will reach $300 billion by the end of 2021.

Table 2. Bitcoin and Ethereum Returns

	Cumulative Return in 2020 (USD %)	2020 % Change (Start-to-End of Year)	Cumulative Return in 2021 (USD %)	2021 % Change (Start-to-End of Year)
BTC	170,9	315,2	77,6	44,8
ETH	226,4	479,1	219,3	254,0

Source: https://finance.yahoo.com/

In Table 2, the returns of Bitcoin and Ethereum are shown as daily and annual returns based on 2020 and 2021. Looking at 2020, Bitcoin's cumulative return was 170.9%, while the change in year-end value was 315.2%. Looking at 2021, these numbers dropped from 77.6% to 44.8%. Looking at these values for Ethereum, while the cumulative return in 2020 was 226.4%, the change in the year-end value in 2020 was 479.1%. Looking at 2021, these values appear to be 219.3%. Looking at the year-end change in 2021, we can see that the Ethereum price is 254.0%.

Looking at this, it can be said that Bitcoin and Ethereum provided very high returns during the pandemic period.

4. Literature Review

Today, with the impact of technological advances, money transfers, and commercial transactions are largely conducted over the Internet. With the increasing use of technology, interest in virtual currencies has grown rapidly. Especially during the COVID-19 pandemic, interest in cryptocurrencies has increased even more with the reduction of physical contact and the acceleration of digitalization. Discussions about the functioning, advantages, disadvantages, price movements, and system of bitcoin occupy an important place in the academic literature. The COVID-19 pandemic added a new dimension to these discussions and drew more attention to the potential role of bitcoin. During the pandemic, the loss of trust in traditional financial systems has increased people’s interest in digital assets. In addition, the uncertainties experienced in traditional financial markets during the pandemic have increased demand for the value of digital assets such as bitcoin and led to significant fluctuations in their prices. The COVID-19 pandemic has accelerated the digitization of financial infrastructure and contributed to the greater acceptance of cryptocurrencies on a global scale.

The study conducted by Kristoufek (2013) analyzed the relationship between search volume and price movements of the cryptocurrency Bitcoin on Google Trends and Wikipedia. The study hypothesized that the popularity and demand of Bitcoin could affect the price of this digital asset. The results of the study show that Bitcoin experiences increased interest during periods when its prices are high, and this interest further increases its prices. Christopher (2014) examined the process of processing Bitcoin in terms of money laundering legislation in the US government, and mentioned the difficulties that Bitcoin can be used as a malicious virtual currency and the possible difficulties in combating crimes in this direction. In this analysis, it was emphasized that the anonymous and decentralized structure of Bitcoin may make it difficult to prevent its use in illegal activities such as money laundering and that existing legal regulations may be inadequate to prevent such misuse of Bitcoin.

MacDonell (2014) studied the price bubble phenomenon in Bitcoin and found that a bubble occurred in 2013. The study highlighted the reasons for this bubble, such as the lack of reliable bitcoin platforms and the intensity of black-market transactions. It also emphasized that the high price volatility in the market created an environment open to speculation. In particular, as demand for bitcoin increased, investors turned to black market transactions due to the scarcity of reliable platforms, creating uncertainty and volatility in the market. It has also been noted that the high volatility of bitcoin prices has contributed to the market being open to speculation. High price volatility can encourage investors to enter and exit the market in search of quick profits, which can lead to bubble-like conditions.

Chu et al. (2015) made a mathematical analysis of eight different exchange rates based on BTC/USD rates. When we consider the last 2 years, they determined that the BTC/USD rate has increased more than 50 times and that Bitcoin has high volatility. Georgoula et al. (2015) used time series analysis in their study to investigate the relationship between the basic financial values of Bitcoin prices, Twitter data, and values developing with technology. According to the results of the study, a positive situation was determined between the pricing made on Bitcoin in the short term and Twitter data. Baek and Elbeck (2015), In their study, researchers used daily return data sets of Bitcoin and the American stock market index and tried to determine whether Bitcoin is open to manipulation. As a result of their analysis, they stated that the Bitcoin money market has a volatility of 26 times that of the S&P 500 and that Bitcoin has a speculative structure. These findings show that Bitcoin has a higher risk and speculative character compared to other assets in the financial markets. In his study, Dyhrberg (2016) investigated the economic viability of Bitcoin using GARCH models. In the model, Bitcoin functions as a hedge against change and risk, similar to gold and dollars, and shares several similar characteristics. In addition, it can be said that Bitcoin's volatility changes over time and is acceptable in the long term. These findings help us better understand Bitcoin's place in financial markets and the opportunities it provides for investors.

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Stavroyiannis (2017) examined Bitcoin, Ethereum, Ripple, Litecoin, and the S&P 500 index as examples of risk management in his study. He tested 10-day VaR and Expected Shortfall (ES) methodologies. The data obtained showed that cryptocurrencies are risky. This finding emphasizes that cryptocurrencies have high volatility and should be carefully considered in terms of risk management. In his study, Katsiampa (2017) investigated the most appropriate model for price volatility in the financial valuation of bitcoin. According to the results of the study, it was analyzed that the long-term variance in the bitcoin market is not constant and varies with the process. However, it was found that the most applicable model is the AR-GARCH model. These results show that the price volatility of bitcoin is not constant and can change over time. The AR-GARCH model was found to be an effective tool for estimating the volatility of bitcoin prices. The study by Yıldırım and Bekun (2023) used weekly opening prices between November 24, 2013 and March 22, 2020, and calculated log returns. The results of the analysis showed that the GARCH model was more successful in capturing the volatility of Bitcoin compared to the ARCH and EGARCH models.

Studies of the cryptocurrency market examine Bitcoin's price volatility and speculative structure from a broad perspective. Studies generally show that Bitcoin's popularity, demand, and price movements are interrelated and that it is a speculative market with high volatility. Volatility estimation models such as ARCH and GARCH have been used as an effective method to analyze bitcoin's price movements, and these methods have contributed to understanding bitcoin's risk dynamics in financial markets. In general, it has been emphasized in the literature that bitco'n carries high risk compared to traditional financial assets and its fluctuations are higher than other assets. In addition, it has been found that macroeconomic indicators and social media data can be determinants of bitcoin price formation.

However, there is no study in the literature that specifically addresses the COVID-19 pandemic period. Examining the dynamics of cryptocurrency markets during the pandemic process is very important to fill this gap in the existing literature. This study aims to both bring a new perspective to the literature and test existing methods in the context of this extraordinary period by analyzing the impact of the pandemic on volatility and investor behavior in cryptocurrency markets. In doing so, it aims to contribute to a better understanding of the impact of extraordinary conditions such as the pandemic on markets.

5. Data and Research Methodology

5.1. Data

In the study, the volatility of bitcoin during the pandemic period was tested using ARCH and GARCH models. The dataset consists of a 763-day price/time series consisting of Bitcoin's daily closing prices, including the weekend between 03/01/2020 and 04/01/2022, and was obtained by generating historical data from the Coinmarketcap.com website. Additional macroeconomic and market factors, such as the post-pandemic recovery and regulatory reforms, would have been included in the dataset if it had been extended past April 1, 2022. This restriction is regarded as a study limitation. In the study, comparisons were made using volatility prediction models for bitcoin, a cryptocurrency.

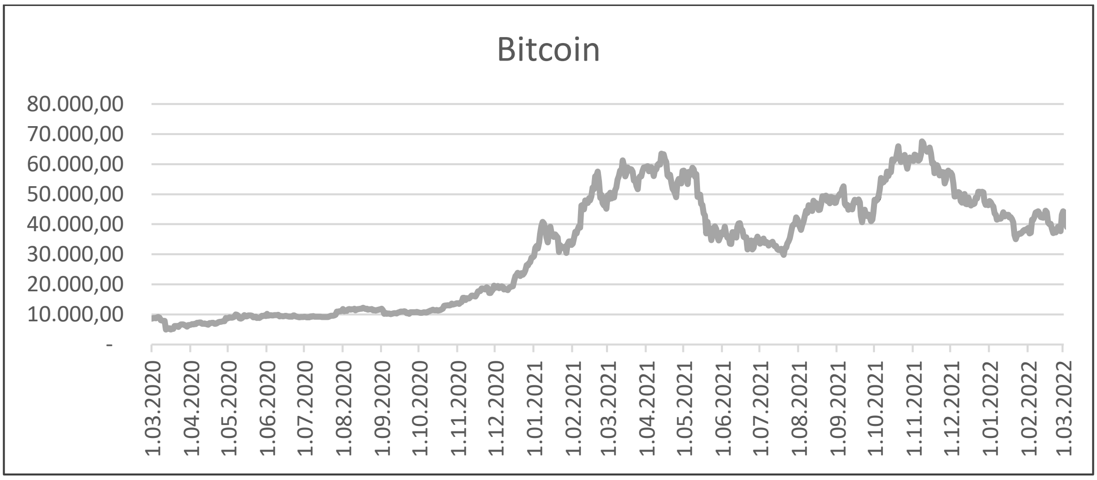

Figure 1. Bitcoin Price Change

Figure 1 shows bitcoin price movements over time. Daily bitcoin price information for the period 01.03.2020-01.04.2022 is shown based on US dollars. At the beginning of 2020, the price was below $10,000, reached $10,000 by mid-year, and increased rapidly after October, reaching

$29,000. In 2021, the increase continues and exceeds $60,000, but prices then fall and fluctuate between $30,000 and $40,000.

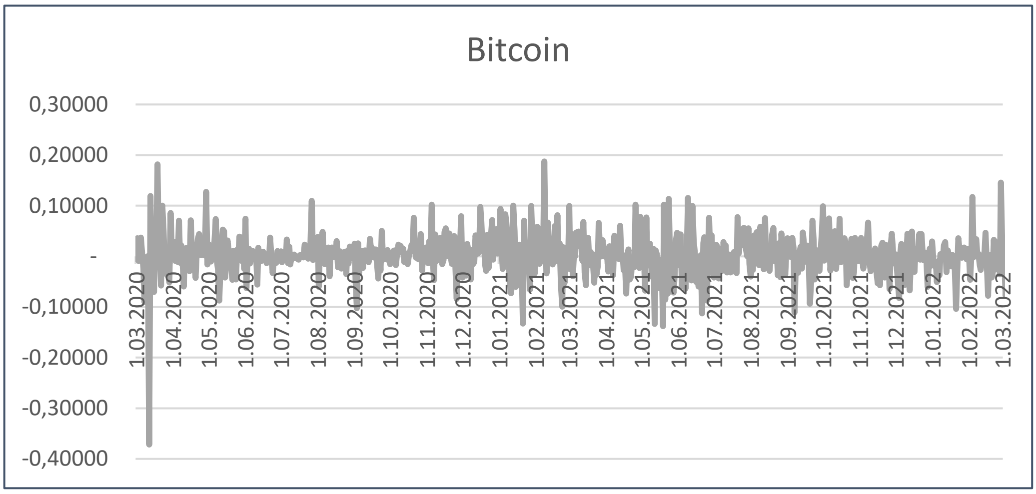

Figure 2. Bitcoin Return Rates

Figure 2 illustrates the daily return rates of Bitcoin over time. During the period from 2020 to 2022, significant fluctuations in return rates can be observed. The graph highlights periods of high volatility while showing that the return rates generally oscillate between positive and negative values.

5.2. ARCH Method

Modeling on time series generally suggests the assumption of constant variance of error terms. However, this assumption is often not valid for data observed in financial markets. The ARCH model is a type of regression model used to model the variance of variables in time series. It was first developed by Robert F. Engle in 1982 and has become well-established in the literature. The ARCH model models how the variance in a time series changes based on past values. For instance, a first-order autoregressive model (AR(1)) is expressed as $y_t = \boldsymbol{a} y_{t-1} + u_t$ (Brooks, 2008). Where y_t: Observed value at time t, $\boldsymbol{a}$: Autoregressive coefficient of the AR(1) model, y_{t-1}: Observed value at time $_{t-1}$, ut: Random error term (noise) at time t.

The parameters of the ARCH model are generally estimated using the Maximum Likelihood Estimation (MLE) method. This method is used to determine the parameter values that best fit the data set. The ARCH(p) model is typically formulated as follows (Engle, 1982).

$$h_t = a_0 \sum_{i=1}^{p} a_I u_{t-i}^2 \qquad (1)$$

Where h_t: Represents the conditional variance at time t, a_0: The constant term, a_i: Coefficients of the ARCH terms for the lagged squared residuals I=1,2,3…,p, u_{t-i}^2: The error term (residual) at time t−i.

The ARCH model aims to capture a volatility structure that changes over time by modeling the effect of the squares of past errors through these terms. Recent developments in financial econometrics suggest the use of nonlinear time series models to model risk and expected return.

Bera and Higgins (1993: 315) note that an important contribution of the ARCH literature is that it shows that changes in volatility in economic time series are predictable and that these changes may be due to certain types of nonlinear dependencies rather than to external structural changes. The assumption of constant volatility over a given period is statistically inappropriate, and it has been argued that volatility is an inconsistent concept as the series progresses over time (Engle, 1982: 987-1008). The situation observed in financial markets is that large returns are accompanied by larger returns and small returns are accompanied by smaller returns, suggesting that there is a serial relationship between returns. Homoscedasticity means that the error terms are constant when the expected value is squared (Brooks, 2003). However, ARCH and GARCH models are designed to model the heterogeneous variance observed in financial data (Bollerslev, 1986: 307-327). These models reflect the fact that the variances of the error terms are not equal and may be larger in some periods than in others. ARCH and GARCH models are widely used forecasting models in financial applications. Therefore, it was decided that the above methods were appropriate to use in the study of bitcoin price volatility during the pandemic period.

5.3. GARCH Method

The GARCH model, which is an improved and differentiated version of the ARCH model, was proposed by Bollerslev (1986) as an alternative to the problem of excessive data estimation in the ARCH model. Unlike the old model, this model has deeper past-period effects and a more flexible structure. In GARCH models, the conditional variance at time 't' does not only depend on the previous values of the error term but also has to take into account the previous values of the conditional variance. The two factors affecting the past values are the variance due to the error term and the conditional variance (Bollerslev, 1986).

$$h_t^2 = \alpha_{0+}\ \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots\ldots\ldots + \alpha_q \varepsilon_{t-q}^2 + \beta q h_{t-q}^2 \quad (2)$$

Non-negativity Condition α_0>0 which ensures that the conditional variance is non-negative.

$$\mathrm{A_i} \geq 0,\ \mathrm{I} = 1, \quad \ldots,\ \mathrm{p} - 1,\ \alpha_p > 0\ ,\ \beta_i \geq 0\ ,\ = 1\ ,\ \ldots\ ,\ \mathrm{q} - 1\ ,\ \beta_q > 0 \quad (3)$$

Using the relevant lag terms, the model can be expressed as:

$$\alpha(\mathrm{L}) = \alpha_1\mathrm{L} + \ldots + \alpha PLP \quad \beta(\mathrm{L}) = \beta_1\mathrm{L} + \ldots + \beta qLq \quad (4)$$

This results in the following formulation:

$$h_t^2 = \alpha_0 + \alpha(\mathrm{L})\ \varepsilon^2_{\mathrm{t}} + \beta(\mathrm{L})\ h^2_t \quad (5)$$

By following this method, it becomes evident that $\varepsilon_t{}^2$ directly follows the process. Considering these equations, the model structure and parameter constraints can be understood.

$$v_t = \varepsilon_t^2 \quad (6)$$

$$\mathrm{E}[v_t \mid I_{t-1}] = \mathrm{E}[\varepsilon^2_{\mathrm{t}} - h^2_t \mid I_{t-1}] = 0 \quad (7)$$

Thus, the relationship with v does not exist, and it satisfies the condition of having zero mean. The white noise condition will have been fulfilled.

$$\varepsilon_t^2 = h_t^2 + v_t \quad (8)$$

$$\varepsilon^2_{\mathrm{t}} = \alpha_0 + \alpha_1 + \alpha_2 \varepsilon_{t-2}^2 + \ldots.. + \alpha_q\ \varepsilon^2_{\mathrm{t-p}} + \beta_{1(}\varepsilon^2_{\mathrm{t-1}} - v_{t-1}) + \ldots + \beta_{\mathrm{p}(}\varepsilon^2_{\mathrm{t-p}} - v_{t-\mathrm{p})+}\ v_t \quad (9)$$

$$\varepsilon^2{}_{t} = \alpha_{0+} \sum_{i=1}^{n} (a + \beta i)\ \varepsilon^2{}_{t\text{-}I} + v_t) - \sum_{i=1}^{p} \beta i\ v_{t-I} \tag{10}$$

The key point for estimating the equation of unconditional variance and serial dependence is its similarity to the ARCH methodology (Kirchgässner and Wolters, 2007: 252–254).

$$V\ (\varepsilon_t) = E[\varepsilon^2{}_t] = \frac{\alpha 0}{1 - \alpha(1) - \beta(1)} \tag{11}$$

For the existence of variance in the following method:

$$\alpha(1) + \beta(1) = \sum_{i=1}^{p} \alpha i + \sum_{i=1}^{q} \beta i < 1 \tag{12}$$

The above equality must hold.

The GARCH model, like the ARCH model, is limited in that it responds the same way to both negative and positive effects. Additionally, recent studies on high-frequency financial time series have shown that the GARCH model's distribution does not decline as rapidly as the student's t-distribution (Tsay, 2005). GARCH models include features such as the conditional variance being a stochastic variable with sequential dependency, εt^2 following an ARMA model, and errors being unconditionally leptokurtic and symmetrically distributed.

The conditional variance can be expressed as follows (Brooks, 2008):

$$h_t^2 = \alpha_0 + \alpha(L)\ \varepsilon_t^2 + \beta(L)\ h_t^2$$

When the unconditional variance of the process is given as:

$$\sigma_y^2 = \frac{\alpha 0}{1 - a(1) - \beta(1)} \tag{13}$$

By substituting α_0 with σ_y^2 (1- α(1) – β(1)) into the equation:

$$h_t = \sigma_y^2 (1 - \alpha(1) - \beta(1)) + \alpha(L)\ \varepsilon_t^2 + \beta(L)\ h_t^2$$

This can be rearranged as:

$$ht - \sigma_y^2 = \alpha(L)\ \varepsilon_t^2 - \sigma_y^2\ \alpha(1) + \beta(L)\ h_t^2 - \sigma_y^2 \beta(1) \tag{14}$$

Simplified as:

$$= \alpha(L)(\ \varepsilon_t^2 - \sigma_y^2\ ) + \beta(L)(\ h_t - \sigma_y^2\ )$$

In conclusion, the unconditional distribution is symmetric and leptokurtic. GARCH models exhibit complexity in their moment structure. The equation holds only when the respective parameters are zero. Changes in high or low volatility are dependent on such variations.

6. Empirical Findings

To address stationarity issues, return rates were used instead of cryptocurrency prices. The study was conducted using the most comprehensive data available, covering the beginning and progression of the COVID-19 pandemic. The data period for Bitcoin spans from 01.03.2020 to 01.04.2022, which includes the COVID-19 pandemic. Table 3 provides information explaining Bitcoin's return rates.

Table 3. Descriptive Statistics of Cryptocurrency Return Rates

Average	0,00305
Maximum	0,18746
Minimum	-0,37170
Standard Deviation	0,04022
Skewness	-0,076301
Kurtosis	11,3570
Jarque-Bera Test (P-Value)	3944,44(0,000)*
Number of Observations	763

Note: * Statistically significant at the level of $p < 0.01$.

Bitcoin's average daily return is calculated to be 0.305%. This generally indicates a positive return rate and shows that bitcoin, on average, provides investors with a positive return over the long term. Bitcoin's yield rates fluctuate within a wide range. The maximum return rate was 18.746% on 02/08/2021, while the minimum return rate was -37.170% on 03/12/2020. This shows that there are large fluctuations in the price of bitcoin and investors should be prepared for such fluctuations. The standard deviation value of 0.04022 shows that bitcoin's return rates have high volatility. High volatility means both large profit opportunities and large losses for investors. The skewness value is -0.076301, indicating that the distribution of returns is not symmetric and has a slightly negative skew. This shows that bitcoin returns are concentrated slightly below the mean. The kurtosis value is 11.3570, indicating that the distribution has sharper peaks and thicker tails than the normal distribution. Higher kurtosis indicates that extreme return rates occur more frequently.

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The Jarque Bera test result is 4169.14 and the p-value is 0.000. This result clearly shows that bitcoin return rates do not conform to a normal distribution. This Jarque Bera test result shows that Bitcoin's return rates violate the assumption of normal distribution, and therefore the assumption of normal distribution should be used cautiously in financial models. This analysis was performed using a total of 763 days of data. This period includes the COVID-19 pandemic. The high volatility and uncertainty in the markets during the pandemic period also caused significant fluctuations in the return rates of cryptocurrencies.

Tablo 4. Unit Root Test Results for Bitcoin

ADF(p)		PP(p)	
Constant	**Constant and Trend**	**Constant**	**Constant and Trend**
-29,68*(0)	-29,69*(0)	-29,69*(1)	-29,68*(1)
[0,000]*	[0,000]*	[0,000]*	[0,000]*

Note: * Significant at the 1% level, ** Significant at the 5% level, *** Significant at the 10% level. The values in square brackets represent the p-values. The number in parentheses next to the test statistic indicates the optimal lag length, determined according to the Schwarz information criterion. The PP unit root test applies the Newey-West Bandwidth and Bartlett Kernel automatic selection method.

The study analyzed whether the model had a unit root prior to estimation. According to the results of the ADF and PP tests presented in Table 4, it was determined that the series was stationary. The fact that the probability values (p-value) of the tests were less than 0.05 indicates that the series was stationary at the level. The results of the ADF and PP unit root tests support the stationarity hypothesis. Stationarity of financial time series can be considered as an indicator that volatility is predictable. Table 5 shows the results of the ARCH model calculated for the return rates of bitcoin. This analysis explains the volatility dynamics of bitcoin returns and the parameters of the model. No heteroskedasticity problem was observed in the ARCH(1,1) model, where appropriate lag lengths were determined using the ARCH-LM test. The α coefficient of the model was found to be 0.0180 and is statistically significant. This result shows that the model in question can be used effectively in estimating the volatility of Bitcoin.

Tablo 5. ARCH Model Results

Average	0,3046
Standard Deviation	0,040256
Variance	0.001621
Constant	0,003029
Unconditional Variance (omega)	0,001585
ARCH Parameter (alpha)	0,0180
Long-run Volatility	0,040174
Log Likelihood	1368,71

Bitcoin's average daily return rate is calculated to be 0.3046%. This rate shows that Bitcoin generally provides positive returns to investors over the long term. The positive average return indicates that bitcoin can be a profitable investment for investors. However, these returns are highly variable. The standard deviation is 4.0256% and the variance is 0.001621. These values indicate that bitcoin returns are highly volatile and that investors may experience large fluctuations. High volatility means that returns can change significantly in certain periods, which indicates that the level of risk is high. The constant term (mu) in the ARCH model is calculated to be 0.3029%. This value represents the average return level of the model and shows the general trend of bitcoin returns. The unconditional variance (omega) is 0.001585 and indicates the base volatility level of the model. This base level reflects the volatility level of the market under normal conditions. The ARCH parameter (alpha) 0.0180 shows that the effect of the volatility of the previous period on the volatility of the current period is weak, which means that the market is less uncertain and more stable. This means that the market can be more predictable for investors and shows a positive sign in terms of risk management. The long-term volatility is calculated to be 4.0174%. This value shows that bitcoin returns have high volatility in the long run. This level, where volatility levels off over time, is an important indicator for investors to consider in their long-term strategies. High long-term volatility indicates that market fluctuations are continuous and the risk level will be high in the long run. The log-likelihood value was determined to be 1368.71. This value indicates how well the ARCH model fits the data set and explains the data. A high log-likelihood value demonstrates that the model is appropriate and valid, effectively capturing the volatility of Bitcoin returns.

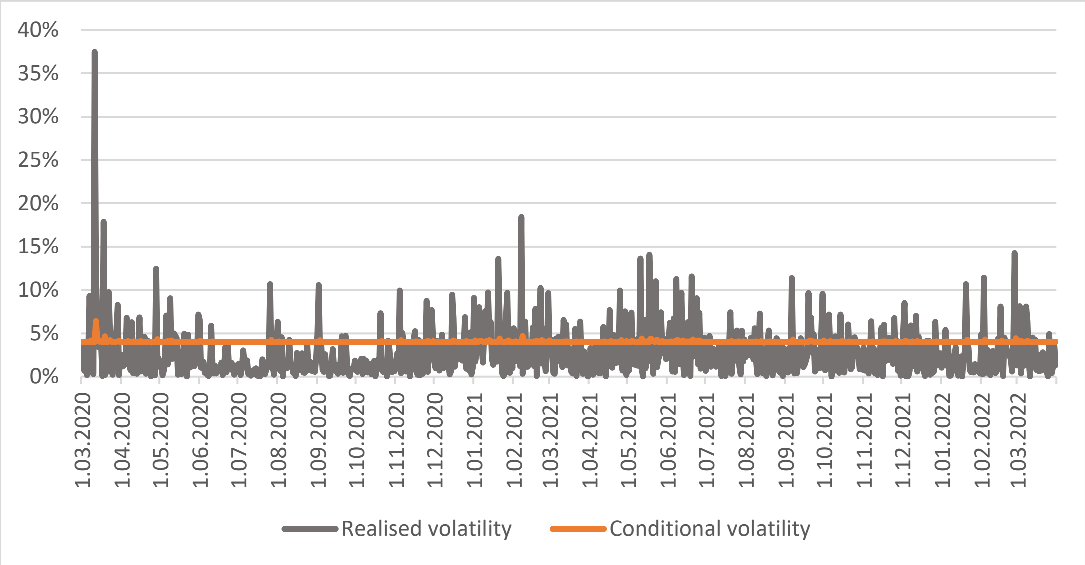

Figure 3. Realized and Conditional Volatility of Bitcoin (ARCH)

Figure 3 shows the realized volatility (gray) and conditional volatility (orange) between 01/03/2020 and 01/04/2022. The pandemic period started around March 2020 and a significant increase is observed on the graph during this period. It is observed that the realized volatility was quite high at the beginning of the COVID-19 pandemic in March 2020. During this period, there was a general atmosphere of uncertainty and panic in the financial markets, and the cryptocurrency markets experienced large fluctuations. After the initial shock of the pandemic, a general decrease in volatility was observed and the market became more stable. It can be seen that the blue line shows sudden spikes at certain intervals throughout the chart; these fluctuations may have occurred due to factors such as news, regulations, and major investment moves in the cryptocurrency market. The orange line, the conditional volatility, shows less fluctuation compared to the realized volatility and shows that the ARCH model is more stable in estimating the expected volatility of the market. In general, we can see that conditional volatility remained low and stable throughout 2020 and 2021, while realized volatility increased at certain intervals. This indicates that unexpected events occurred in the market and caused greater volatility than expected. The chart clearly shows the impact of the pandemic on market behavior and how such global events can threaten financial stability.

Table 6. GARCH Model Results

Average	0,03046
Standard Deviation	0,04023
Variance	0.001618
Constant (mu)	0,001569
Unconditional Variance (omega)	0,000271
ARCH Parameter (alpha)	0,0486
GARCH Parameter (beta)	0,7802
Alpha + Beta	0,8288
Long-run Volatility	0,03976
Average	1378,22

Table 6 shows the results of the GARCH model. Bitcoin's average daily return rate is calculated to be 0.03046%. This rate shows that Bitcoin generally provides positive returns to investors over the long term. The positive average return indicates that bitcoin can be a profitable investment for investors. However, these returns are highly variable. The standard deviation is 4.023% and the variance is 0.001618. These values indicate that bitcoin returns are highly volatile and that investors may experience large fluctuations. High volatility means that returns can change significantly in certain periods, indicating that the level of risk is high. Based on the GARCH model, the constant term (mu) in the model is calculated to be 0.001569%. This value represents the average return level of the model and shows the general trend of bitcoin returns. The unconditional variance (omega) is 0.000271 and indicates the base volatility level of the model. This base level reflects the volatility level of the market under normal conditions. The ARCH parameter (alpha) is calculated to be 0.0486. This parameter indicates that the volatility depends on the squared error (volatility) of the previous period. In other words, large fluctuations in the previous period affect the volatility of the current period, thus ensuring the continuity of volatility. This situation is important in explaining the uncertainty and volatility trend of bitcoin returns over time. The GARCH parameter (beta) was determined to be 0.7802, which represents the long-term effects of volatility. The sum of the alpha and beta parameters, 0.8288, shows that volatility is quite persistent and the effects of shocks last for a long time.

Long-term volatility was calculated as 3.976%. This value shows that Bitcoin returns have high volatility in the long term. This level, where volatility will balance over time, is an important indicator that investors should consider in their long-term strategies. High long-term volatility indicates that market fluctuations are continuous, and the risk level will be high in the long term. The log-likelihood value was determined as 1378.22. This high value shows how well the GARCH model fits the data set and how well the model explains the data. A high log-likelihood value indicates that the model is appropriate and valid and can effectively explain the volatility of Bitcoin returns.

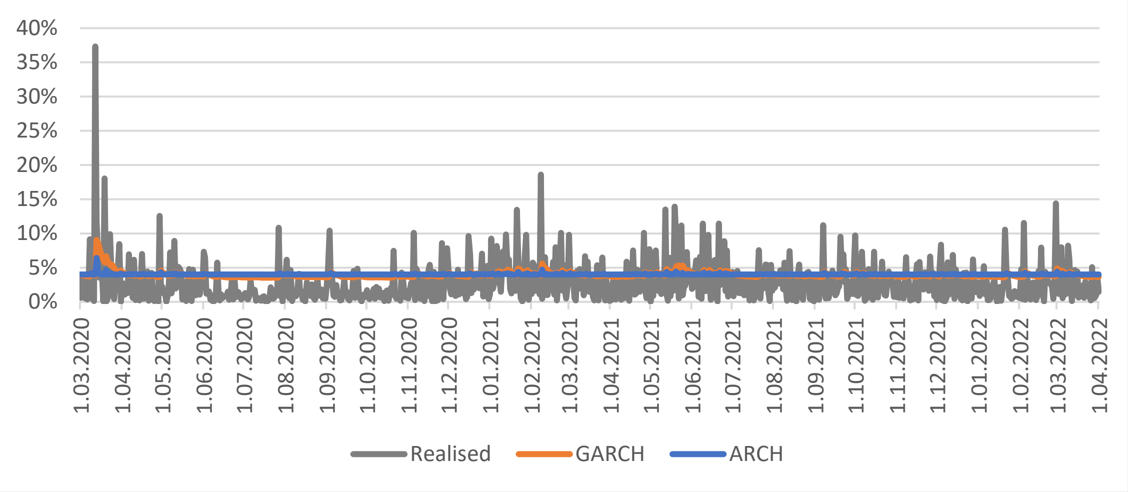

Figure 4. Realized and Conditional Volatility of Bitcoin (GARCH)

Figure 4 compares volatility estimates and realized volatility between 03/01/2020 and 04/01/2022. There are three different time series in the chart: Realized Volatility (gray), GARCH Model Estimated Volatility (orange), and ARCH Model Estimated Volatility (blue). Realized volatility shows higher volatility than the estimates of the other two models. Sharp peaks are observed especially at the beginning of the COVID-19 pandemic and in some other periods (e.g. early 2020). The GARCH line (orange) shows more volatility than the ARCH line (blue) and overlaps more with the realized volatility. The ARCH model has a flatter and more stable line. The COVID-19 pandemic has shaken global economic balances and caused severe fluctuations in financial markets. The volatility observed in the cryptocurrency markets during this period can be considered as a result of the uncertainties and sudden market reactions that occurred during the pandemic. In the presented graph, it can be observed that the volatility that occurred during the initial period of the pandemic in March 2020 increased sharply and reached 35%. This sudden increase is interpreted as an indicator of excessive volatility in the cryptocurrency markets and the panic of investors with the first effects of the pandemic. In the following months and throughout 2021, volatility fluctuations continued, but did not reach the extreme levels of March 2020; this shows that the market adapted to the uncertainties created by the pandemic and volatility became more stable over time.

7. Policy Discussion

The COVID-19 pandemic has had a significant impact on financial markets, causing volatility increases, especially in cryptocurrency markets, due to a combination of macroeconomic, psychological, and system dynamics. Policies such as monetary expansion, low interest rates, and liquidity increases in the financial system have increased both the risk appetite of investors and interest in cryptocurrencies. This process has significantly affected the price movements of digital assets with high market value such as Bitcoin and revealed the complex interaction between macroeconomic conditions and investor sentiment during periods of high uncertainty.

The response of the cryptocurrency market to regulatory news, investment decisions of large companies, and macroeconomic shocks has become even more important during the pandemic period. Large-scale investments by funds and businesses changed the market's dynamics, either increasing speculative activity or stabilizing prices during uncertain times. Sudden jumps in volatility have usually been triggered by such external events, but the psychological aspect of the market has further strengthened the impact of these movements. The sharpening of investor sentiment during periods of uncertainty has led to an intensification of speculative behavior, dramatically directing market dynamics. This also indicates that cryptocurrencies are seen as a “safe haven” in times of uncertainty, as well as being a speculative tool. The empirical results indicate that the effect of shocks on volatility is permanent for Bitcoin during the COVID-19 pandemic, which is supported by the sum of the alpha and beta (0.8288%) obtained from the GARCH model. When the news flow is considered, the effect of positive shocks is found to be stronger than that of negative shocks. However, this interpretation is not supported due to the symmetric structures of the ARCH and GARCH models. Results obtained from the ARCH and GARCH models reveal that cryptocurrency market volatility remains at high levels during and after the pandemic. However, both models are insufficient in predicting extreme volatility increases in crisis periods such as March 2020. This shows that existing volatility models should be reconsidered for extreme situations and high-uncertainty environments. The high volatility observed during the pandemic highlights that cryptocurrency markets are sensitive to global economic developments and should be more closely monitored by regulators. Stronger regulations and security protocols will both protect investors and help the market achieve a more stable structure. In order to reduce speculative activity and stabilize cryptocurrency markets, it may be essential to create precise and binding legal frameworks that require openness in market operations. The lessons learned from this process suggest that more robust volatility management tools should be developed not only for cryptocurrency markets but also for the financial system as a whole. In addition, it is important to focus on education and awareness activities in order to strengthen investors' risk management strategies and be better prepared for market shocks. In this regard, the impact of the pandemic can be a lesson for possible future crises.

8. Conclusion

The COVID-19 pandemic has led to a significant increase in the cryptocurrency market volatility, which, in turn, has affected investor behavior. Understanding the dynamics of cryptocurrency markets and developing investment strategies accordingly is of great importance for both lenders and policymakers. This study provides a crucial understanding regarding the management of the volatility in cryptocurrency markets, alongside providing the basis for future research. Given this importance, the existing study examines the impact of the COVID-19 pandemic on cryptocurrency investments utilizing the ARCH and GARCH models in analyzing the volatility of bitcoin prices. According to the findings, the GARCH model captures long-term volatility trends more consistently, while the ARCH model shows limited accuracy in understanding the short-term dynamics of volatility. However, the impact of shocks on volatility is found to be persistent for bitcoin during the COVID-19 pandemic.

In general speaking, the empirical results show that the volatility in the cryptocurrency market remains at a high level during and after the pandemic. Especially in the early stages of the pandemic, the economic measures taken by governments and the expansionary monetary policies implemented by central banks created a positive atmosphere in the cryptocurrency markets and attracted the attention of investors. During the pandemic, it is observed that the cryptocurrency markets became more speculative. Investors increased their interest in these markets with high potential returns, which also resulted in market volatility. The fluctuations in bitcoin price movements reveal that the market became more risky and unpredictable during this period.

The low alpha value (0.0180%) obtained from the ARCH model indicates that the effect of previous shocks on current volatility is weak and that sudden increases in volatility are not well captured by this model. The GARCH model has a higher beta (0.7802), indicating that volatility shocks have longer-term effects. However, it can be seen that this model cannot adequately predict sudden increases in periods when extreme shocks such as pandemics are experienced intensely. As a result, based on the model results, it can be said that both the ARCH and GARCH models are insufficient to predict extreme increases in volatility during crisis periods such as pandemics. The results obtained are consistent with the findings of the study by Yıldırım and Bekun (2023). The results of the research provide important clues for understanding the dynamics of cryptocurrency markets and designing investment strategies accordingly. High volatility creates both opportunities and risks for investors. Therefore, investors need to make more careful and strategic decisions by taking volatility into account. Especially in times of uncertainty, it is important for investors to diversify their portfolios and implement effective risk management strategies. Regulation and supervision of cryptocurrency markets are critical to ensuring market stability. Regulators should implement appropriate regulations to reduce volatility in cryptocurrency markets and protect investors. In addition, in future studies, similar analyses using different cryptocurrencies and longer data sets can help to better understand the dynamics of the market. To supplement the knowledge gathered from ARCH and GARCH analysis, future research could take into account EGARCH and TGARCH models. Although the basic volatility patterns during the COVID-19 pandemic were well represented by the ARCH and GARCH models, EGARCH and TGARCH may provide additional insights, especially when examining individual asymmetric effects or distinct market reactions in various circumstances. Future studies could include other high-market-value cryptocurrencies alongside Bitcoin to provide a more comprehensive analysis.

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Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate
Statement the authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest
There is no potential conflicts of interest in this study.

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