Print ISSN: 2288-4637 / Online ISSN 2288-4645
doi:10.13106/jafeb.2021.vol8.no3.0171

The Contagion of Covid-19 Pandemic on The Volatilities of International Crude Oil Prices, Gold, Exchange Rates and Bitcoin

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Received: November 20, 2020 Revised: January 26, 2021 Accepted: February 03, 2021

Abstract

In the international markets, financial variables can be volatile and may affect each other, especially in the crisis times. COVID-19, which began in China in 2019 and spread to many countries of the world, created a crisis not only in the global health system but also in the international financial markets and economy. The purpose of this study is to analyze the contagious effect of the COVID-19 pandemic on the volatility of selected financial variables such as Bitcoin, gold, oil price, and exchange rates and the connections between the volatilities of these variables during the pandemic. For this aim, we use the ARMA-EGARCH model to measure the impact of volatility and shocks. In other words, it is aimed to measure whether the impact of the shock on the financial variables of the contagiousness of the epidemic is also transmitted to the markets. The data was collected from secondary and daily data from September 2th 2019 to December 20th, 2020. It can be said that the findings obtained have statistically significant effects on the conditional variability of the variables. Therefore, there are findings that the shocks in the market are contaminated with each other.

Keywords: COVID-19, Exchange Rate, Crude Oil, Gold. Bitcoin

JEL Classification Code: F30, F31, F65

1. Introduction

Volatility is the fluctuations in financial variables and generally derived from short-term speculations, panic, and epidemics. In an uncertain environment, the returns and risks of these variables determine investor's decisions (hedging, seeking a safe haven, etc.) and the violence of volatilities. Volatilities can be contagious among variables in the global economy due to connectedness to each other. In this study, we selected oil, gold, exchange rates, and bitcoin as financial variables to analyze.

Oil is essential for industrial manufacturing as raw material and a non-renewable source of fossil fuels. Oil prices affect output, unemployment, inflation, trade, and the global economy. And affected by the flow of global production levels that can be changed by wars, revolutions, OPEC's decisions, financial factors, and dollars. The crude oil prices may be more volatile than other energy prices. This volatility can be very sharp in specific times as it was in the 1970s.

Gold has always been precious because of its limited supply during history. After the collapse of the Bretton Woods System in 1971, gold prices were determined by supply and demand in free-market conditions and have begun more volatile. In the short run, gold demand predominately determines the price of gold because of the inelasticity of gold supply (Sjaastad, 2008). However, in the long run, the gold price is determined by both supply and demand. Gold price is mostly affected by political events, uncertainty, and especially monetary macroeconomic variables.

The exchange rate is the price of some foreign currency expressed in terms of a domestic currency (Feenstra & Taylor, 2014), and exchange rate markets are the world's biggest financial markets (Tunç, 2004). There are three types of exchange rate regimes: fixed, flexible, and pegged. The fixed exchange rate can be used to avoid uncertainty and volatility. In general, developing countries choose to anchor

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their currencies to a key currency to have some benefits such as to stabilize the domestic currency prices of their imports and exports, to reduce inflation rates, and to avoid exchange rate volatility. While flexible exchange rate regimes cause to increase in the level of exchange rate uncertainty, the incentives to trade may reduce.

Cryptocurrency is a digital currency using the science of cryptography. It has become one of the most controversial economic concepts in recent years. Bitcoin is the major cryptocurrency, and other cryptocurrencies link to it. Bitcoin is a virtual currency based on computer cryptology and decentralized network (Li & Wang, 2017). It is not represented by a legal currency such as the Dollar and Euro, and it has not indexed any precious metal; and hence it doesn't give any guarantee (Tschorsch & Scheuermann, 2016). It also has a higher volatility than gold and exchange rates.

There are two objectives of this study. The first one is to analyze the contagion effect of the Covid-19 pandemic on the volatility of exchange rates, bitcoin, crude oil, and gold prices. The second one is to investigate the correlations between these volatilities. The section 'Literature Review' consists of two parts. The first part explains the linkage between volatilities of international crude oil price, gold, exchange rate, and bitcoin by theoretical background and empirical results of the studies in the literature. The second part examines what happened due to the Covid-19 pandemic by studies investigating the relationship between the Covid-19 pandemic and mentioned variables. The following section provides an overview of the models used to measure the contagion effect of the Covid-19 pandemic and the relationship between the volatilities in those variables in Turkey. The final section summarizes the chapter and draws together the conclusions.

2. Literature Review

2.1. The Linkages between Volatilities of International Crude Oil Price, Gold, Exchange Rate, and Bitcoin

Because of the globalization and connectivity of the countries, the volatilities in a country's financial markets can be contagious to the other's financial markets. Besides, international correlation increases in periods of high market volatility (Solnic et al., 1996). When volatility occurs in a financial variable, other variables are affected due to connections among them and opportunity costs.

The correlation between exchange rates and crude oil prices has been investigated by many studies. Oil is one of the commodities traded in dollar terms. Therefore, the dollar has an impact on oil prices. Dollar and oil prices are mostly inversely related. Plenty of studies revealed a correlation between exchange rate and oil prices in the long run (Camarero &Tamarit, 2002; Rautava, 2004; Cologni & Manera, 2008; Mensah et al., 2017). Chen and Chen (2007) used panel data analysis for G7 countries between 1972 to 2005. They claimed that real oil prices may be the most effective factor on real exchange rate volatilities. Nikbakht (2010) found the long-run correlation between oil price and exchange rate for OECD countries. Le and Chang (2011) revealed that oil price nonlinearly causes the gold price and thus can be used for predicting the gold price. Brahmasrene et al. (2014) indicated that oil price volatilities had a significant effect on exchange rate changes for the US economy in the medium run and the long run. Fratzscher et al. (2013) demonstrated that exchange rate volatilities have a negative and significant effect on crude oil prices. Singhal et al. (2019) found that oil prices negatively affect the exchange rate in the long run and gold price does not influence the exchange rate in Mexico.

Changes in oil price can affect the gold price as it can also affect other economic variables. Zhang et al. (2009) found a significant co-integration correlation among crude oil and gold prices. Toraman et al. (2011) demonstrated a positive relationship between gold prices and oil prices using the data from 1992 to 2010 with the MGARCH model. Simakova (2011) used the Granger causality test and identified causality between gold and oil price. Zhang and Tu (2016) reported that due to the oil-intensive metal industry of China, the fluctuations in oil price influence gold and other metals in the market. Erdoğdu (2017) investigated the factors affecting the price of gold in the United States with the data from 2003 to 2016 using the exponential GARCH model and revealed that there are a strong linear correlation and a negative correlation among return of gold, oil price, the return of dollar and silver price. Hashim et al. (2017) investigated macroeconomic variables for United States, China, India, Saudi Arabia, and Turkey from 1996 to 2015. They found a significant positive relationship between crude oil price with the gold price. Lodha (2017) found unidirectional Granger causality from crude oil to gold. Stoklasová (2018) revealed an increase in gold prices is followed by the rise of oil prices within one month. Bedoui et al. (2019) found that gold and oil prices are positively influenced each other.

Gold price is highly sensitive to monetary variables, especially to exchange rates, as indicated in many studies in the literature. Sjaastad (2008) indicated that gold prices have frequently changed after Bretton Woods System because of volatile exchange rates. Toraman et al. (2011) also explored a strong and negative relationship between gold prices and the USA exchange rate. Simon and Hausner (2012) showed that gold prices were affected by the euro crisis and reached an all-time high in September 2011 in Switzerland. Srinivasan (2014) used monthly data from 1990 to 2014 with ARDL bound and Granger tests for India. They revealed that exchange rate and gold price are correlated in the long- run. Nair et al. (2015)

also revealed for India that the exchange value of the US Dollar is a key factor explaining the volatilities in gold prices. Yaqoob and Iqbal (2021) found a long-run relationship between precious metals and exchange rates.

Although many studies addressed that bitcoin is uncorrelated with financial assets, for example, with the exchange rates as dollar and Euro (Nakamoto, 2008; Yermack, 2013; Bhattacharjee, 2016; Içellioglu & Ozturk, 2017), other studies defended that bitcoin is correlated to financial assets. Even Ciaian et al. (2015) claimed that oil price is considered a determinant of bitcoin volatility. The main reason for this can be explained by Krugman (2008)'s study in which oil price is the main source of demand and cost pressures. Vassiliadis and Papadopoulos (2017) proved that bitcoin has a cross-correlation with gold and oil price. Okorie and Lin (2020) found bitcoin has a significant and unidirectional volatility spillover to the crude oil markets. For the 2012–2015 time period, there was a high degree of co-movement across the 8–16 weeks frequency band between Bitcoin and gold futures prices, especially when Europe was in a debt crisis (Kang et al., 2019).

2.1.2. What Exactly Happened to Markets During Covid-19 Pandemic?

Covid-19 is an infectious disease caused by a virus that emerged in China in 2019. At the end of 2020, the death toll exceeded one and half million worldwide. Like other epidemics before, Covid-19 has also had economic consequences. Since Covid-19 has begun in China, the Chinese financial market was first affected by pandemic and the volatilities of market instruments spillover worldwide. Because of panic and worsening economic conditions, investors tried to find safe havens, consumers changed their consumption expenditures. As a result, markets have become more volatile during pandemics (Sharma, 2020).

Before the pandemic, the oil market was more efficient during upward trends. In contrast, the gold market was more efficient during downward trends. During the pandemic, these were reversed. It can be said that gold and oil markets became more speculative and Covid-19 has a negative impact on these market efficiency (Mensi et al., 2020). The upward trend of gold is mainly sourced by investors seeking a safe haven. Although its returns turned negative after the pandemic spread to the USA, gold acted safe haven during the pandemic (Dutta et al., 2020; Mzoughi et al., 2020; Omane et al., 2020; Ji et al., 2020), and hence demand and prices for gold increased.

As the virus is contagious, people preferred or were forced to spend much more time in their homes, demand for oil decreased. As the biggest importer, China played a critical role in reducing oil prices due to declining oil demand during the pandemic. Oil prices were almost hourly volatile and reached even negative values. The pandemic caused an increase in daily global oil price volatility by between 8% and 22% (Devpura & Narayan, 2020). The uncertainty caused by the pandemic was a predictor of energy market volatilities (Salisu & Adediran, 2020). Mensi et al. (2020) interpreted that both gold and oil markets were inefficient during the pandemic. Mzoughi et al. (2020) showed the Covid-19 pandemic affected Bitcoin and oil prices adversely.

Covid-19 had a strong, significant, and positive effect on the volatility of the exchange rate (Corbet et al., 2020). As a currency is a significant indicator of the strength of an economy, currencies, and exchange rates were affected by the pandemic. According to the study of Aslam et al. (2020), the Australian dollar, Japan Yen, and Euro were the currencies which efficiency levels decreased during the pandemic.

Bitcoin is highly volatile and has speculative characteristics. Bitcoin's volatility has significantly increased during pandemic (Liu & Lee, 2020). Corbet et al. (2020) found an important and directional effect of the pandemic on the Bitcoin market. Although Chen et al. (2020) demonstrated that Bitcoin failed to act as a safe haven, some studies defended vice versa. Mnif et al. (2020) argued that Bitcoin became more efficient after the spread of the pandemic. Despite the high volatilities, Bitcoin kept its safe haven feature (Bouoiyour & Selmi, 2020; Jalal et al., 2020). Towards the end of 2020, bitcoin prices reached the highest value. The probable reasons may be as follows: it is found as a safe haven and expected to be used in the near future as the increasing importance of hygiene and digitalization due to the pandemic.

Some studies also investigated the effect of the Covid-19 pandemic on connectedness among the financial assets. Omane-Adjepong et al. (2020) found a significant causal effect, and they argued that there was strong volatility spread between exchange rates, gold, bitcoin, oil, and stocks. According to them, gold and US dollar were receivers by pandemic while others were transmitters. Dutta et al. (2020) found a significant change in the correlations among crude oil, gold, and bitcoin.

3. Methodology

Volatility contamination effect is defined as seen in market shocks have a significant additive effect on the volatility of another market. Also, the volatility of the variables is not only by their delayed values but also by the volatility of other variables. It also makes it possible to investigate whether it is affected or not. Unexpected changes occurring in these variables cause significant effects on complex linkages and other economic variables. Shocks occurring in financial markets have a spreading effect and cause price changes. The solution to these complex effects in the market is possible with volatility modeling.

ARCH by Engle (1982) and GARCH by Bollerslev (1986) models are the methods frequently used in estimating

the varying variances of economic variables. Since GARCH models consider the time-dependent variability, it is possible to model the change in the variables' variances. This characteristic is that the variability in economic conditions over time helps to be taken inside the model. GARCH-based models today develop different variations, which is particularly common in financial time series. It enabled asymmetric effects to be evaluated within the scope of the model. So, on the one hand, the effect of external information on variability can be measured; on the other hand, asymmetric features that positive or negative information can be obtained. Therefore, the EGARCH method developed by Nelson (1991) also shows the asymmetric response. It can be used to investigate the contamination effect.

The method used in this study was determined as the ARMA-EGARCH method. This method results from a specific model of a variable established to measure the contamination effect use the residual value. It determines this residue by putting it in the variance equation of the other variable. Residue significant coefficient as an evidence for the presence of contamination effect is being evaluated (Ozengin, 2008).

The method includes a two-step process. In the first stage, each ARMA-EGARCH, which reveals the mean and conditional variance structure for the variable model, is estimated. Second, in the first stage, the shock variable estimated in the first stage is added as a separate variable into the ARMA-EGARCH variance model determined for the other variable. Thus, both asymmetric information and inter-variable the infectious effect can be tested.

In the models shown in Equation (1) and Equation (2), the residual of the system is an indicator of the shocks of the variable in question. Thus, the shock occurring in one variable in the model will be possible to analyze the effect of the variable on its conditional variance.

In the first stage, for each variable (bitcoin, crude oil, gold, exchange rate), the created ARMA-EGARCH model is as follows:

$$R_{a,t} = c + \sum_{i=1}^{r} \tau_i R_{a,t-i} + \varepsilon_{a,t} + \sum_{j=1}^{s} \theta_j \varepsilon_{a,t-j} \quad (1)$$

$$\ln h_{a,t} = \omega_0 + \sum_{l=1}^{p} \alpha_1 \left| \frac{\varepsilon_{a,t-1}}{\sqrt{h_{a,t-1}}} \right| + \sum_{m=1}^{v} \phi_m \frac{\varepsilon_{a,t-m}}{\sqrt{h_{a,t-m}}} + \sum_{k=1}^{q} \beta_k \ln h_{a,t-k} + \psi(K_{b,t}) \quad (2)$$

The variable ($K_{b,t}$) in equation (2) is the ARMA-EGARCH variable of another variable is the residual of the model. Accordingly, the significance of ψ the parameter is the first ARMA-EGARCH of the model; it is obtained by calculating the residual. This shock is evaluated as a finding regarding the presence of the contagion effect on the conditional variance of the other variable.

Another approach in the transmission literature is based on volatility spreading. Regarding the crisis, some authors who drew attention to the volatility that increased during the period investigated the contagion effect chose to determine the spillover effect of volatility. According to the authors who prefer this approach, high volatility in more than one market during a crisis can be considered as an indication that it is moving. Therefore, the volatility spread also shows the smearing or spreading effect.

Another method that has come to the fore in determining the contamination effect in recent years is GARCH-based. It is a Dynamic Conditional Correlation (DCC) model. As stated, investor behavior to determine the crisis transfer arising from change, the correlations decide whether or not it has changed or not has been preferred by many researchers.

4. Results

The sample period discussed in the study covers the period between September 2th 2019, and December 20th, 2020. The data is daily data and has been selected to cover the Covid-19 period. Therefore, it was aimed to investigate the effect of Covid-19 on the financial markets. Within the framework of EGARCH modeling described in the methodology, the appropriate ARMA model was determined firstly, then the EGARCH model was created. Time series are frequently used, especially in finance, which falling steadily or have an upward trend. Thus, the results depending on the analysis made, may not be at a reliable level. In order to obtain correct results, stability tests and the establishment of correct models are essential.

First, to examine the stationarity of the variables used in the analysis, appropriate ARMA models will be selected. At the next stage, if the ARCH effect sought is found in the residues obtained from the model, the stage of selecting the most suitable EGARCH model is initiated.

To test the stationary variables, the Augmented Dickey-Fuller (ADF) test was applied. According to the test results, the stability was achieved by applying the first difference procedure to the non-stationary variables. Hypothesis for the existence of unit root in series at 1% significance level has been rejected. Then the structure of the process of ARMA model estimating has been started. In order to determine the autocorrelation structure of each variable in the determination of the ARMA model, firstly, the correlograms of the variables has been examined. By setting up models for delay values that exceed the limits, AIC and SCI by establishing the most suitable ARMA models according to the criteria, the parameters of the models, its significance has been tested.

Using ARMA models to investigate suitability for ARCH modeling, the presence of the ARCH effect has been studied. It was seen that all variables with the ARCH effect were appropriate for ARCH modeling, and these values were transferred to Table 2.

In Table 3, the estimated α1 for all models included in the Heteroscedasticity equation part was examined. The significance of the parameters and the conditional variances of the variables were analyzed. Accordingly, on conditional variances, it is seen that the information coming to the market is effective at the 5% significance level, except for the exchange rate variable. When the $\alpha 1$ parameters are analyzed, with a parameter of 0.8351, it can be said that the conditional variance of the highest gold prices is affected by the information entering the market. After the gold price variable, the variables most affected by the information in the market are the conditional variances of the variables of bitcoin prices, exchange rate, and crude oil prices, respectively. The variable least affected by the asymmetric information entering the market is the conditional variance of crude oil prices has been with 0.2613.

According to Table 3, the parameter ϕ, which shows the asymmetric effect, is statistically significant for the analyzed variables. It makes sense it is seen to be positive for all variables except gold prices. Hence, negative shocks have a more significant impact on the prices than positive shocks for the gold market. It can be said that it has an effect, and the opposite is true for all other variables. When B1, the parameter which shows the persistence of information entering the market on conditional variance, is examined, it shows whether the volatility and contagiousness are permanent for the variables. It is seen that the effect of information entering the market on conditional variance is permanent for bitcoin, oil prices, exchange rate, and gold prices (0.5013, 0.7378, and 0.4372, with 0.7563 parameter values, 5%, 1%, 1%, 5% significance levels).

Finally, in order to test whether the ARCH effect remains in the models, the ARCH-LM test has been done. The findings shown in Table 3 are the result of this test ARCH effect is not left in the residues. ARMA-EGARCH models were applied to each variable shown in Table 3 residual values for the same period ARMA-EGARCH belonging to another determined variable as an explanatory variable ($K_{b,t}$) for the variance equation of the model has been used.

Thus, in the period examined, the shock occurring in the relevant variable and the significance of its effect on another variable can be tested. Firstly, detection of the contamination effect in ARMA-EGARCH established for both bitcoin and oil prices. The remnants of the model are mutually exclusive to each other's ARMA-EGARCH models, used as an explanatory variable in equations of variance. This way, the significance of the ψ parameter has been tested. The results achieved are that it contains findings that the variables are intertwined in two ways.

Table 1: Augmented Dickey-Fuller (ADF) Test Results Applied for Variables

Variables	ADF Test Statistics	Applied to First Differences ADF Test Statistics
Bitcoin Price	−2.5963 (0.3910)	−8.6237 (0.000)
Crude oil	−6.7902 (0.9152)	−9.3671 (0.000)
Exchange rate	−8.2714 (0.2871)	−10.1276 (0.000)
Gold price	−7.1193 (0.5412)	−9.1125 (0.000)

*Note: *p* values are shown in parentheses.

Table 2: The Preferred ARMA models and ARCH-LM Test

Variables	ARMA Model	Coefficient	*p*-value	ARCH-LM Test (*p*-value)
Bitcoin Price	MA (1)	−0.8614	(0.0000)	(0.0000)
	MA (2)	−0.2153	(0.0000)	(0.0010)
Crude oil	AR (1)	−0.3527	(0.0000)	(0.0006)
	MA (1)	−0.8123	(0.0005)	(0.0000)
Exchange rate	AR (1)	−0.6204	(0.0000)	(0.0000)
	AR (2)	−0.2163	(0.0000)	(0.0000)
	MA (1)	−0.5471	(0.0012)	(0.0002)
Gold price	AR (1)	0.4327	(0.0000)	(0.0000)
	MA (1)	2.0532	(0.0007)	(0.0000)

* Significant at 1% level.

Table 3: ARMA-EGARCH Models Established for Variables

	Bitcoin Price		Crude oil		Exchange rate		Gold price	
	Coefficient	***p*-value**	**Coefficient**	***p*-value**	**Coefficient**	***p*-value**	**Coefficient**	***p*-value**
Mean Equation								
AR (1)			1.4227*	(0.0000)	0.0128	(0.7241)	−0.2133	(0.5698)
AR (2)					−0.4197*	(0.0000)		
MA (1)	−0.4861*	(0.0000)	−0.2148*	(0.0003)	0.7620*	(0.2387)	0.4344	(0.2290)
MA (2)	−0.3781*	(0.0000)						
Heteroscedasticity Equation								
ω_0	−20.2341*	(0.0000)	−3.3187*	(0.0000)	−0.7369*	(0.0000)	−3.7206	(0.0000)
α_1	0.7492**	(0.0005)	0.2613**	(0.0001)	0.5701*	(0.0002)	0.8351**	(0.0005)
ϕ	0.2750**	(0.0003)	0.3650***	(0.0000)	0.3427*	(0.0000)	−0.1754**	(0.0037)
β	0.5013**	(0.0000)	0.7378*	(0.0000)	0.4372*	(0.0000)	0.7563**	(0.0000)
Heteroscedasticity Test								
ARCH-LM	0.1242	(0.4826)	0.2139	(0.8327)	0.3564	(0.4541)	0.1837	(0.4597)

* Significant at 1% level, ** Significant at 5% level, *** Significant at 10% level.

During the epidemic period, which included the Covid-19 period, findings that the shocks experienced in bitcoin caused the volatility of oil prices; in oil prices that the shocks experienced also have a significant effect on bitcoin volatility have been reached in conformity with Dutta et al. (2020) study. Likewise, detecting the presence of contamination effect in the ARMA-EGARCH model established between gold prices and bitcoin, ψ parameter its significance has been tested. The results obtained show that both of these variables contain findings that it is contaminated with each other. During the study period, it was concluded that the shocks mutually affect the gold prices on bitcoin volatility.

Also, the existence of mutual contagion effect between exchange rate and bitcoin has been detected with the ARMA-EGARCH model. The results obtained as a result of the testing the significance of ψ the parameter includes findings that the volatility of variables has bilaterally interfered with each other. During the study period, it was concluded that the shocks experienced in the exchange rate had a significant effect on crude oil prices, gold prices, and bitcoin volatility, and thus were contaminated.

The mutual effects of all variables used in the analysis were tested and evaluated one by one with the help of models. The results obtained are bidirectional analysis of all variables which contains findings that it is contaminated with each other.

5. Discussion

In the time period between 2th 2019 and December 20th, 2020, it is observed that prices of financial instruments fluctuated excessively. Under the results obtained, it can be said that bitcoin, exchange rate, gold price, and crude oil prices are open to speculative effects. Shocks experienced in bitcoin caused the volatility of oil prices; in oil prices that the shocks experienced also have a significant effect on bitcoin volatility that has been reached. Likewise, there is a mutual effect between gold prices and bitcoin volatility. Also, the existence of mutual contagion effect between exchange rate and bitcoin has been detected. The shocks experienced in the exchange rate have a significant impact on crude oil prices, gold prices, and bitcoin volatility, and thus were contaminated.

Considering in general, the price relationship between the gold price and crude oil is often directly proportional. The increase in gold prices causes the value of oil to increase. Likewise, its fall is a harbinger of the negative trend of price movements. Rising oil prices are negatively affected by growth, which lowers share prices. Investors turn to gold in search of alternative investments, and the price of gold increases with the rising demand. In other words, this is the general trend in the relationship between gold and crude oil prices in the markets. In this study, it overlaps with the result that gold prices and crude oil prices, which are among the variables considered during the pandemic process, mutually affect each other.

Exchange rate volatility, fluctuations in the exchange rate and expresses the frequency of fluctuations. Many factors such as the supply and demand for foreign exchange, inflation, interest rate, capital movements cause volatility changes. (Sağlam & Başar, 2016). These changes in the market cause the volatility propagation mechanism. Volatility propagation, resulting from shocks occurring in a market, the transfer of volatility to another market, or change of variables within the economy affects variables (Verma & Jackson, 2012).

6. Conclusions

Coronavirus has been spreading since 2019 and causing serious problems not only in healthcare but also in economic, psychological, and social facts. Due to increasing death rates and contagion, people have changed their living conditions and decisions in the effect of fear and panic. As consumption and investment decisions reshaped, all economic activities and indicators were affected and influenced each other during the pandemic. The financial system was by no means prepared for such an epidemic risk. It was not possible to be prepared, either. Because the current understanding of risk is limited to only modeling the risks that have dealt with in the past. Especially in March 2020, when the pandemic was seen in many countries, the value of bitcoin and other cryptocurrencies decreased. The effect of the same process can be said to have an impact on all markets.

In this study, we aimed to investigate these effects, especially for the period of Covid-19. We examined the volatilities of bitcoin, crude oil prices, exchange rate, and gold prices using ARMA-EGARCH modeling for the time period between 2th 2019–December 20th, 2020. We also analyzed the mutual transmission of shocks in bitcoin, crude oil prices, exchange rate, and gold prices variables. According to the results, gold, exchange rates, oil prices, and bitcoin were very volatile during the pandemic, and Covid-19 had statistically significant effects on the conditional variability of the variables. Therefore, our results show the contagion effect of the Covid-19 pandemic on the bitcoin, oil, gold, exchange markets, and shocks in the market are contaminated with each other.

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