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CRYPTOCURRENCY VOLATILITY: BEFORE, DURING AND AFTER COVID-19

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ABSTRACT

The World Health Organization (WHO) announced the Covid-19 pandemic in March 2020, which had a negative impact on economic activities and financial markets. Cryptocurrencies with blockchain technology, whose history is not old, took off in the Covid-19 period thanks to digital transformation and became popular in the financial markets. However, the fact that cryptocurrencies lose blood after the pandemic period. This study examines the volatility of cryptocurrencies before, during and after the pandemic Covid-19 using data from 4 cryptocurrencies (Bitcoin, Ethereum, Binance and Litecoin) and the CCI30 index, using autoregressive conditional variance models with two dummy variables. According to the results, the volatility of cryptocurrencies decreases throughout the pandemic period, moreover, decreases more after the pandemic compared to the pre-pandemic period. Investors should be cautious about investing in these risky instruments, which may become popular again in the future, just in case.

Keywords: Covid-19, Cryptocurrencies, Volatility, Blockchain.

Jel Codes: *G23, O32*.

KRİPTOPARA OYNAKLIĞI: COVID-19 ÖNCESİ, SÜRESİ VE SONRASI

ÖZ

Dünya Sağlık Örgütü'nün (WHO) Mart 2020'de Covid-19 pandemisini duyurması, ekonomik faaliyetleri ve finansal piyasaları olumsuz etkiledi. Geçmişi çok da eski olmayan blockchain teknolojisine sahip kripto paralar, dijital dönüşüm sayesinde Covid-19 döneminde yükselişe geçti ve finansal piyasalarda popüler hale geldi. Ancak, kripto para birimleri pandemi döneminden sonra kan kaybetti. Bu çalışma, 4 kripto para birimi (Bitcoin, Ethereum, Binance ve Litecoin) ve CCI30 endeksi verilerini kullanarak, iki kukla değişkenli otoregresif koşullu değişen varyans modelleri ile kripto para birimlerinin Covid-19 pandemi öncesi, süresi ve sonrasındaki volatilitesini incelemektedir. Sonuçlara göre, kripto para birimlerinin oynaklığı pandemi dönemi boyunca azalmaktadır, bunula birlikte pandemi döneminden sonra pandemi öncesine kıyasla daha da fazla azalmaktadır. Yatırımcılar, gelecekte yeniden popüler olma ihtimali olan bu riskli enstrümanlara yatırım yapma konusunda temkinli olmalıdır.

Anahtar Kelimeler: Covid-19, Kripto paralar, Oynaklık, Blok zincir.

Jel Kodları: *G23, O32*

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INTRODUCTION

The World Health Organization declared the beginning of the outbreak of Covid-19 (WHO, 2023) on 11 March 2020. Since then, the epidemic has spread around the world, profoundly affecting social life and economic markets. There are many studies investigating the impact of the pandemic on macro and traditional financial markets. There are also studies on cryptocurrency, the new technology of the last decade. It is seen that the demand for cryptocurrencies has increased for purposes such as high return expectations, safe haven and portfolio diversification (Almeida, 2022). In general, the literature states that the risks of cryptocurrencies increase only at the beginning of the pandemic period. (Demiralay and Golitsis, 2021; Mariana et al., 2021; Conlon and McGee, 2020; Kececi, 2020).

Bitcoin, the first cryptocurrency, was introduced in 2009 by an anonymous individual named Satoshi Nakamoto. Cryptocurrencies are digital assets that make use of blockchain technology to secure and record transactions. This technology eliminates centralization through user-to-user connectivity, resulting in a decentralized, transparent and participatory system. The decentralized nature of cryptocurrencies distinguishes them from conventional financial systems.

This paper provides a comprehensive overview of the volatility of cryptocurrencies, with a particular focus on the period before, during and after the Covid-19 pandemic. The selected cryptocurrencies are the Bitcoin, Ethereum, Binance and Litecoin, which has the highest market value as of October 2023, as well as The Crypto Currencies Index (CCI30) that calculated index of aggregated 30 cryptocurrencies. The study uses data covering the pre-pandemic, pandemic, and post-pandemic periods from January 2018 to October 2023, including daily return information. The focus of the study is to understand how volatility changed during and after the Covid-19 pandemic in comparison to the pre-pandemic period.

Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) models were used to model cryptocurrency volatility. To investigate how the pandemic affected volatility, the models include two dummy variables in the variance equations: DMY1, representing the period during the Covid, and DMY2, representing the period after the Covid. Notable studies found that cryptocurrency volatility increased at the beginning of the pandemic (Demiralay and Golitsis, 2021; Mariana et al., 2021; Conlon and McGee, 2020; Kececi, 2020). However, the results show that after the Covid-19 pandemic, volatility decreased compared to the pre-pandemic period.

1. Literature Review

1.1. Cryptocurrency Background

The main purpose of cryptocurrency is to represent a digital asset as a medium of exchange, using cryptography to secure all transactions. Everything that appears is controlled by its own system. Cryptocurrencies are a subset of digital currencies. As digital currencies do not have blockchain technology, they are open to abuse. The ledgers in which digital currency transactions are recorded can be copied and altered by parties, and there are barriers to reconciliation. However, because cryptocurrencies are built with blockchain technology, each transaction is encrypted by combining it with the previous block using cryptography. Therefore, it is difficult and costly to resolve the entire block (Türk and Uslu, 2020).

In an article published in 2008, Satoshi Nakamoto defined the technology component of cryptocurrency as a chained cryptographic data block, although the term 'blockchain' is not used precisely (Avunduk and Aşan, 2018). One of the strengths of blockchain technology is that it eliminates centralization through user-to-user connectivity. A blockchain is simply a set of timestamped, immutable data records managed by a cluster of computers that do not belong to a single entity. Each of these blocks of data is secured and linked (i.e. chain) using cryptographic principles. The blockchain network has no central authority and is the very definition of a democratized system. Because it is a shared and immutable ledger, the information it contains is available to all. Therefore, anything built on the blockchain is inherently transparent and participatory. It is possible to list the reasons why the blockchain has gained such admiration as follows (Darlington, 2021):

- It is not owned by a single organization; therefore, it is decentralized.
- Data is stored cryptographically (block link encrypted) within it.
- The blockchain is unbreakable, so no one can undo or change it.

It is still not known for certain who created bitcoin. In the article "Bitcoin: Peer-to-Peer Electronic Payment System" on www.bitcoin.org, Satoshi Nakamoto described the electronic payment system based on encryption without the need for a financial intermediary between the two parties, referring to the "b-money" study by Wei Dai. The first bitcoin blockchain was created on 3 January 2009 (Türk and Uslu, 2020). After bitcoin, many alternative cryptocurrencies, called altcoins, were traded on exchanges. Bitcoin does not have a centralized system; it is not possible to control everything as in electronic banking systems. While in banking systems there are institutions that can issue and print money, there is no such centralization in cryptocurrencies. All information is kept scattered at user points (clients). All information and data are collected using cryptography, and everything passes through blockchains that represent the distributed ledger (Milutinović, 2018).

1.2. Literature for Cryptocurrency Volatility

Although, cryptocurrencies were born in 2009, they were very popular among investors, especially in the first year of the pandemic. With the effect of monetary expansion, many investors turned to this risky instrument. They were also described as a safe haven because they are a high-yielding asset and provide hedge (Mensi et al., 2019). It was obvious that their risks were as high as their returns. There has been a significant decline in the stability of cryptocurrency markets, accompanied by a notable rise in irregularities (Lahmiri & Berikos, 2020). Some prior studies found that volatility increased at the start of the covid pandemic. (Demiralay & Golitsis, 2021; Mariana et al., 2021; Conlon and McGee, 2020; Keçeci, 2020). Besides, cryptocurrency market liquidity has increased significantly after the pandemic started (Corbet et al., 2021).

The cryptocurrency market may not be conducive for investors with a short-term orientation due to the potential for substantial losses within a brief timeframe. However, despite its inherent volatility, the cryptocurrency market demonstrates the ability to attain the greatest excess return relative to the level of risk (Ankenbrand & Bieri, 2018). Evidence suggests that the impact of good news on cryptocurrency's volatility surpasses that of bad news, highlighting an asymmetric effect. This distinctive characteristic aligns with the suitability of cryptocurrencies as a safe haven asset (Almeida, 2022).
This study examines volatility of cryptocurrencies during and after the pandemic period compared to the pre-pandemic period. However, since the volatility of cryptocurrencies in the literature was increased by the beginning of the pandemic, the novelty of this paper is how the volatility behaves after the Covid-19 pandemic.

2. Data and Modelling

2.1. Data

In the study, the interval of data was picked between 2018, January and 2023, October consisting of Covid-19 period. Daily price data of the top 4 cryptocurrencies—Bitcoin (BTC), Ethereum (ETH), Binance (BNB) and Litecoin (LTC), the highest market value as of 2023 October, were used and CCI30. Cryptocurrencies data was obtained from investing.com and CCI30 was derived from cci30.com. Return data was created by calculating from price data as Equation 1.

$$R_i = (P_i/P_{i-1})-1 \quad (1)$$

2.2. Modelling

The aim of this study is to understand the periodical changes in volatilities. For this reason, Literature states that variance changing models provide better results for modelling volatilities in high frequency series (Özer and Ece, 2016; Cheteni, 2016). ARCH and GARCH models are nonlinear econometric models that predict that the variance does not remain constant for financial time series with variable volatility (Ozaydin, 2019). ARCH models are a widely used method in financial market analysis (Gökbulut & Pekkaya, 2014). R program was used for modelling.

Engle (1982) proposed an autoregressive conditional variable variance (ARCH) model, in which the (current) value of the variance of the model's error terms ut in the period t (current) depends on the squares of the past error terms u(t-1,2…n). Bollerslev (1986) introduced a useful model that generalizes ARCH models as GARCH. Developed a model structure with more historical information and flexible delay structure. According to the GARCH model, the conditional variance depends not only on the lagged values of the past period error squares, but also on the past values of the dependent variable's past conditional variance. This model parameterizes volatility as a function of unexpected information shocks to the market (Ozaydin, 2019).

GARCH models assume that volatility responds symmetrically to positive and negative shocks. However, there are cases where this assumption is not valid, and volatility responds asymmetrically to possible shocks. Instead of GARCH models, which are not sufficient to model the leverage effect in financial time series, exponential GARCH (EGARCH) models were first developed by Nelson (1991) to overcome this shortcoming.

$$\log(h_t) = \omega + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) + \sum_{i=1}^{q} \alpha_i \frac{|u_{t-i}|}{\sqrt{h_{t-i}}} + \sum_{i=1}^{q} \gamma_i \frac{u_{t-i}}{\sqrt{h_{t-i}}} \qquad (2)$$

In the EGARCH model (Equation 2), the natural logarithm of the conditional variance is conditional on its lagged values and on the standardized error term $\frac{|u_{t-i}|}{\sqrt{h_{t-i}}}$ instead of the lagged error term squared. At the same time, the conditional variance h_t depends on both the magnitude and the sign of the lagged error terms. Since the EGARCH model takes the logarithm of the conditional variance, the parameters are positive. As a result, the parameters in ARCH and GARCH models do not need to be greater than 0 (there are no restrictions on the parameters α_i and β_i) (Brooks, 2008, p. 406). Here, $\gamma_i \neq 0$ implies that there is an asymmetric effect. If γ is not equal to zero, the impact is asymmetric. If γ does not impact symmetrically, a statistically significant $\gamma > 0$ indicates a leverage effect, in which positive news in the past increases volatility more than negative news. Similarly, a statistically significant $\gamma < 0$ indicates a leverage effect, in which negative shock in the past increases volatility more than positive shock. (Ural & Demireli, 2019).

The general mean equation (Equation 3) and variance equation (Equation 4) are used. A total of five conditional variance models were established. To understand the volatility the before, during and after Covid-19 pandemic two dummy variables were added to variance models. DMY1 is a proxy of during covid period, DMY2 is a proxy of after covid period.

$$R_t = \beta_1 + \beta_2 R_{t-1} + \ldots + u_t,\ u_t \sim \mathrm{N}(0,\ \sigma_t^2) \qquad (3)$$

$$\log(CC_k(h_t)) = \omega + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) + \sum_{i=1}^{q} \alpha_i \frac{|u_{t-i}|}{\sqrt{h_{t-i}}} + \sum_{i=1}^{q} \gamma_i \frac{u_{t-i}}{\sqrt{h_{t-i}}} + DMY1_t + DMY2_t \qquad (4)$$

Rt : Returns of the CCI30, Bitcoin, Ethereum, Binance, Litecoin.

CCk : Variances of the CCI30, Bitcoin, Ethereum, Binance, Litecoin.
DMY1: Dummy variable of the during Covid-19 Period
DMY1: Dummy variable of the after Covid-19 Period

In the case of multiple dummy category variables, one dummy variable is omitted for each category variable and dummy coefficients in the model are relative to left out category. Therefore, two dummy variables included to the variance models as external regressors to compare three period each other. They provide to compare during and after the Covid-19 period compared to pre-Covid-19 period. Number of the Covid-19 death is negatively correlated with cryptocurrencies' price (Demir et al., 2020), so death number was used as a determinant for three periods in the research: before, during and after Covid-19. The World Health Organization reported the start of the Covid-19 outbreak (WHO, 2021) on 11 March 2020. At that time, the number of deaths from Covid-19 increased rapidly. After two years of the covid outbreak, the end of spring in May 2022, deaths due to Covid-19 decreased, as shown in Figure 1. Thus, the during-Covid period is assigned to the DMY1 proxy from 2020, March to 2022, May and the after-Covid period is assigned to the DMY2 proxy from 2022, May to 2023, October.

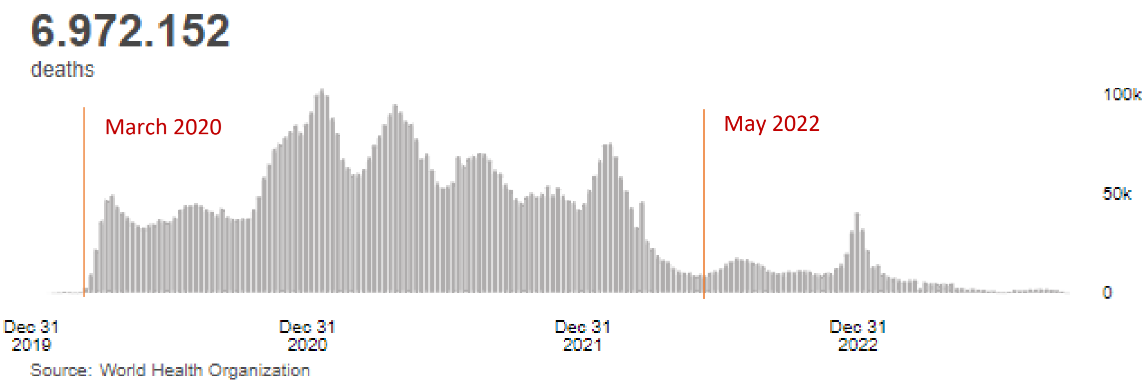

Figure 1. Worldwide Covid-19 Deaths (WHO, 2023)

3. Results

Between beginning of the year 2018 (2 January 2018) and near end of the year 2023 (13 October 2023) descriptive statistics of the series (Bitcoin, Ethereum, Binance, Litecoin and CCI30) are shown in Table 1. Looking at the explanatory statistical values of the data, the classic financial data characteristics show that the kurtosis values are well above the value of 3, which should be within the limits of normal distribution (Table 1).

Table 1. Descriptive Statistics of the Series

Variable	Min	Mean	Med	Max	Std	Var	Skw	Kur
CCI30	-0,3840	0,0005	0,0024	0,2161	0,0423	0,0018	-0,7209	9,6562
BTC	-0,3818	0,0010	0,0004	0,1956	0,0372	0,0014	-0,4032	10,8096
ETH	-0,4455	0,0015	0,0004	0,2596	0,0482	0,0023	-0,3161	9,3743
BNB	-0,4407	0,0030	0,0011	0,6999	0,0558	0,0031	1,8931	30,6211
LTC	-0,3854	0,0008	-0,0005	0,3316	0,0522	0,0027	0,1387	9,2164

Working with time series data, structural breaks, changes in mean and variance can be seen in various, and the series may not be stationary. Including non-stationary series in the regression causes spurious regression (Yerdelen, 2017). For this reason, traditional unit root tests Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) were used in the study to examine whether the daily return series are stationary. Table 2 shows the results of the Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) unit root tests. CCI30, BTC, ETH, BNB and LTC return data are stationary at the 1% significance level according to unit root tests.

Table 2. t-statistics for Unit Root Tests

	ADF									PP		
	none Trend			with Drift			with Trend			with Trend		
Variable	t-stat.	prob.		t-stat.	prob.		t-stat.	prob.		t-stat.	prob.	
CCI30	-17,70	0,00	***	-17,64	0,00	***	-17,65	0,00	***	-49,96	0,00	***
BTC	-32,00	0,00	***	-31,99	0,00	***	-31,99	0,00	***	-49,00	0,00	***
ETH	-31,94	0,00	***	-14,06	0,00	***	-14,08	0,00	***	-49,55	0,00	***
BNB	-30,66	0,00	***	-30,71	0,00	***	-30,70	0,00	***	-47,47	0,00	***
LTC	-33,15	0,00	***	-33,14	0,00	***	-33,14	0,00	***	-49,42	0,00	***

*Note: ***, **, * denotes significance at the level of 1%, 5%, 10%, respectively.*

In the classical least squares method, the assumption is that the variance of the error terms is constant, that is, it does not change over time. However, in the case of changes, such as significant decreases and increases in the series, the error terms are affected and do not remain constant. Therefore, they cannot have a constant variance. This situation, which is particularly prevalent in the case of financial series, gives rise to anomalous and inconsistent results. The ARCH model, introduced by Engle in 1982, was developed to overcome this problem. The ARCH-LM is a test for whether there is an ARCH effect in the study. All variables individually used in the study have an ARCH (Autoregressive Conditional Heteroskedasticity) effect as shown in Table 3.

Table 3. ARCH LM Test Results of the Series

Variable	ARCH Chi-Sq	prob.		Max Lag
CCI30	129,8394	0,00	***	12
BTC	69,6176	0,00	***	12
ETH	115,0682	0,00	***	12
BNB	224,2165	0,00	***	12
LTC	91,1787	0,00	***	12

ARCH effect for all series exists upon 12 lag.

Table 4 shows the statistical values and coefficients of the conditional variable variance models built on the returns of all cryptocurrencies. EGARCH(1,1) model was deployed to all series that gives significant results. Looking at the coefficients of the variance equations: constant term (omega), arch term (alpha), garch term (beta) and asymmetry term (gamma) give significant results. Coefficients of gamma(γ) terms are all different from zero (0) and positive, indicating the existence of asymmetry. Thus, a statistically significant $\gamma > 0$ indicates in which positive news in the past increase volatility more than negative news. (Ural & Demireli, 2019; Sapuric et al., 2020) for the entire data period from the beginning of 2018 to the end of 2023. Almeida et al. (2022) also argue for similar results on the volatility behavior of cryptocurrencies.

Table 4. EGARCH Variance Models Statistics

EGARCH(1,1)	CCI30			BTC			ETH			BNB			LTC		
	Coef.	prob.		Coef.	prob.		Coef.	prob.		Coef.	prob.		Coef.	prob.	
Omega(ω)	-0,47	0,02	**	-0,51	0,02	**	-0,24	0,00	***	-0,24	0,00	***	-0,56	0,00	***
Alpha(α)	-0,07	0,01	***	-0,06	0,01	***	-0,02	0,01	***	-0,02	0,06	*	-0,06	0,00	***
Beta(β)	0,92	0,00	***	0,92	0,00	***	0,96	0,00	***	0,95	0,00	***	0,90	0,00	***
Gamma(γ)	0,20	0,00	***	0,17	0,00	***	0,17	0,00	***	0,29	0,00	***	0,20	0,00	***
Dmy1-during	-0,02	0,11		-0,01	0,44		-0,01	0,06	*	-0,02	0,04	**	-0,02	0,18	
Dmy2-after	-0,08	0,01	***	-0,07	0,02	**	-0,05	0,00	***	-0,07	0,00	***	-0,07	0,00	***

*Note: ***, **, * denotes significance at the level of 1%, 5%, 10%, respectively.*

In the models (Equation 4), dummy variables were added to the variance equation as an external independent variable. The Covid-19 period is assigned to the DMY1 proxy from 2020, March to 2022, May. After the Covid-19 period is assigned to the DMY2 proxy from 2022, May to 2023, October. So, it has been investigated to how periods impact on volatility during and after the pandemic period compared to before the pandemic. During Covid-19 period, just two cryptocurrencies, ETH and BNB, give significant negative results. BTC, LTC and CCI30 index are not significant. All these five variables' coefficients are negative. Thus, result tells that the during Covid-19 period volatility had small decreases compared to pre-Covid period. Some literature found the volatility increased on the beginning of the Covid-19, namely, the risks of cryptocurrencies raised during the pandemic period. (Demiralay and Golitsis, 2021; Mariana et al., 2021; Conlon and McGee, 2020; Kececi, 2020). An explanation for this, new investors who see cryptocurrencies as a safe haven or high-yield investment tool, had an impact on the increase in crypto currency volatility at the beginning of the pandemic period. However, one of this study findings shows that the during pandemic volatility decreased compared to pre-pandemic because research data range covers entire pandemic period, so it is acceptable the differences from other prior literature. The main novelty finding of the paper is that all DMY2 variables' coefficients, which are proxy of the after-Covid period, are significant and negative. Namely, the after Covid-19 period volatility decreased -with high magnitude- more than the during Covid-19 period compared to pre-Covid-19. Thus, cryptocurrencies lost popularity as an investing tool or "asset" on after-Covid period.

Table 5. EGARCH Model Residuals Ljung-Box and ARCH LM Test Results

Residuals	CCI30		BTC		ETH		BNB		LTC	
	Stat.	prob.	Stat.	prob.	Stat.	prob.	Stat.	prob.	Stat.	prob.
Ljung-Box	0,02	0,89	0,13	0,72	1,32	0,25	0,47	0,49	0,02	0,89
ARCH LM Lag [3]	1,65	0,20	0,83	0,36	0,37	0,54	0,66	0,42	1,05	0,30
ARCH LM Lag [5]	4,40	0,14	2,45	0,38	2,20	0,43	1,22	0,67	2,46	0,38
ARCH LM Lag [7]	5,64	0,17	2,73	0,57	2,53	0,61	1,52	0,82	3,10	0,50

Note: Residuals are not autocorrelated. There are no ARCH effect model residuals.

For robustness of the models, ARCH LM test was deployed again later. Results show that there is no ARCH effect in the residuals of models. Besides, the Ljung-Box test result tells there is no autocorrelation problem (Table 5).

CONCLUSION AND EVALUATIONS

There is widespread speculation that cryptocurrencies will be the medium of exchange of the future. The technology and free spirit that underpin cryptocurrencies support such speculation. However, in the digitalized world with the impact of the pandemic, the demand for cryptocurrencies, which are seen as a high-yield opportunity or rather as an investment tool, has increased. It can be said that the increase in the speed of the world's digitalization has made an important contribution. The literature has emphasized the need to pay attention to the risks as well as the short-term returns of cryptocurrencies. The reasons for the increase in volatility in cryptocurrencies can be explained as new inexperienced investors want to get high returns in a short time and trade with incomplete market information pre- and during pandemic.

In this study, how the periods -before, during and after Covid-19 pandemic- effect to the volatility of Bitcoin, Ethereum, Binance, Litecoin cryptocurrencies and CCI30 index, which have the highest market value as of October 2023. The volatilities of cryptocurrencies have increased the beginning of the Covid-19 period according to literature. However, this paper’s result shows that when expanded the time range to end of the Covid-19, volatilities decreased according to pre-pandemic. Moreover, main finding is that, after the pandemic volatilities are lower than during the pandemic. Cryptocurrencies are therefore losing popularity. This result can be explained by the fact that the end of monetary expansion after the pandemic led people to turn to conventional investment assets, i.e. bonds, gold and shares. Moreover, similar to the literature, another finding of this study is that the impact of good news on cryptocurrency volatility outweighs that of bad news. Investors should be cautious about investing in these risky instruments, which tend to become popular future.

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EXTENDED ABSTRACT
GENİŞLETİLMİŞ ÖZET

KRİPTOPARA OYNAKLIĞI: COVID-19 ÖNCESİ, SÜRESİ VE SONRASI

Giriş ve Çalışmanın Amacı: Bu makale, Covid-19 pandemisinin öncesinde, sırasında ve sonrasındaki dönemlerde kripto paraların oynaklığını incelemeyi amaçlayan bir araştırmayı sunmaktadır. 11 Mart 2020'de başlayan Covid-19 salgınının dünya çapında etkilerini anlamak ve kripto paraların bu dönemdeki oynaklığına odaklanmak temel amaçtır. Bitcoin, Ethereum, Binance ve Litecoin gibi en yüksek piyasa değerine sahip kripto paralar ile The Crypto Currencies Index (CCI30) gibi 30 kripto parayı içeren endeks verisi kullanılmıştır. Pandemi öncesi, pandemi sırası ve pandemi sonrası dönemleri kapsayan bu çalışma, Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) modelleri kullanarak kripto para oynaklığını modellemektedir. Sonuçlar, pandemi sonrası dönemde kripto paraların oynaklığının pandemi öncesi döneme göre azaldığını ve bu dönemde kripto paraların popülerliğinin azaldığını göstermektedir. Ayrıca, iyi haberlerin kripto para oynaklığı üzerindeki etkisinin kötü haberlere göre daha fazla olduğuna dikkat çekmektedir.

Kavramsal/Kuramsal Çerçeve: 2009 yılında doğan kripto paralar, özellikle pandeminin ilk yılında yatırımcılar arasında oldukça popülerdi. Parasal genişlemenin etkisiyle birçok yatırımcı, bu riskli enstrümana yöneldi ve yüksek getiri beklentileri ve risk koruma sağlama özelliği nedeniyle güvenli liman olarak kabul edildi ancak getirileri kadar riskleri de yüksekti. Kripto para piyasalarındaki istikrarın önemli ölçüde azaldığı ve düzensizliklerin belirgin bir şekilde arttığı görüldü. Bazı önceki çalışmalar, Covid pandemisinin başlangıcında oynaklığın arttığını bulmuştur. Kripto para piyasası, kısa vadeli yatırımcılar için büyük kayıpların yaşanma potansiyeli nedeniyle uygun olmayabilir, ancak doğasındaki oynaklığa rağmen, kripto para piyasasının, risk seviyesine göre en büyük fazla getiriyi elde etme yeteneğini sergilediği görülmüştür. Olumlu haberlerin kripto paranın oynaklığı üzerindeki etkisinin kötü haberlerden daha fazla olduğuna dair kanıtlar, kripto paraların güvenli bir liman varlığı olarak uygunluğuyla örtüşmektedir. Bu çalışma, pandemi dönemi öncesine kıyasla pandemi dönemi sırasında ve sonrasında kripto paraların oynaklığını incelemektedir. Literatürde kripto paraların pandeminin başlangıcından itibaren oynaklığının arttığına dair bulgulara karşı pandemi sonrası dönemde oynaklığın nasıl davrandığını ele almaktadır.

Yöntem ve Bulgular: Bu çalışma, 2018 yılının başından 2023 yılının sonuna kadar olan dönemi kapsayan Bitcoin, Ethereum, Binance, Litecoin ve CCI30 kripto para serilerinin analizini sunmaktadır. Günlük getiri serilerinin durağan olup olmadığı incelenmiş ve tüm kripto paraların ADF ve PP birim kök testleri ile durağan olduğu tespit edilmiştir. Kripto paraların ARCH etkilerine sahip olduğu bulunmuş, bu nedenle varyans modelleri oluşturulmuştur. EGARCH(1,1) modeli kullanılarak varyans modelleri oluşturulmuş ve asimetri terimlerinin anlamlı olduğu gözlemlenmiştir. Bu asimetri, olumlu haberlerin, olumsuz haberlere göre kripto para oynaklığını daha fazla artırdığını göstermektedir. Esas bulgu olarak, Covid-19 pandemi döneminde ve sonrasında kripto para oynaklığının önceki döneme kıyasla azaldığı tespit edilmiştir. Bulgular, kripto paraların pandemi sonrası dönemde yatırım aracı olarak popülerliğini kaybettiğini göstermektedir.

Sonuç ve Öneriler: Kripto paraların geleceğin değişim aracı olacağı yönünde yaygın bir spekülasyon bulunmaktadır. Teknoloji ve özgürlükçü yaklaşım, bu spekülasyonu desteklemektedir. Pandeminin etkisiyle dijitalleşen dünyada yatırım aracı olarak görülen kripto paralara olan talep artmıştır. Literatür, kısa vadeli getirilerin yanı sıra kripto paraların risklerine dikkat edilmesi gerektiğini vurgulamıştır. Çalışma, Covid-19 öncesi, sırası ve sonrasında Bitcoin, Ethereum, Binance, Litecoin kripto paraları ve CCI30 endeksinin oynaklığı üzerine etkilerini incelemektedir. Literatüre göre, kripto paraların oynaklığı pandeminin başlangıcında artmıştır. Ancak bu çalışma, Covid-19 sonuna kadar olan süreyi kapsadığında oynaklıkların önceden önceki döneme göre azaldığını göstermektedir. Ana bulgu, pandemi sonrası dönemde oynaklıkların, pandemi sırasındakinden daha düşük olduğudur. Kripto paraların popülerliği azalmaktadır. Bu sonuç, pandemi sonrası para arzının sona ermesinin insanları geleneksel yatırım araçlarına yönlendirmesinden kaynaklanabilir. Benzer şekilde, bu çalışmanın diğer bir bulgusu da, kripto paraların oynaklığı üzerinde olumlu haberlerin etkisinin olumsuz haberlerden daha fazla olduğudur. Bu nedenle yatırımcıların bu riskli enstrümanlara yatırım yaparken dikkatli olmaları gerekmektedir.

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