Did the Covid-19 Pandemic Affect the Relationship Between Trading Volume and Return Volatility in the Cryptocurrencies?

Serkan Samut
Karadeniz Technical University
serkan.samut@ktu.edu.tr

Rahmi Yamak
Karadeniz Technical University
yamak@ktu.edu.tr

Summary

In this study, it was investigated whether the Covid-19 pandemic, which started to affect the world in early 2020, influenced the relationship between return volatility and trading volume in the cryptocurrency market. In the empirical part of the study, 40 cryptocurrencies were included in the analysis. The data were divided into two separate periods as before and during the pandemic. Two alternative estimators developed by Garman and Klass (1980) and by Rogers and Satchell (1991) were used to measure the return volatility of cryptocurrencies. With causality and simultaneous correlation analyses, it was determined that the sequential information arrival hypothesis was valid in the cryptocurrency market in the pre-pandemic period. In the pandemic period, the sequential information arrival hypothesis lost its effect and left its place to the mixture of distribution hypothesis.

Keywords: Cryptocurrency Market, Covid-19, Return Volatility, Trading Volume

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The coronavirus, which emerged in China in December 2019 and spread all over the world at the beginning of 2020, caused the restriction of social and economic life in many countries. The Covid-19 pandemic brought along economic uncertainties in the form of a global financial crisis. Preventions and prohibitions taken within the scope of the pandemic have affected many sectors in the economies. The spread of the coronavirus has led to stock market crashes and increased volatility in financial asset prices. (Hong et al., 2021: 2). The pandemic has also led to changes in investment preferences of both national and international investors. Investors have preferred USD and gold from traditional investment tools since the first days of the pandemic. Cryptocurrencies have been one of the new investment tools preferred by investors over time in this pandemic period. The market value of cryptocurrencies, at the beginning of the pandemic in January 2020 was \$195 billion, while in April 2021 by increasing about 10 times it reached \$2 trillion. Similarly, the daily trading volume increased by more than 2 times during the pandemic period, from 63 billion dollars to 144 billion dollars (coinmarketcap.com). In a nutshell, very serious trading volume increases were experienced in cryptocurrencies, especially during the pandemic period.

Since cryptocurrencies are a completely digital technology, their productions and exchanges have remained global and open 24 hours a day, 7 days a week. They are not affected by prolonged national quarantines in the pandemic. Although the cryptocurrency market has been positively affected by the pandemic in terms of both trading volume and return, it is not known whether the causal relationships between trading volume and return volatility in this market have changed with the pandemic. The direction and degree of the causal relationships between these two variables provide important information about the structure and efficiency of the cryptocurrency market. For this reason, it is important to know whether the cryptocurrency market structure, which occurred before the pandemic, continues during the pandemic, in order to predict the future of this digital market, which does not have time and place restrictions.

In the financial economic literature, there are two alternative hypotheses according to the correlation and causal relationship between the return volatility and the trading volume of any financial asset. These hypotheses are the mixture of distribution hypothesis and the sequential information arrival hypothesis. In the mixture of distribution hypothesis, it is assumed that all traders access the information at the same time. Therefore, for the validity of this hypothesis, there should be a simultaneous positive correlation between the return of the financial asset and the trading volume. On the other hand, in the sequential information arrival hypothesis, it is assumed that buyers and sellers do not access new market information at the same time. Therefore, for the hypothesis to be valid, there must be a bidirectional causal relationship between return volatility and trading volume.

The main purpose of the present study is to determine whether the market structure prevailing in the cryptocurrency market before the pandemic continues during the pandemic within the scope of the relationship between the return volatility and trading volume in cryptocurrencies. For the purpose of the study, the probable causal relationships between the return volatility and trading volume of the forty cryptocurrencies were investigated within the scope of time series analysis. The cryptocurrencies were divided into four different categories according to whether the mining process is done and whether there is a supply limit. Thus, the effect of mining and supply limitation on the cryptocurrencies on the validity of both hyotheses was also investigated in this study. In the analysis, the correlation between return volatility and trading volume for each cryptocurrency was obtained by using the Pearson linear correlation coefficient. Causal relationships were investigated by Granger causality test under VAR and Toda-Yamamota methodology. The data set was divided into two periods: before and during the pandemic. While the pre-pandemic period covers the period between September 1, 2018 and December 31, 2019, the pandemic period covers the period between January 1, 2020 and April 30, 2021.

The structure of this study is as follows. In Section 1 applied literature on the subject is presented. In Section 2 the econometric method and variables used in this study are explained. In Section 3 the causal relationship between the return volatility and trading volume in the selected cryptocurrencies is analyzed and the results are discussed. In the last section concluding remarks are presented.

LITERATURE REVIEW

With the release of Bitcoin in 2008, which is a peer-to-peer electronic payment system that works as an independent currency, the interest in cryptocurrencies has increased and since then many cryptocurrencies have been introduced to the market. As of 2021, there are more than 10.000 types of cryptocurrencies (coinmarketcap.com). In the report published by the European Central Bank (ECB) in 2015, it was stated that cryptocurrencies are not legal currencies. However, in the same report, cryptocurrencies are defined as a digital representation of value that is not issued by a central bank, credit institution or e-money institution, which can be used as an alternative to money in some cases (ECB, 2015: 4). Also, in another report published by the ECB in 2019, Crypto asset is defined as a new type of asset that is recorded in digital form and enabled by the use of cryptography, which does not represent a financial claim or obligation on any identifiable asset (ECB, 2019: 3). Although it has been 12 years since Bitcoin was released and many cryptocurrencies have been released during this time, it is still controversial whether cryptocurrencies can be seen as money. This discussion focuses on the functions of money. According to *Luther and White* (2014), especially Bitcoin has the function of being a medium of exchange as in traditional currencies, but it cannot fulfill this function for many reasons. In addition, they argued that the fluctuations in its price hinder the use of Bitcoin as a means of payment and make it risky to hold for a short time. *Ali et al.* (2014) argued that cryptocurrencies are used by relatively few people as a means of payment, primarily as a store of value.

In the early stages of the pandemic, it has been a matter of curiosity whether cryptocurrencies have a safe haven feature for investors. *Corbet et al.* (2020) argued that cryptocurrencies have a safe-haven property similar to precious metals, even when considering the role of negative emotions in the development of the pandemic. *Jana and Das* (2020), on the other hand, claimed that Bitcoin is poorly hedged and therefore not a very safe haven in extraordinary times. According to *Kristoufek* (2020), Bitcoin is not an alternative investment to gold as a safe haven especially in the Covid-19 pandemic. Similarly, *Iqbal et al.* (2020) claimed that the vast majority of cryptocurrencies are able only to absorb the minor shocks of Covid-19. On the other hand, in their study *Lahmiri and Bekiros* (2020) found that the Covid-19 pandemic affected the cryptocurrency markets more than the international stock markets. Therefore, in terms of information efficiency, investing in digital assets during major crisis periods such as the Covid-19 pandemic may be considered riskier than stocks. *Conlon and McGee* (2020) argued that Bitcoin did not have a safe haven feature during the Covid-19 period. According to them, holding Bitcoin in the portfolio along with the S&P 500 significantly increased the investment risk. In another study, *Conlon et al.* (2020) observed that during the Covid-19 pandemic, Bitcoin and Ethereum did not constitute a safe haven for international stock markets. In the same study, it was emphasized that Tether, which is a stable coin, is less risky compared to other cryptocurrencies. However, it was stated that Tether may be unnecessary as an asset because it is pegged to the US dollar. In the same study, it has been proven that this price fixing has not been consistently maintained over the period under consideration and undermines the consistency of hedging features.

In the financial economic literature, there are two competing hypotheses on the relationship between trading volume and return volatiliy. One of them is the mixture of distribution hypothesis developed by *Clark* (1973), *Epps and Epps* (1976), *Harris* (1986) and *Andersen* (1996). The mixture of distribution hypothesis predicts a positive simultaneous correlation between return volatility and trading volume. This hypothesis assumes that the joint distribution of volume and return volatility is conditionally normal depending on the flow of information. All traders access new information at the same time and prices react immediately to this information (Darrat et al., 2003: 2036; Wang et al., 2019: 392). According to this hypothesis, return volatility and trading volume change simultaneously, so the simultaneous correlation coefficient between these two variables should be significantly positive, but there should be no causal relationship between the two variables. The other hypothesis about the causal relationship between return volatility and volume is the sequential information arrival hypothesis developed by *Copeland* (1976) and *Jennings et al.* (1981) and *Smirlock and Starks* (1988). In this hypothesis, it is assumed that new information for buyers and sellers in the asset market is sequential. At first, buyers and sellers are in balance because they have the same information. When new information comes to the relevant market, buyers and sellers can reconsider their expectations. However, new information coming to the market does not reach buyers and sellers at the same time. Thus, when all market participants access new information and revise their expectations accordingly, the final balance in the market is achieved. According to this hypothesis, since the response to information is sequential, there should be a bidirectional causal relationship between these two variables.

In applied literature, *Wang et al.* (2019) investigated the validity of both hypotheses for Bitcoin in fifteen foreign currencies. As a result of linear and non-linear correlation tests, it was determined that the mixture of distribution hypothesis is not valid for Bitcoin. On the other hand, the sequential information arrival hypothesis was found to be valid under linear and non-linear Granger causality analyses. *Balcılar et al.* (2017) and *Bouri et al.* (2019), investigated possible causal relationships on trading volume and return volatility for Bitcoin and for seven leading cryptocurrencies, respectively. Balcılar et al. (2017) determined that trading volume is the Granger cause of return in cases where bear or bull markets are not valid. On the other hand, no causality has been detected for the return volatility and trading volume measured by squares of the return series. In their study, Bouri et al. (2019) found results that trading volume is the Granger cause of crypto returns in the left and right tails of the return distribution. In addition, in the same study, no causal relationship was found in any quantile between trading volume and return volatility. In addition to these studies, *Yamak et al.* (2019) found a bidirectional causality between volume and price volatility for Bitcoin. At the same time, a positive and statistically significant simultaneous correlation was found between the two variables. Both findings support the sequential information arival hypothesis for the Bitcoin market. In another empirical study, *Samut and Yamak* (2018) detected that there is a one-way causal relationship from prices to volume for Bitcoin, Ethereum, Bitcoin Cash and Litecoin. As a result of their findings, it is claimed that the sequential information arrival hypothesis is not valid for the cryptocurrency market.

DATA SET AND METHOD

In this study, unlike previous studies, it was examined whether the Covid-19 pandemic has any effect on the possible causal relationship between the return volatility and trading volume of the forty cryptocurrencies. The price and volume values of the cryptocurrencies were obtained from the website coinmarketcap.com in dollars. The cryptocurrencies analyzed are 0xBitcoin (0xBTC), Bancor (BNT), Binance Coin (BNB), Bitcoin (BTC), Bitcoin Cash (BCH), Bitcoin Gold (BTG), Cardano (ADA), Chainlink (LINK), Dash (DASH), Decentraland (MANA), Decred (DCR), Dero (DERO), Dogecoin (DOGE), Energi (NRG), EOS (EOS), Ethereum (ETH), Ethereum Classic (ETC), Filecoin (FIL), ICON (ICX), INO COIN (INO), IOTA (MIOTA), iExec RLC (RLC), Lisk (LSK), Litecoin (LTC), Monero (XMR), NEO (NEO), NIX (NIX), Peercoin (PPC), Ripple (XRP), Stealth (XST), Stellar (XLM), Storj (STORJ), Stratis (STRAX), Tezos (XTZ), THETA (THETA), TRON (TRX), Ubiq (UBQ), VeChain (VET), Waves (WAVES) and Zcash (ZEC). The price and volume data of these cryptocurrencies are of daily frequency and cover the period of September 1, 2018 - April 30, 2021. In order to see the impact of the Covid-19 pandemic on the causal relationship between return volatility and trading volume, the data was divided into two sub-periods: pre-pandemic and during pandemic. While the pre-pandemic period consists of data between September 1, 2018 and December 31, 2020, the period of the pandemic includes data between January 1, 2020 and April 30, 2021. At the same time, the cryptocurrencies analyzed in the study were divided into four different groups according to whether the mining activity is carried out or not and whether there is a maximum supply limit. While the first of these groups consists of cryptocurrencies with mining activity and maximum supply limit, in the second group, there are cryptocurrencies that have mining activity but the maximum supply limit is not certain. Cryptocurrencies without mining activity are included in the third and fourth groups. Among these cryptocurrencies, those with a maximum supply limit are in the third group, while those whose maximum supply limit is not certain are in the fourth group.

In the applied literature, the volatility measure of any asset price is produced under two different approaches, traditional and modern. The traditional approach is based on the standard deviation of the asset price. This is usually calculated from the daily closing prices of the asset in question. However, if there are more observed prices such as the highest and lowest prices during the day besides closing prices, the standard deviation estimator employing all available intraday prices will give more information about the distribution of the series (Petneházi and Gáll, 2019). In the current study, two alternative volatility measures were produced by using two different standard deviation estimators and each was used separately in causality analyzes. One (GK) of the estimators is developed by *Garman and Klass* (1980) and the other (RS) by *Rogers and Satchell* (1991). GK version of the standard deviation estimator given into equation (1) takes into account not only lowest and highest prices during the day, but also daily opening and closing prices.

$$GK_t=\sqrt{\frac{\sum_{t=1}^{n}0{,}5((lnP_t^H-lnP_t^L)^2-(2ln(2)-1)(lnP_t^c-lnP_t^o)^2)}{n}} \quad (1)$$

In equation numbered (1) above P_t^H, P_t^L, P_t^c and P_t^o represent the highest, lowest, opening and closing prices of the cryptocurrency on day *t*, respectively.

Criticizing the assumption of the GK estimator that the series in question had a continuous Brownian process without drift, *Rogers and Satchell* (1991) developed the RS estimator in equation (2), which allows the existence of drift in the series.

$$RS_t=\sqrt{\frac{\sum_{t=1}^{n}(F_t^1\times F_t^1-F_t^2)+(F_t^3\times F_t^3-F_t^2)}{n}} \quad (2)$$

In equation numbered (2) above

$F_t^1=ln\left(\frac{P_t^H}{P_t^o}\right)$, $F_t^2=ln\left(\frac{P_t^c}{P_t^o}\right)$ and $F_t^3=ln\left(\frac{P_t^o}{P_t^o}\right)$.

After producing the volatility series, the causal relationship between the return volatility (RV) and trading volume (LV) of cryptocurrencies was investigated by Granger causality test under VAR and Toda-Yamamoto methodology. In equations (3) and (4) below, the Toda-Yamamoto causality test is shown.

$$RV_t=\lambda_1+\sum_{i=1}^{k}\beta_{1i}RV_{t-i}+\sum_{i=k+1}^{k+d_{max}}\beta_{2i}RV_{t-i}+\sum_{i=1}^{k}\alpha_{1i}LV_{t-i}+\sum_{i=k+1}^{k+d_{max}}\alpha_{2i}LV_{t-i}+\mu_{1t} \quad (3)$$

$$LV_t=\lambda_2+\sum_{i=1}^{k}\delta_{1i}RV_{t-i}+\sum_{i=k+1}^{k+d_{max}}\delta_{2i}RV_{t-i}+\sum_{i=1}^{k}\theta_{1i}LV_{t-i}+\sum_{i=k+1}^{k+d_{max}}\theta_{2i}LV_{t-i}+\mu_{2t} \quad (4)$$

Where RV is the return volatility produced by the GK and RS estimators, LV is logarithm of trading volume, *k* is optimal lag length, d_{max} is the maximum integrated degree of variables, β_i, α_i, δ_i and θ_i are coefficients of the variables and, λ_1 and λ_2 are constant terms. If α_{1i}'s in equation (3) are statistically significant as a whole, there is a causality from trading volume to return volatility. Similarly, in order to have a causal relationship from return volatility to volume, δ_{1i}'s in equation (4) must be statistically different from zero.

RESULTS

As it is known, in order to investigate the possible causal relationship between any two time series, it is necessary to have a prior knowledge about the stationarities of these variables. For this reason, a stationarity test was applied to both trading volume and return volatility series of 40 cryptocurrencies. The periods before and during the pandemic were taken into account when examining the stationarity of these variables. Augmented Dickey and Fuller (ADF) unit root test was preferred for the stationarity test. Since the variables analyzed in the study were generally stationary in their first differences, the possible causal relationships between both variables were investigated by the Granger causality test under the Toda-Yamamota methodology. However, in some cryptocurrencies, both series were found to be stationarity in their levels. The causality test for these cryptocurrencies was performed using the traditional VAR model. The cryptocurrencies to which the VAR model was applied are Ripple, Cardano, Bitcoin Cash, Theta, Waves, Decred, Peercoin, Ubiq, NIX, 0xBitcoin and Stealth for the pre-pandemic period, and Cardano, Decentraland, Bitcoin Cash, Storj, Ubiq, INO Coin, NEO and iExec RLC for the pandemic period. In all Granger causality analyses, the maximum lag length was assumed to be 30 days and the optimal lag length was determined by by the Akaike Information Criterion (AIC). Critical values for causality tests were calculated by Bootstrap with 1000 iterations.

Correlation coefficients between return volatility and volume for cryptocurrencies with maximum supply limit and mining activities are presented in *Table 1*. For the pre-pandemic perid, a statistically significant correlation coefficient is found in 8 cryptocurrencies for the volatility created by the GK method and in 9 cryptocurrencies for the volatility created by the RS method. The correlation coefficient is positive in BTC, ETC, FIL and ZEC. In the same period, that is, before the pandemic, it is negative and statistically significant in BCH, TRX and DASH. In the pandemic period, there is a statistically significant positive correlation in more cryptocurrencies. Moreover, in almost each cryptocurrency, the significance level of the correlation coefficient calculated for the pandemic period is higher than that of the pre-pandemic period. Cryptocurrencies with a positive correlation to the pandemic period are BTC, BCH, LTC, ETC, TRX, DASH and ZEC. In the pandemic, only FIL and DCR have a statistically significant and negative correlation. When both periods are compared, it is understood that the mixture of distribution hypothesis for cryptocurrencies in the first group has become stronger during the pandemic period. The findings from the

Table 1

CORRELATION COEFFICIENTS BETWEEN VOLATILITY AND VOLUME (FOR THE CRYPTOCURRENCIES WITH MINING AND SUPPLY LIMIT)

Cryptocurrency	GK		RS	
	Before Pandemic	Pandemic Period	Before Pandemic	Pandemic Period
Bitcoin (BTC)	0.364***	0.478***	0.375***	0.499***
Bitcoin Cash (BCH)	–0.185***	0.433***	–0.16***	0.426***
Litecoin (LTC)	0.065	0.561***	0.073	0.562***
Ethereum Classic (ETC)	0.082*	0.441***	0.102**	0.429***
TRON (TRX)	–0.133***	0.445***	–0.169***	0.439***
Filecoin (FIL)	0.163***	–0.228***	0.192***	–0.249***
Dash (DASH)	–0.165***	0.165***	–0.149***	0.152***
Zcash (ZEC)	0.093**	0.112**	0.108**	0.094**
Decred (DCR)	–0.083*	–0.102**	–0.06	–0.144***
Bitcoin Gold (BTG)	0.035	0.13***	0.09*	0.074

Note: ***, ** and * indicate that the coefficient is significant at 1%, 5% and 10%, respectively.

Source: Own edited

correlation analysis are also confirmed by the causality test results reported in *Table 2*.

The number of cryptocurrency that does not have a causal relationship before the pandemic was two (FIL and ZEC), while during the pandemic it increased to three (BTC, FIL and DASH). However, the pre-pandemic positive correlation in FIL, one of these cryptocurrencies, turned into negative with the pandemic. Before the pandemic, there was a bidirectional causal relationship in four cryptocurrencies (BTC, BCH, LTC and TRON), while during the pandemic, only two cryptocurrencies (ZEC and BTG) have had a bidirectional causality. These results obtained in the causality analysis are exactly the same for

Table 2

CAUSALITY TEST RESULTS FOR THE CRYPTOCURRENCIES (WITH MINING AND SUPPLY LIMIT)

Cryptocurrency	H0 Hypothesis	GK		RS	
		Before Pandemic	Pandemic Period	Before Pandemic	Pandemic Period
Bitcoin (BTC)	Volume ↛ Volatility	47.988**	5.929	54.672***	8.107
	Volatility ↛ Volume	54.478**	4.191	83.39***	11.689
Bitcoin Cash (BCH)	Volume ↛ Volatility	43.964*	32.642	44.841*	39.577
	Volatility ↛ Volume	87.474***	77.437***	76.732***	71.503***
Litecoin (LTC)	Volume ↛ Volatility	68.221***	22.965	66.315***	29.45
	Volatility ↛ Volume	95.578***	74.578***	90.613***	70.824***
Ethereum Classic (ETC)	Volume ↛ Volatility	52.802***	37.226	46.323**	38.299
	Volatility ↛ Volume	42.198	55.74***	38.375	50.436**
TRON (TRX)	Volume ↛ Volatility	53.581***	23.799	66.733***	34.76
	Volatility ↛ Volume	87.593***	49.715**	90.941***	50.163**
Filecoin (FIL)	Volume ↛ Volatility	22.954	1.481	21.704	0.72
	Volatility ↛ Volume	32.942	2.311	26.455	1.185
Dash (DASH)	Volume ↛ Volatility	13.405**	32.752	16.224**	32.08
	Volatility ↛ Volume	4.278	30.479	5.494	28.855
Zcash (ZEC)	Volume ↛ Volatility	29.846	15.996**	29.664	19.678**
	Volatility ↛ Volume	29.479	10.504*	33.187	11.961*
Decred (DCR)	Volume ↛ Volatility	50.744*	32.418	47.092*	36.67
	Volatility ↛ Volume	23.801	54.389**	19.513	55.066**
Bitcoin Gold (BTG)	Volume ↛ Volatility	11.728*	48.585**	11.595*	46.785**
	Volatility ↛ Volume	6.724	52.416**	7.637	53.171**

*Note: ***, ** and * indicate that the coefficient is significant at 1%, 5% and 10%, respectively.*

Source: Own edited

the volatility series created by both methods. During the simultaneous evaluation of the the correlation and causality results, it can be concludedthat the sequential information arrival hypothesis - which is dominant before the pandemic, in the market formed by the cryptocurrencies in the first group - lost its validity with the pandemic. However, the mixture of distribution hypothesis is found to be somewhat stronger during the pandemic period. *Table 3* shows the correlation coefficients for cryptocurrencies where mining can be performed but the maximum supply limit is not clear.

Also can be observed from the table, that there are statistically significant positive correlation coefficients in three cryptocurrencies (DOGE, PPC and NIX) for volatility calculated by the GK method in the pre-pandemic period. This number increases to 7 (ETH, DOGE, NRG, DERO, UBQ, 0xBTC and XST) during the pandemic period. However, when the RS method was used, statistically significant positive correlations were detected in 4 cryptocurrencies both before and during the pandemic. While these cryptocurrencies are DOGE, PPC, NIX and XST for the pre-pandemic period, they are ETH, DOGE, 0xBTC and XST in the pandemic period. In addition, for the pre-pandemic period a statistically negative correlation was found between the volatility series and the trading volume in 4 cryptocurrencies (ETH, NRG, UBQ and 0xBTC). However, no statistically significant negative correlation was detected in any of the cryptocurrencies in this group during the pandemic period. Similarly, no statistically significant correlation was found between the return volatility calculated by the GK method and the trading volume in

Table 3

CORRELATION BETWEEN VOLATILITY AND VOLUME (FOR THE CRYPTOCURRENCIES WITH MINING AND WITHOUT SUPPLY LIMIT)

Cryptocurrency	GK		RS	
	Before Pandemic	Pandemic Period	Before Pandemic	Pandemic Period
Ethereum Classic (ETC)	–0.134***	0.558***	–0.093**	0.603***
Dogecoin (DOGE)	0.159***	0.405***	0.216***	0.395***
Monero (XMR)	–0.019	0.054	0.039	0.056
Energi (NRG)	–0.293***	0.109**	–0.314***	0.058
Dero (DERO)	–0.019	0.124***	–0.046	0.07
Peercoin (PPC)	0.096**	0.008	0.106**	0.028
Ubiq (UBQ)	–0.139***	0.152***	–0.159***	0.053
NIX (NIX)	0.301***	–0.002	0.308***	–0.012
OxBitcoin (0xBTC)	–0.114**	0.184***	–0.109**	0.253***
Stealth (XST)	0.068	0.174***	0.108**	0.169***

Note: ***, ** and * indicate that the coefficient is significant at 1%, 5% and 10%, respectively.

Source: Own edited

3 cryptocurrencies for both periods. While there are statistically insignificant correlations in 3 cryptocurrencies using the RS estimator, before the pandemic, this number increased to 6 during the pandemic period. When the correlation results of the pandemic period are evaluated, it is observed that the mixture of distribution hypothesis with the GK method and the sequential information arrival hypothesis with the RS method are valid.

Table 4 presents the causality results for cryptocurrencies where mining can be performed but the maximum supply limit is not clear. According to the table, the mixture of distribution hypothesis became stronger during the pandemic period. This result is

Table 4

CAUSALITY TEST RESULTS (FOR THE CRYPTOCURRENCIES WITH MINING AND WITHOUT SUPPLY LIMIT)

Cryptocurrency	H0 Hypothesis	GK		RS	
		Before Pandemic	Pandemic Period	Before Pandemic	Pandemic Period
Ethereum Classic (ETC)	Volume ↛ Volatility	47.759**	29.834	55.167***	37.332
	Volatility ↛ Volume	65.044***	50.272**	84.345***	57.567***
Dogecoin (DOGE)	Volume ↛ Volatility	26.495	26.679	27.458	39.663
	Volatility ↛ Volume	66.666***	81.81***	64.457***	114.98***
Monero (XMR)	Volume ↛ Volatility	2.667	2.959	2.628	2.404
	Volatility ↛ Volume	10.127	2.323	10.398	2.547
Energi (NRG)	Volume ↛ Volatility	45.394*	1.761	47.869**	1.749
	Volatility ↛ Volume	48.092**	0.845	57.105***	0.823
Dero (DERO)	Volume ↛ Volatility	44.803*	29.935	50.913**	29.47
	Volatility ↛ Volume	34.54	27.063	31.013	27.448
Peercoin (PPC)	Volume ↛ Volatility	8.024*	47.791**	19.7**	57.41***
	Volatility ↛ Volume	5.432	55.271***	9.452	63.582***
Ubiq (UBQ)	Volume ↛ Volatility	34.642	37.711	30.882	33.15
	Volatility ↛ Volume	39.447	57.706***	32.017	61.095***
NIX (NIX)	Volume ↛ Volatility	7.145	2.325	7.513	3.556
	Volatility ↛ Volume	30.811***	2.66	29.245***	2.384
OxBitcoin (OxBTC)	Volume ↛ Volatility	29.535	1.79	30.644	1.176
	Volatility ↛ Volume	25.56	7.057	35.04	5.504*
Stealth (XST)	Volume ↛ Volatility	55.566**	29.018	15.906	29.339
	Volatility ↛ Volume	32.445	32.721	18.001	33.961

Note: ***, ** and * indicate that the coefficient is significant at 1%, 5% and 10%, respectively.

Source: Own edited

more obvious with the GK method. Because, according to the GK method, while there is no causal relationship in 3 cryptocurrencies (XMR, UBQ and 0xBTC) for the pre-pandemic, the number of cryptocurrencies without a causal relationship increased to 6 (XMR, NRG, DERO, NIX, 0xBTC and XST) for the pandemic period. In the RS method, no causal relationship was detected in 4 (XMR, UBQ, 0xBTC, and XST) cryptocurrencies for the pre-pandemic and in 5 (XMR, NRG, DERO, NIX and XST) cryptocurrencies for the pandemic. Furthermore, while bidirectional causality was found in ETH and NRG before the pandemic, it was found only in PPC during the pandemic period. This finding is the same for both volatility estimation methods. As a result, the mixture of distribution hypothesis has become stronger during the pandemic period for the cryptocurrencies in the second group. This result is more evident in the volatility series created with the GK method.

The correlation analysis results for cryptocurrencies with no mining activity but with a maximum supply limit are presented in *Table 5*. According to the pre-pandemic correlation coefficients, there is a statistically significant relationship between the two series in all cryptocurrencies except EOS and XLM. Among the cryptocurrencies with a significant correlation, only XRP has a negative sign. During the pandemic period, a statistically significant positive correlation was detected in all cryptocurrencies in this group. With the correlation coefficient results, it can be argued that the mixture of distribution hypothesis is valid in the cryptocurrencies in the third group both before and during the pandemic period, and this hypothesis is further strengthened with the pandemic.

Table 5

CORRELATION BETWEEN VOLATILITY AND VOLUME (FOR THE CRYPTOCURRENCIES WITHOUT MINING AND WITH SUPPLY LIMIT)

Cryptocurrency	GK		RS	
	Before Pandemic	Pandemic Period	Before Pandemic	Pandemic Period
Binance Coin (BNB)	0.112**	0.537***	0.126***	0.519***
Ripple (XRP)	–0.14***	0.556***	–0.161***	0.526***
Chainlink (LINK)	0.159***	0.107**	0.154***	0.121***
Stellar (XLM)	–0.069	0.549***	–0.067	0.553***
VeChain (VET)	0.347***	0.395***	0.344***	0.423***
EOS (EOS)	0.037	0.316***	0.042	0.299***
THETA (THETA)	0.222***	0.332***	0.203***	0.345***
Cardano (ADA)	0.221***	0.654***	0.223***	0.674***
NEO (NEO)	0.257***	0.404***	0.252***	0.404***
IOTA (MIOTA)	0.328***	0.47***	0.313***	0.489***

Note: ***, ** and * indicate that the coefficient is significant at 1%, 5% and 10%, respectively.

Source: Own edited

This result reached by the correlation coefficients is not fully supported by the causality test findings in *Table 6*. In the pre-pandemic period, the mixture of distribution hypothesis is only supported regarding THETA and MIOTA. On the one hand, in the pandemic period, a causal relationship is observed between the volatility calculated with the GK method and the trading volume in 3 cryptocurrencies (LINK, VET and MIOTA) and only regarding LINK with the RS method. On the other hand, bidirectional causality is detected in 4 cryptocurrencies (XRP, XLM, ADA and NEO) prior to the pandemic. During the pandemic period, bidirectional causality was

Table 6

CAUSALITY TEST RESULTS
(FOR THE CRYPTOCURRENCIES WITHOUT MINING AND WITH SUPPLY LIMIT)

Cryptocurrency	H0 Hypothesis	GK		RS	
		Before Pandemic	Pandemic Period	Before Pandemic	Pandemic Period
Binance Coin (BNB)	Volume ↛ Volatility	51.595**	22.703	53.356**	23.858
	Volatility ↛ Volume	39.96	56.582***	41.875	67.595***
Ripple (XRP)	Volume ↛ Volatility	54.274**	56.704***	57.29**	58.137***
	Volatility ↛ Volume	116.66***	115.71***	118.44***	128.38***
Chainlink (LINK)	Volume ↛ Volatility	70.134***	3.571	36.122	2.919
	Volatility ↛ Volume	36.018	2.11	74.875***	1.814
Stellar (XLM)	Volume ↛ Volatility	56.352***	45.451*	53.487***	54.648**
	Volatility ↛ Volume	56.71***	74.15***	55.186***	92.728***
VeChain (VET)	Volume ↛ Volatility	28.342	37.736	30.829	42.919*
	Volatility ↛ Volume	48.208**	19.015	47.555**	22.493
EOS (EOS)	Volume ↛ Volatility	34.131	35.064	35.567	41.307
	Volatility ↛ Volume	50.937**	99.71***	54.698***	98.711***
THETA (THETA)	Volume ↛ Volatility	40.641	48.646**	38.713	49.949**
	Volatility ↛ Volume	40.921	55.283***	39.43	55.132***
Cardano (ADA)	Volume ↛ Volatility	51.712**	38.564	51.248**	46.576**
	Volatility ↛ Volume	53.861**	47.558*	57.547***	44.866
NEO (NEO)	Volume ↛ Volatility	55.459***	10.926**	65.833***	11.558**
	Volatility ↛ Volume	71.883***	20.578***	75.713***	15.169**
IOTA (MIOTA)	Volume ↛ Volatility	31.329	31.538	39.479	12.053**
	Volatility ↛ Volume	40.806	38.269	32.765	3.705

Note: ***, ** and * indicate that the coefficient is significant at 1%, 5% and 10%, respectively.

Source: Own edited

lost in ADA, but it also occurred in THETA, in addition to the other 3 cryptocurrencies. For the cryptocurrencies in the third group, there was no change in the number of cryptocurrencies supporting the sequential information arrival hypothesis before and during the pandemic.

Table 7 demonstrates correlation coefficients for cryptocurrencies in the last group. Statistically significant correlation coefficients are found in 8 cryptocurrencies (XTZ, WAVES, BNT, LSK, STORJ, INO, RLC and STRAX) for the pre-pandemic. Except for BNT, there is a positive correlation in all of these cryptocurrencies. For the pandemic, a statistically significant positive correlation is determined in 8 cryptocurrencies (XTZ, WAVES, MANA, BNT, ICX, LSK, STORJ and STRAX). At first glance, by looking at the sign and significance of the correlation coefficients, it can be argued that the mixture of distribution hypothesis is valid in the cryptocurrencies in this group and this result has not changed with the pandemic.

Findings from the correlation analysis for the last group of cryptocurrencies are not fully confirmed by the causality results in *Table 8*. For the pre-pandemic period a bidirectional causal relationship exists only in WAVES and INO. During the pandemic, a bidirectional causal relationship is found only for XTZ. In the same period, no causal relationship was determined in WAVES and MANA. This findings obtained for the pandemic period are the same for both volatility estimators. When evaluated in general, it can be said that the sequential information arrival hypothesis, which is weakly valid in cryptocurrencies in this group, and was replaced by the mixture of distribution hypothesis with the pandemic.

Table 7

CORRELATION BETWEEN VOLATILITY AND VOLUME (FOR THE CRYPTOCURRENCIES WITHOUT MINING AND WITOUT SUPPLY LIMIT)

Kriptovaluta	GK		RS	
	Before Pandemic	Pandemic Period	Before Pandemic	Pandemic Period
Tezos (XTZ)	0.293***	0.336***	0.336***	0.358***
Waves (WAVES)	0.377***	0.407***	0.401***	0.424***
Decentraland (MANA)	0.063	0.272***	0.058	0.129***
Bancor (BNT)	-0.151***	0.173***	-0.105**	0.176***
ICON (ICX)	0.012	0.501***	0.017	0.517***
Lisk (LSK)	0.12***	0.435***	0.119**	0.459***
Storj (STORJ)	0.318***	0.275***	0.218***	0.25***
INO COIN (INO)	0.197***	-0.018	0.137***	-0.058
iExec RLC (RLC)	0.181***	0.072	0.17***	0.071
Stratis (STRAX)	0.21***	0.192***	0.218***	0.201***

Note: ***, ** and * indicate that the coefficient is significant at 1%, 5% and 10%, respectively.

Source: Own edited

Table 8

CAUSALITY TEST RESULTS (FOR THE CRYPTOCURRENCIES WITHOUT MINING AND WITOUT SUPPLY LIMIT)

Cryptocurrency	H0 Hypothesis	GK		RS	
		Before Pandemic	Pandemic Period	Before Pandemic	Pandemic Period
Tezos (XTZ)	Volume ↛ Volatility	31.198	8.823*	28.855	11.468**
	Volatility ↛ Volume	43.841*	4.806	41.58*	11.793**
Waves (WAVES)	Volume ↛ Volatility	47.606**	38.763	38.134	42.134
	Volatility ↛ Volume	73.839***	37.754	65.022***	37.781
Decentraland (MANA)	Volume ↛ Volatility	16.646	2.773	17.008	2.678
	Volatility ↛ Volume	3.616	1.399	3.88	0.346
Bancor (BNT)	Volume ↛ Volatility	38.493	16.89	42.118	26.557
	Volatility ↛ Volume	44.17*	47.044**	40.446	51.564**
ICON (ICX)	Volume ↛ Volatility	30.304	31.013	27.819	29.866
	Volatility ↛ Volume	47.883**	55.103***	42.435	58.26***
Lisk (LSK)	Volume ↛ Volatility	32.715	37.455	30.765	41.082
	Volatility ↛ Volume	70.12***	62.062***	55.947***	70.316***
Storj (STORJ)	Volume ↛ Volatility	34.699	37.092	36.905	36.452
	Volatility ↛ Volume	92.718***	44.699*	104.43***	51.55**
INO COIN (INO)	Volume ↛ Volatility	32.623***	45.242*	15.061*	52.218**
	Volatility ↛ Volume	13.008*	33.852	6.493	34.183
iExec RLC (RLC)	Volume ↛ Volatility	27.026	38.961	25.072	41.295
	Volatility ↛ Volume	53.73**	43.927*	45.084*	43.853*
Stratis (STRAX)	Volume ↛ Volatility	25.421	50.146**	23.785	51.985**
	Volatility ↛ Volume	52.384**	32.952	46.905*	37.733

Note: ***, ** and * indicate that the coefficient is significant at 1%, 5% and 10%, respectively.

Source: Own edited

However, the effect of the pandemic on cryptocurrencies in this group is not as explicit as in the other group cryptocurrencies.

CONCLUSIONS

Due to the coronavirus, which emerged in late 2019 and affected the whole world starting from the first quarter of 2020, economic activities in many countries have almost come to a halt. As a result of the Covid-19 pandemic, investors preferred to invest in USD, gold and cryptocurrencies instead of other traditional investment tools.

Especially in the cryptocurrency market, the daily trading volume has increased by 2 times on average throughout 2020. This development in cryptocurrency market shows that the cryptocurrencies have been positively affected by prolonged national quarantines, on the contrary to traditional investment tools. The most important factor that plays a role in this result is undoubtedly that these coins are completely digital and traded 24 hours a day, 7 days a week. Although the cryptocurrency markets have been positively affected by the pandemic in terms of both trading volume and return, it is not known whether the causal relationships between trading volume and return volatility in this market have changed due to the pandemic. The direction and severity of the causal relationships between these two variables provide important information about the structure and efficiency of the cryptocurrency market. Therefore, in order to predict the future of the cryptocurrency market, it is important to know whether the cryptocurrency market structure prevailing before the epidemic is valid during the pandemic.

In this study, it was investigated whether Covid-19 has any effect on the structures of cryptocurrencies markets, based on the correlation and possible causal relationship between return volatility and trading volumes. In this context, 40 cryptocurrencies traded in cryptocurrency market were selected. The analyzed period covers the period from September 1, 2018 to April 30, 2021. In order to observe the effect of the pandemic, the data set was divided into two sub-periods. The first sub-period covers the period from 1 September 2018 to 31 December 2019 and is called the pre-pandemic period. The second sub-period includes the period from 1 January 2020 to 30 April 2021 and is called the pandemic period. In addition, the cryptocurrencies were divided into 4 different categories according to whether the mining process is done and whether there is a supply limit. In the analysis, return volatility series were created with Garman and Klass and Rogers and Satchell methods, based on the opening, closing, lowest and highest price levels of cryptocurrencies during the day. The correlation between the volatility series and the trading volumes was calculated with the Pearson linear correlation coefficient. Causal relationships were investigated by Granger causality test under VAR and Toda-Yamamota methods.

According to the results of the linear correlation coefficient, the mixture of distribution hypothesis, which is valid for the pre-pandemic in cryptocurrencies with mining activities, became stronger during the pandemic period. On the one hand, in cryptocurrencies without mining activities, it was seen that the mixture of distribution hypothesis is valid for both periods and there are no big differences between the two periods. On the other hand, when the causality results are examined, it is observed that the effect of the mixture of distribution hypothesis increased during the pandemic period. However, this increase is not as significant as in the linear correlation coefficient. The most significant increase has been experienced in cryptocurrencies where mining activity is present but the maximum supply limit is not certain. According to the correlation coefficient findings, the sequential information arrival hypothesis is valid for fewer cryptocurrencies during the pandemic period compared to the pre-pandemic period. This finding is independent of mining activity and maximum supply limit, and is also obtained by causality tests, except for cryptocurrencies where there is no mining activity and the maximum supply limit.

In general, it can be stated that the sequential information arrival hypothesis, which was dominant in the cryptocurrency market in the pre-pandemic period, lost its effect during the pandemic, and was replaced by the mixture of distribution hypothesis. The emergence of such a result can be attributed to the large number of new investors entering the cryptocurrency markets, especially during the pandemic period, and the increase in the daily trading volume in cryptocurrencies. In the cryptocurrency markets, another reason why the mixture of distrıbution hypothesis is valid with the pandemic is probably home quarantines around the world. With the effect of staying at home, many people have had a lot of free time to deal with cryptocurrencies, which are technological investment tools rather than conventional investment tools. Therefore, every new information entering the cryptocurrency markets has created the opportunity to reach investors both quickly and simultaneously compared to the pre-pandemic period. However, it may be necessary to repeat the current study after the end of the pandemic in order to make more reliable generalizations. Therefore, it is recommended for future research to reanalyze the relationships between return volatility and trading volume in the same cryptocurrencies within the scope of hypotheses in question. ■

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