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ÖZGÜN ARAŞTIRMA

The Volatility Transmission Between Cryptocurrency And Global Stock Market Indices: Case Of Covid-19 Period

Sinem ATICI USTALAR [1] , Enes AYAR [2] , Selim ŞANLISOY [3]

Abstract

The uncertainty originated by the COVID-19 pandemic and the unpredictability of both real and financial market indicators have increased the volatility of global financial markets. As a result of globalization, the determination of risk and information transfer between financial markets has gained importance during the pandemic process. In this context, the spread of volatility between the cryptocurrency market and the global stock markets was analyzed by considering the pandemic process. Bitcoin, which represents 42% of the total market cap, was used to represent the cryptocurrency market in the analysis. S&P500, FTSE100, SSEC and NIKKEI indices, which are among the world's leading indices in terms of market cap, were used to represent the global stock market. Constant Conditional Correlation Multivariate GARCH model was used for the analysis of volatility transmission. Daily closing prices covering the date range from 1st December 2019 to 1st July 202 were used for the analyses. The model results were positive and significant for all predicted conditional correlation parameters. In this context, there is volatility transmission and information transfer between BTC and stock returns. The model findings are expected to be a supporting element for financial market participants to make the right decision in the optimal portfolio allocation process.

Keywords: *Cryptocurrencies Market, Stock Market, Volatility Transmission, Constant Conditional Correlation Multivariate GARCH Model*

Jel Codes: *G15, C32, C58*

Kripto Para Ve Küresel Borsa Endeksleri Arasındaki Volatilite Aktarımı: Covid-19 Dönemi Örneği

Özet

COVID-19 pandemisinin yarattığı belirsizlik ortamının yanı sıra hem reel hem de finansal piyasa göstergelerininin öngörülememesi küresel finans piyasalarının oynaklığını arttırmıştır. Küreselleşmenin de bir sonucu olarak, finansal piyasalar arasındaki risk ve bilgi aktarımının belirlenmesi pandemi sürecinde önem kazanmıştır. Bu bağlamda çalışmada, kripto para piyasası ile küresel hisse senedi piyasaları arasındaki oynaklık yayılımı pandemi süreci dikkate alınarak analiz edilmiştir. Analizde kripto para piyasasını temsilen toplam piyasa değerinin %42'sini temsil eden Bitcoin kullanılmıştır. Küresel hisse senedi piyasasını temsil etmesi için ise piyasa değeri açısından dünyanın önde gelen endekslerinden S&P500, FTSE100, SSEC ve NIKKEI endeksleri kullanılmıştır. Oynaklık yayılımının analizi için Sabit Koşullu Korelasyon Çok Değişkenli GARCH modeli kullanılmıştır. Analizlerimiz 1 Aralık 2019 ile 1 Temmuz 2021 tarih aralığını kapsayan günlük kapanış fiyatları kullanılarak gerçekleştirilmiştir. Model sonuçları, tahmin edilen tüm koşullu korelasyon parametrelerinin pozitif ve anlamlı elde edilmiştir. Bu bağlamda, BTC ve hisse senedi getirileri arasında bir oynaklık yayılımı ve bilgi aktarımı vardır. Model bulgularının, finansal piyasa katılımcılarının optimal portföy tahsis sürecinde doğru karar vermeleri için destekleyici bir unsur olması beklenmektedir.

Anahtar Kelimeler: *Kripto Para Piyasası, Hisse Senedi Piyasas, Oynaklık Geçişkenliği, Sabit Koşullu Korelasyon Çok Değişkenli GARCH Modeli*

Jel Kodu: *G15, C32, C58*

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[1]Res. Ass., Atatürk Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, Yakutiye / ERZURUM,
EMAIL: sinem.ustalar@atauni.edu.tr, **ORCID:** 0000-0001-8475-2581.

[2]Master Student, Dokuz Eylül Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, Buca / İZMİR,
EMAIL: ayar.enes@ogr.deu.edu.tr, **ORCID:** 0000-0002-0286-6698.

[3]Ass. Prof., Dokuz Eylül Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, Buca / İZMİR,
EMAIL: selim.sanlisoy@deu.edu.tr, **ORCID:** 0000-0002-0629-0905.

1. INTRODUCTION

The financial markets of many countries are adversely affected by COVID-19 to varying degrees, and the uncertainty created by the pandemic caused the markets to become quite unpredictable and volatile (Zhang, Hu and Ji, 2020: 5). In this stage, it is important for portfolio managers and individual market participants to analyse the volatility transmission in different financial instruments because COVID-19 induced uncertainty in financial markets may impact on optimal portfolio choice of financial investors. In this context, the aim of the study is to analyse the volatility transmission between cryptocurrency Bitcoin and stock markets during COVID-19 period.

Compared to other diseases, the COVID-19 pandemic has caused more dramatic and more frequent daily fluctuations in financial markets than any other previous diseases (Schell, Wang, and Huynh, 2020: 4). As of April 19, 2020, the financial crisis caused by the pandemic in the G7 countries has spread all over the world, as the G7 countries accounted for 59% of the total global cases and 65% of the total number of global deaths (A. Ustalar and Şanlısoy, 2021: 447). In early March 2020 the Coronavirus epidemic caused a sharp decline in economic growth firstly in China, and the epidemic eroded expectations on economic performance in other countries (OECD, 2020). For instance, The Asia Dow fell over 29% from the end of December 2019 until the end of March 2020. Therefore, while trying to predict how far the epidemic will spread, countries have adopted various monetary and fiscal policies to ensure the continuity of stability in their financial markets, and the policies implemented have varied according to the regions (IMF, 2021). On the other hand, increasing case reports on a global scale have increased the uncertainty, and the reflection of the uncertainty on the markets was the deterioration of financial stability. The pandemic era had led to a market environment of uncertainty. Uncertainty leads to risk and panic; in this situation, policy makers devise policies on the face of this uncertainty. This in turn affects the price of financial products. Investors have the tendency to choose financial instruments with relatively lower risks while investing in times of uncertainty (Bilik and Aydın, 2021:22). Therewithal, whereas the Chicago Board Options Exchange Volatility Index (CBOE VIX) was 13.78 on 31st December 2019, when the first viral pneumonia case was reported to the WHO, and the index reached a value of 76.83 one day after, on 12th March 2020, the WHO declared that COVID-19 was an epidemic, and rose to the closing value of 82.69 within a week.[4] During the increasing uncertainty period, the S&P 500 fell by 23.2%, SSEC by 4.2%, NIKKEI 225 by 21.6% and FTSE 100 by 30.6%, while Bitcoin rose by 695%. The environment of uncertainty created by these developments required portfolio managers and individual investors to make significant changes in their portfolios.

Dyhrberg (2016: 144) found that Bitcoin can be used as a hedge against FTSE stocks and can be used against the US dollar in the short-term. Bitcoin has similar features with gold in terms of hedging and it can be included among the tools used for market-specific risk hedging. Ajmi et al. (2021: 940) state that the gold market also led to a sharp decline in the crude oil market, especially during the COVID-19 period, and that the gold commodity acted as a portfolio diversifier rather than a hedging tool during the crisis. Ghorbel and Jeribi (2021: 465) says that while gold is a safe haven for those investing in energy and financial assets during the COVID-19 period, Bitcoin is not. Huang, Duan and Mishra (2021: 8) taking five different regions, found that in each economy, Bitcoin contributes to diversification benefits and/or risk reduction, while its protective role against traditional assets differs between different economies. Shahzad et al. (2019: 328) found that Bitcoin can basically be

[4] "On 31st December 2019, the WHO China Country Office was informed of cases of pneumonia unknown cause detected in Wuhan City, Hubei Province of China." (WHO, 2020)

considered a safe-haven asset given its weak correlation with stock market indices, but the safe-haven feature has changed over time and differed between stock market indices examined.

According to our observations and the mentioned studies, due to the increasing uncertainty on a global scale during the COVID period and depending on other assets in the portfolios of portfolio managers, Bitcoin has entered the portfolio of some financial market participants as a hedging tool and some as a portfolio diversifier. We also stated that while all the stock market indices we included in the sample decreased at different rates, the price of Bitcoin increased approximately six fold.

While discussing how the global financial markets will return to normal after the COVID-19 pandemic, we think that the interactions between the most followed stock market indices and Bitcoin should be scrutinized. This is because understanding the volatility transmission mechanism between different financial markets and the alternative cryptocurrency market over time is important to improve our understanding of these markets. In this context, the interaction between cryptocurrencies such as Bitcoin and traditional stock markets may be another matter of curiosity. This will be something that portfolio managers and individual investors want to know when diversifying their portfolio in a time of uncertainty like COVID-19. When examining the financial markets of the countries affected by the epidemic at different levels, the connection effect between the markets is important. Stock indices are widely used to summarize country markets. However, the movements of Bitcoin, which is accepted as the proxy of cryptocurrencies, during the crisis periods have been the subject of several researches before. Given the severity of the current situation the connection and relations between exchanges in different regions and Bitcoin during the COVID period, which is a crisis period, are worth examining too.

Determining the volatility transmission between financial markets could be a determinant factor in risk analysis and investment decisions of all market participants, as well as domestic and foreign investors. Our findings will be a supportive element for financial market participants to make the right decision in the optimal portfolio allocation process in an environment of uncertainty inflicted by COVID-19. In addition, our findings will be useful in establishing accurate models in asset pricing and in predicting future volatility transmission between different markets.

To test the volatility transmission between cryptocurrency and stock markets, we used the Constant Conditional Correlation Multivariate GARCH (CCC- MGARCH) model. This model takes advantage of the risk transmission and parsimonious estimated parameter than other GARCH models. Bitcoin (BTC) is used to represent the cryptocurrency market, and the S&P500, FTSE100, SSEC and NIKKEI indices are used to represent the global stock market. These indexes have the higher market capitalization values of the world financial markets. CCC-MGARCH model results show that the estimated all conditional correlation parameters are positive and significant that the returns on BTC and stocks rise or fall together. On the other hand, the increase or decrease volatility of BTC increases or decreases to the volatility of stock market returns, and vice versa.

The paper is organised as follows. Section 2 discusses the literature on volatility transmission between Bitcoin and the stock market. Section 3 reviews data and methodology employed. Section 4 discusses empirical results. Section 5 concludes.

2. LITERATURE

There are several studies in the literature that examine the contagion effect of markets or transmission of return and volatility between stocks, bonds, cryptocurrency, and various other commodities. In recent years, studies examining the return and volatility transmission of cryptocurrencies have begun to emerge. However, studies investigating the impact of a crisis period such as COVID-19 on the transmission of returns and volatility between stock markets and cryptocurrencies are quite limited. This study aims to fill this gap in the literature.

We briefly summarize the literature we have discussed. The index created by Diebold and Yilmaz (2008) has an important place in the literature in terms of investigating the dynamics of return spillover and volatility spillover. Ajmi et al. (2021) and, Ghorbel and Jeribi (2021), while examining volatility transmission and spillovers, discussed Bitcoin's hedging tool properties and whether it is a safe haven for various asset classes such as gold, stock market and energy commodities. In addition, Dyhrberg (2016) investigated whether Bitcoin is a hedging tool for FTSE and different parities. Also, Corbet et al. (2020) investigated the contagion effects between the main Chinese stock markets and various assets and commodities including oil, gold and Bitcoin for COVID period. Bala and Takimoto (2017), Luo and Wang (2019) and Uzonwanne (2021) examined the volatility spillover dynamics between international stock markets and various other markets. Yousaf and Ali (2020) investigated how the yield and volatility of Bitcoin, Ethereum and Litecoin pairs affect and transfer between each other. Detailed explanations regarding the related studies are presented below.

Diebold & Yilmaz (2008) have created a simple framework based on the broad Engle et al. (1990) Vector Autoregression (VAR) models to measure the links between asset returns and return volatilities; but their approach become different with focusing on variance decompositions which are already calculated. They investigated the link in the dynamics between return spillovers vs. volatility spillovers and created a spillover index that was formulated to measure these two factors separately, and then they ran it. The tested period in the study is the daily nominal local currency stock market indices in the January 1992–November 2007 date range. 7 developed stock markets and 12 emerging stock markets are included in the scope of the study. The methodology they developed makes it easier to study both crisis and non-crisis occurrences, along with trends and spillover bursts. In summary, as a result of the study emphasizing that volatility spillovers behave differently against return spillovers, the theory that addresses the distinction between return and volatility spreads has been proposed.

Dyhrberg (2016) investigated whether the use of Bitcoin as a hedging tool against the FTSE and exchange rate fluctuations is similar to gold. In the study based on daily observation values for the date range 19th of July 2010 to 22nd of May 2015, the asymmetric GARCH model was estimated in order to define the dynamic relationship between USD-EUR, USD-GBP and Financial Times Stock Exchange Index (FTSE) stocks. According to the findings, while Bitcoin can be used as a hedge against FTSE stocks, it has only short-term hedging capability against the US dollar. With these features, Bitcoin is a hedging tool that can be used for market specific risk.

Katsiampa (2017) discussed the daily Bitcoin Coindesk Index closing prices for the period 18th July 2010 to 1st October 2016. Considering its suitability to the data, it was concluded that the GARCH type model has the best ability to explain Bitcoin price volatility is AR-CGARCH. With the findings of the study, it was determined that Bitcoin, as an asset class, is different from all other assets in the financial markets, and that it can be a useful tool for portfolio and risk management with the role it plays in the markets.

Bala and Takimoto (2017) analysed the market volatility spillovers in selected developed market indices (DJIA, FTSE-100, Nikkei-225) and selected emerging market indices (NSEASI, BVSP, Hang-Seng). They also investigated the impacts of 2008 global financial crisis on stock market volatility interactions and assessed the effect on volatility spillovers. They used weekly adjusted close prices data for indices from Nigeria, Japan, USA, UK, Brazil, and Hong Kong-China markets. The data of the study used the period January 1994 to January 2016. They used seven types of MGARCH variants and BEKK MGARCH type models. The study's findings showed correlations in developing markets are lower than in developed markets, and that they increase during financial crises. As a result, developed markets interact with one another more than emerging markets. Hence, the idea that stock market correlation will be higher during periods of significant market volatility is supported.

To investigate asymmetric volatility transfers in international stock markets Luo and Wang (2019) developed the MHAR-DCC model. The S&P 500, Nikkei 225, Hang Seng, and Straits Times indexes were utilized to span the period from 1st June, 2009 to 31st May, 2014. Two different findings were determined in terms of total volatility transfer effect and asymmetric volatility transfer effect. Accordingly, the highest points in the total volatility spillover indices correspond to the most volatile times in the stock market, and vice versa. Bad news in the turbulent period of the stock market and good news in the stable period has a more important transmission effect.

Yousaf and Ali (2020) used intraday data and employed the VAR-DCC-GARCH model to examine return and volatility transmission among Bitcoin, Litecoin and Ethereum cryptocurrency pairs. They used high frequency hourly data for Bitcoin, Ethereum and Litecoin pairs covering the date range from January 1, 2019, to April 22, 2020. The relevant date range has been made into two samples as the pre-COVID period and the COVID period. The results showed that the return spillovers for the BTC-ETH, BTC-LTC, and ETC-LTC pairs change between the pre-COVID and COVID phases. They found that dynamic conditional correlations between BTC, LTC and ETH pairs are more significant during the COVID phase compared to the pre-COVID phase. Accordingly, during the pre-COVID period, there was no major volatility transmission between any cryptocurrencies. Also, during the COVID period, the volatility spillover is unidirectional from BTC to ETH and bidirectional between ETH and LTC, but it is not substantial between BTC and LTC.

Corbet et al. (2020) investigated the contagion effects between the main Chinese stock markets and various assets and commodities with the impact of the COVID-19 epidemic and examined the dynamic correlation using Shanghai and Shenzhen Stock Markets, representing the Chinese stock markets. The analysis includes the Dow Jones Industrial Average (DJIA) as a measure of worldwide financial performance, as well as oil and gold as indicators of safe haven and Bitcoin for diversification purposes. According to the analysis made with high-frequency daily and hourly data, sharp increases were seen in the dynamic correlations between Chinese stock indices and gold and Bitcoin markets at the beginning of the COVID-19 epidemic. Results show that, in times of high financial stress stages like COVID-19, cryptocurrencies act as a contagion amplifier, not as a hedging or safe haven. Furthermore, the analysis reinforces the literature that claims there is a substantial adverse association between Bitcoin and gold coin sales.

Uzonwanne (2021) adopted to determine whether the peaks and troughs in one of the stock and Bitcoin markets cause volatility spillovers in the other markets' purpose in his study. The study confirmed returns and volatility spillovers between the five major stock markets S&P 500, FTSE 100, CAC 40, DAX 30 and Nikkei 225 indices and the Bitcoin market based on daily data covering the date range March 2013 to March 2018. In the study, using a multivariate VARMA-AGARCH model was found that volatility spillovers are bidirectional in some markets and unidirectional in other markets. Investors migrate between the relevant market pairs at the peak and through points of the stock market for profit maximization and risk aversion purposes, resulting in spillover of returns and volatility.

In their article, Ajmi et al. (2021) looked at how volatility was transferred across equities, gold, and crude oil before and during the COVID-19 crisis. The sample, which started from the date 02.01.2019 and ended at the date 05.10.2020, was divided into two periods, the pre-COVID period and the COVID crisis period. In the study using multivariate VAR and BEKK-GARCH methodology the findings demonstrate that hedging opportunities have decreased over the COVID-19 period, whereas market interconnectivity has increased during the crisis. In particular, the sharp decline in the crude oil market in the COVID-19 period was led by the stock and gold markets. In addition, it was revealed that the gold commodity acted as a portfolio diversifier rather than a hedging instrument during the crisis.

Aydın and Yıldız (2021), investigated the impact of pandemic, having versatile effects, on financial instruments in Turkey. In this context, the variables of share certificate closing prices, gold prices per gram, USD/TRY exchange rates, Bitcoin, and overnight repo interest rates were considered as alternative financial instruments. The impact of COVID-19 pandemic was measured by the numbers of active cases, and deaths. In the study, by the use of daily return series regarding the aforementioned variables, analysis was made for the period between January 02, 2020 and July 30, 2021 with the help of EGARCH model. As distinct from literature, by the half-life volatility modeling, the asymmetric volatility construct of alternative investment instruments against the shocks in the period of COVID-19 pandemic was estimated, and shocks' period of effect was calculated. According to the results obtained, it was observed that the permanence of volatility was present on Bitcoin and interest rate, and on the other hand that the permanence period of shock on volatility was low in gold market.

Ghorbel and Jeribi (2021) investigated the volatility relationship between energy commodity prices and financial assets and indicators during COVID-19. S&P500, FTSE, Nikkei, CAC40, Dax30, S&P/TSX and FTSEMIB G7 stock market indices, NYSE energy index, WTI oil, Henry Hub Natural Gas spot prices, Bitcoin and gold prices were included in the study. Daily frequency-based values were used for the date range from January 1, 2016 to July 23, 2020 in the study in which the volatility spillover was tested by creating a regime change on the volatility dynamics of the pandemic with multivariate MS-GARCH models. According to the results, there is a significant dynamic correlation between energy assets and stock indices during the COVID-19 period, proving the contagious effect of the pandemic. However, throughout the same time span, the relevant connection between energy assets and gold prices has weakened. In conclusion, while gold is a safe haven for individuals investing in energy and financial assets during the COVID-19 pandemic, Bitcoin is not.

3. EMPIRICAL METHODOLOGY AND DATA

The relationship across financial market indicators, the risk transmission and spillover across markets, and finally, investor perceptions towards the creation of optimal portfolio structures are changing via the globalization of the world financial markets. So the price movements in one financial market can spread easily and instantly to other financial markets (Ural and Demireli, 2015: 24). Therefore, it is important to use models that take into account the risk transmission across different financial assets and decompose the effects of shocks. For this purpose, the use of multivariate GARCH models has increased. The GARCH model was created by Bollerslev (1986) by extending and generalizing the conditional variance of the ARCH model by taking a generalized derivative containing its own past values. One of the most used models is the constant conditional correlation (CCC) model.

CCC-MGARCH model was developed by Bollerslev (1990) . The CCC MGARCH model is derived as follows:

$$y_t = Cx_t + \epsilon_t \tag{1}$$

$$\epsilon_t = H_t^{1/2} v_t$$

In Eq. (1), y_t is $mx1$ vector of the dependent variable, C is mxk matrix of the parameters and x_t is $kx1$ vector of the independent variables that include the lags of y_t. H_t is the time-variant conditional covariance matrix and $H_t^{1/2}$ is also the Cholesky factor. v_t is I.D.D. innovations. So the conditional covariance matrix is defined in Eq. (2). The conditional covariance matrix, H_t, includes both the conditional variances and unconditional variances.

$$H_t = D_t^{1/2} R D_t^{1/2} \tag{2}$$

In Eq. (2), D_t is the diagonal matrix of conditional variances and defined in Eq. (3):

$$\mathbf{D}_t = \begin{pmatrix} \sigma_{1,t}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{2,t}^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{m,t}^2 \end{pmatrix} \tag{3}$$

One of the $\sigma_{i,t}^2$ values are taken from the following univariate GARCH models. These models are shown in Eq. (4) and Eq. (5).

$$\sigma_{i,t}^2 = s_i + \sum_{j=1}^{p_i} \alpha_j \varepsilon_{i,t-j}^2 + \sum_{j=1}^{q_i} \beta_j \sigma_{i,t-j}^2 \tag{4}$$

or,

$$\sigma_{i,t}^2 = exp\left(\gamma_i z_{i,t}\right) + \sum_{j=1}^{p_i} \alpha_j \varepsilon_{i,t-j}^2 + \sum_{j=1}^{q_i} \beta_j \sigma_{i,t-j}^2 \tag{5}$$

In Eq. (5), γ_i is the $1xp$ vector of the parameters and z_i is the $px1$ vector of the independent variables that include the constant term. α_j and β_j parameters stand for the ARCH and GARCH parameters of the model, respectively. R variable in Eq. 1 is also defined as the matrix of time-varying unconditional correlations of the standardized errors. It is shown as Eq. (6):

$$R = D_t^{-1/2} \varepsilon_t \tag{6}$$

Bollerslev (1990) bases H_t being positive on the assumption that the unconditional correlation, R, is positive. The representation of R in matrix format is shown in Eq. (7).

$$\mathbf{R} = \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1m} \\ \rho_{12} & 1 & \cdots & \rho_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1m} & \rho_{2m} & \cdots & 1 \end{pmatrix} \tag{7}$$

In Eq. (7), ρ_{im} is invariant to time, so R unconditional correlation matrix is also time-invariant. Thus, this model is defined as a constant conditional correlation multivariate GARCH model.

We conduct the CCC-MGARCH model with 579 observation values covering the date range from 1st December, 2019 to 1st July, 2021. The indices discussed in the study have been selected from the leading stock market indices, which have the largest share in terms of global market value and have been adopted by market participants. In index selections, indices that are widely used in similar studies were preferred in order to be compared with the literature more accurately. The world's largest stock exchanges and selected indices by market value are shown in Table 1.

Table 1: Global Stock Market Ranking by Market Capitalization

Rank	Stock Market	Market Cap (Trillion USD)	Country	Chosen Index
1	NYSE	24,9	United States	S&P 500
2	NASDAQ	22,53	United States	-
3	Shanghai Stock Exchange	7,27	China	SSEC
4	Tokyo Stock Exchange	6,6	Japan	Nikkei 225
5	Hong Kong Exchanges Group	6	Hong Kong	-
6	Shenzhen Stock Exchange	5,59	China	-
7	London Stock Exchange	3,8	United Kingdom	FTSE 100

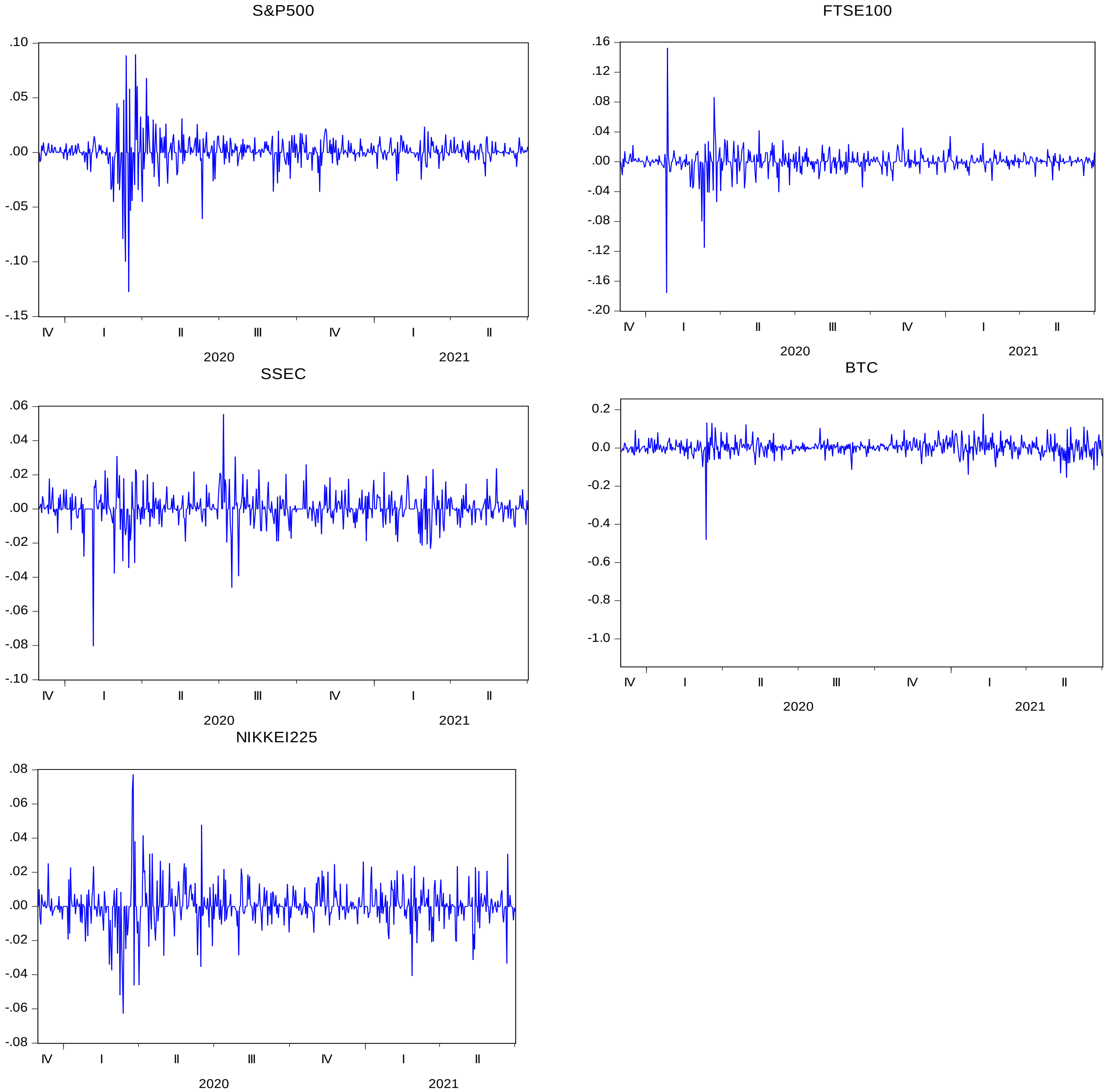
Source: tradinghours.com

Bitcoin accounts for 42% of the global cryptocurrency market cap of approximately $2.5 Trillion (Coinmarketcap). That's why we chose Bitcoin to represent the cryptocurrency market. The four indices we chose to represent the global financial markets are S&P 500 from New York Stock Exchange, SSEC from Shanghai Stock Exchange, Nikkei 225 from Tokyo Stock Exchange and FTSE 100 from London Stock Exchange. In addition, for Bitcoin prices, we used Bitfinex Exchange prices with a volume of 61.3 million dollars in order to be a widely used source in the literature and to compare the results more consistently with existing studies (Bitcoinity). Bitcoin accounts for 42% of the global cryptocurrency market cap of approximately $2.5 trillion, that's why we chose Bitcoin to represent the cryptocurrency market (Coinmarketcap). We used daily closing prices for all variables and accessed all the data on the investing.com website. We calculated logarithmic returns using the logarithmic transformation, which provides increased consistency by reducing the variance of the estimators over the series, look Eq. (1).

$$r_{it} = ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right) \tag{8}$$

In Eq. (8), p_{it} is the price of the asset i at time t, r_{it} is the return of the asset i at time t. The return graphs of the stock market indices are presented in Figure 1.

Figure 1: Return Charts for Bitcoin and Stock Market Indices



Whether the variables considered in the analysis contain a unit root was tested with Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. In addition, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, which directly tests the stationarity by testing the presence of deterministic effects in the series, was also applied.

4. EMPIRICAL MODEL RESULTS

Series of financial assets with random walk feature may contain unit root and may not be stationary. For this reason, it is necessary to examine the descriptive statistics of the variables and to control the stationarity of the series. Also, the time-varying variance of the error terms of the high-frequency logarithmic return series obtained from the prices of financial assets requires testing the ARCH effect.

Descriptive statistics analysed to obtain more detailed information about the return series and; ADF, PP, KPSS test results; and also ARCH test results are presented in Table 2.

Table 2: Descriptive Statistics, Unit Root and Stationary Tests, ARCH Test Results

	BTC	S&P500	SSEC	NIKKEI225	FTSE100
			Descriptive Statistics		
Mean	0.002565	0.000550	0.000385	0.000361	-0.000053
Median	0.001833	0.000000	0.000000	0.000000	0.000000
Maximum	0.178685	0.089683	0.055543	0.077314	0.152618
Minimum	-0.480904	-0.127652	-0.080391	-0.062736	-0.175813
Std. Dev.	0.041312	0.014996	0.009615	0.012042	0.016189
Skewness	-2.285526	-1.167687	-1.049817	0.177002	-1.464849
Kurtosis	30.45267	22.63919	15.37296	10.97055	46.21262
Jarque-Bera	18685.86	9436.53	3799.65	1535.68	45256.42
	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)
			Unit Root Tests		
ADF Test	-27.7346a	-6.3966b	-24.3890a	-14.8646b	-28.8477b
PP Test	-27.4921a	-30.1674b	-24.3889a	-23.3397a	-28.9490b
KPSS Test	0.1696b	0.0818a	0.0364a	0.1438a	0.1945a
			ARCH Test		
ARCH	0.193462	19.58873	1.116416	20.79451	7.823507
	(0.9987)	(0.0000)	(0.3437)	(0.0000)	(0.0000)
Observations	567	567	567	567	567

Note: It represents the minimum test statistic value for each variable obtained from a: with constant term, b: with constant & trend, c: without constant & trend equations. The critical values of MacKinnon (1996) at the 1% significance level for the ADF and PP Test are -3.441434 for with constant term equation (a), -3.974012 for with constant & trend equation (b), and -2.568969 for without constant & trend equation (c), respectively. Asymptotic critical values at 1% significance level for the KPSS test; it is 0.7390 including constant-term test results, and it is 0.2160 including constant-trend test results. The ARCH test was performed with lag of 12. The values in brackets are the probability values of the relevant values

Descriptive statistics of Bitcoin and world stock market indices are shown in Table 2. When we look at the standard deviation values to get an idea of the market volatility, Bitcoin shows higher volatility than all stock market indices, but the SSEC index shows the highest volatility among stock market indices. According to the Skewness values, which are an asymmetry indicator, all series are affected by negative developments and news in the market and show negative skewness, and all series are asymmetrical, the index most affected by negative developments is Nikkei 225. Kurtosis values greater than three, which is the critical threshold, indicate that leptokurtic features are observed in the series (Kallner, 2018). Therefore, the effect of an external shock to the series is relatively more permanent for the FTSE 100 compared to other indices. Looking at the statistical values of the Jarque-Bera test, which tests the normality assumption of the series, none of the Bitcoin and index return series have a normal distribution feature.

Augmented-Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Philips-Perron (PP) (Philips and Perron, 1988) tests were performed to test whether the return series contained a unit root, and the Kwiatkowski-Philips-Schmidt-Shin (KPSS) (Kwiatkowski *et. al.*, 1992) test to examine the stationarity of the series. According to the ADF and PP unit root test results, for each of the Bitcoin and index return series, the null hypothesis testing the existence of the unit root in the series is rejected at the 1% significance level. Parallel with this, the KPSS test results, which directly tests the stationarity of the series, the null hypothesis, which tests that the stationarity is valid for all return series, are accepted at the 1% significance level. All return series do not contain unit roots and are stationary at I(0).

The existence of variance in the return series is tested using the ARCH test, which is performed by determining the optimum ARMA structure. According to the ARCH test results, the null hypothesis testing the absence of varying variance in error terms for all indices and Bitcoin return series is rejected. Accordingly, the error term of all series varies with time.

In the CCC model, Bollerslev (1990) assumed that the conditional correlation matrix is constant over time. Therefore, Tse (2000) developed a method to test constant correlations. The null hypothesis tests the validity of the CCC-MGARCH model, which assumes that the conditional correlation is constant over time, and the alternative hypothesis tests the validity of the DCC-MGARCH (Dynamic Conditional Correlation) model, which assumes that the conditional correlation is variable over time. The LM test results of Tse (2000) are presented in Table 3.

Table 3: LM Test of Tse (2000) for constant correlation

	S&P500	**FTSE100**	**SSEC**	**NIKKEI**
LMC	1.7907 (0.1828)	1.7683 (0.1835)	0.5357 (0.4641)	4.5056 (0.2197)

Note: The values in parentheses are the probability values of the relevant test statistic.

Accordingly, the null hypothesis proposing the CCC model is accepted in all models. Since the conditional correlation between Bitcoin and S&P500, FTSE100, SSEC and NIKKEI indices is constant over time, the CCC-MGARCH model is preferred. Model results are presented in Table 4.

Table 4: GARCH (1,1)-CCC Model Results for Volatility Transmission

	S&P500	**FTSE100**	**SSEC**	**NIKKEI**
Conditional Variance Eq. for BTC				
$ARCH_{BTC}$	0.1430* (0.1331)	0.1430* (0.1331)	0.1430* (0.1331)	0.1430* (0.1331)
$GARCH_{BTC}$	0.8537* (0.0530)	0.8537* (0.0530)	0.8537* (0.0530)	0.8537* (0.0530)
$ARCH_{BTC} + GARCH_{BTC}$	0.9967	0.9967	0.9967	0.9967
$constant\ term$	0.0050* (0.0020)	0.0050* (0.0020)	0.0050* (0.0020)	0.0050* (0.0020)
Conditional Variance Eq. for INDEXs				
$ARCH_{INDEX}$	0.2085* (0.0605)	0.2124** (0.1029)	0.0405** (0.0205)	0.0934** (0.0384)
$GARCH_{INDEX}$	0.7857* (0.0371)	0.6236* (0.0871)	0.9118* (0.0203)	0.8516* (0.0651)
$ARCH_{INDEX} + GARCH_{INDEX}$	0.9942	0.8360	0.9523	0.9451
$constant\ term$	0.0010* (0.0003)	0.0006*** (0.0005)	0.0004*** (0.0003)	0.0006*** (0.0003)
Conditional Corelation Eq.				
$\rho(BTC, INDEX)$	***0.2472* (0.0375)***	***0.1549*** (0.0919)***	***0.0727** (0.0324)***	***0.1069** (0.0446)***
Q(5)	21.5581 (0.3649)	20.9556 (0.3997)	33.6435 (0.0286)	46.5579 (0.0006)
Q(10)	49.5257 (0.1437)	33.6424 (0.7507)	44.8075 (0.2771)	61.8397 (0. 1490)
$Q^2(5)$	22.7651 (0.1997)	8.2313 (0.9749)	8.1203 (0.9768)	58.5066 (0.0000)
$Q^2(10)$	35.0560 (0.6063)	9.2796 (0.9999)	11.4179 (0.9999)	75.2758 (0.2845)
Observations	579	579	579	579

Note: The values in parentheses are the standard residuals values of the relevant coefficients. Li and McLeod's Multivariate Portmanteau Statistics is used for serial correlation and heteroscedasticity. The values in parentheses are the probability values of the Li and McLeod's test statistic.

In the CCC-MGARCH model, the lagged values of the BTC variable and stock market indices are added to the conditional mean equation, but they are not included in the model because they are statistically insignificant. This shows that there is no mean equation for BTC, S&P500, FTSE100, SSEC and NIKKEI and that these variables have no effect on the estimated conditional variance parameters.

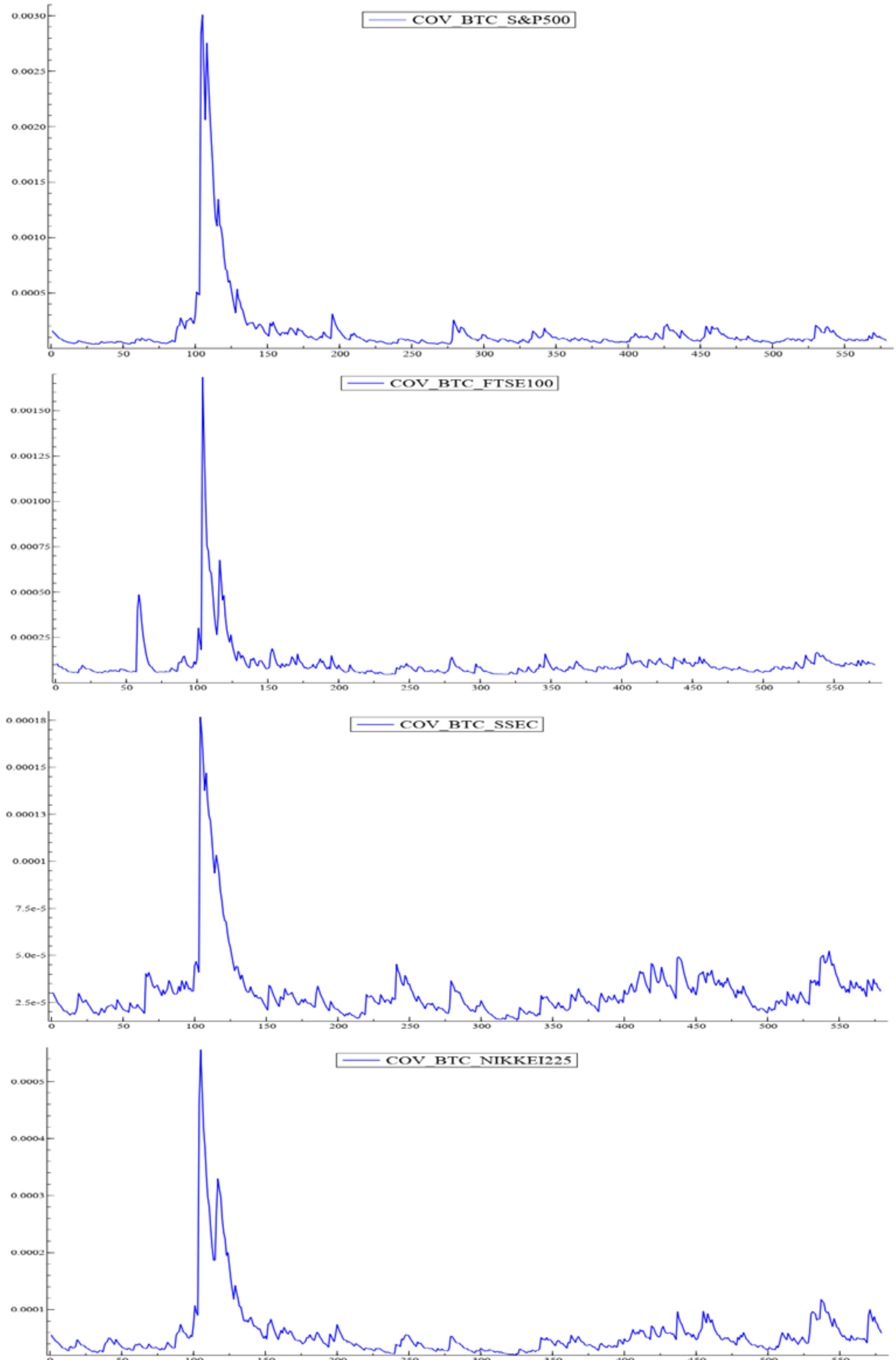
According to the CCC-MGARCH model results, the estimated ARCH parameters measure the magnitude of the shock occurring in the system. The ARCH parameter of the BTC variable (0.1430) is smaller than the ARCH parameters of the S&P500 (0.2085) and FTSE100 (0.2124) variables. This shows that a shock in the S&P500 and FTSE100 index returns is greater than the shock in BTC's return. On the contrary, the ARCH parameter of the BTC variable is larger than the ARCH parameters of the SSEC (0.0405) and NIKKEI (0.0934) variables. Thus, the shock to the BTC return is greater than the shock to the SSEC and NIKKEI index returns.

The estimated GARCH parameters measure the persistence of the shock occurring in the system. The GARCH parameter obtained from the BTC equation (0.8537) is greater than the GARCH parameters calculated from the S&P500 (0.7857), FTSE100 (0.6236) and NIKKEI (0.8516) equations. Thus, the persistence of a shock in the return of BTC is higher than the persistence of a shock in the S&P500, FTSE100 and NIKKEI index returns. Since the GARCH parameter of the SSEC (0.9118) variable is calculated higher than BTC, the persistence of the shocks to the SSEC index return is higher than the return of BTC.

The ρ parameter shows the conditional correlation between the standardized residuals for BTC and stock market indices returns. The conditional correlation between the for BTC and S&P500, FTSE100, SSEC and NIKKEI indices returns is estimated to be 0.24, 0.15, 0.07 and 0.10, respectively. And that all the estimated conditional correlation parameters are positive and significant that the returns on BTC and stocks rise or fall together. A positive ρ parameter indicates the existence of volatility transmission between BTC and stock market indices. The estimated conditional correlation parameters are estimated higher for S&P500 index and lower for SSEC index than other stock market indices.

Each of the univariate ARCH, univariate GARCH, and the conditional correlation parameters are statistically significant. In order to satisfy the conditional variance positivity condition in univariate GARCH models, the constraint is placed on the model to be positive for ARCH and GARCH parameters and their sums less than 1 (Bollerslev, 1987). According to the CCC-GARCH model results, the estimated ARCH and GARCH parameters of both BTC and stock market indices are positive and their sums are less than 1. Thus, the model complies with GARCH constraints and can be used for analysis of volatility transmission. Post-model diagnostic statistics also support the usability of the CCC-MGARCH model. Li and McLeod's Multivariate Portmanteau Statistics are used for serial correlation and heteroscedasticity. To test results, there is no serial correlation and heteroscedasticity problem in CCC-MGARCH model at 10% statistical inference. Figure 2 shows the conditional covariance graphs between BTC and stock market indices estimated from the CCC-MGARCH model.

Figure 2: Conditional Correlation Graphs



When Figure 2 is examined, it is seen that the conditional covariance between BTC and stock market indices were positive between 9 March 2020 and 13 April 2020 (between the 100th and 135th observation). The positive volatility observed between the relevant dates decreases over time.

5. CONCLUSION

The determination of the risk and information transmission across different financial markets and assets has a key role in portfolio selection. Especially during the crisis periods, the volatility transmission mechanism is more important due the changing perception of investors about optimal portfolio choice. In this context, the aim of the study is to analyse the volatility transmission between cryptocurrency market and global stock markets during the COVID-19 crisis period.

The Constant Conditional Correlation Multivariate GARCH (CCC-MGARCH) model is used for the analysis of the volatility transmission between cryptocurrency market and global stock markets. In the analysis, we use the bitcoin to represent the cryptocurrency market and S&P500, FTSE100, SSEC and NIKKEI indices for the global stock markets. The CCC-MGARCH model has been estimated for 1st December 2019/ 1st July 2021. According to the model results, the conditional correlation between the standardized residuals for BTC and stock market indices returns was found statistically significant. The returns on BTC and stocks rise or fall together because the estimated all conditional correlation parameters are positive and significant. A positive conditional correlation parameter indicates the existence of the volatility transmission between BTC and stock market indices. The estimated conditional correlation parameters are estimated higher for S&P500 index and lower for SSEC index than other stock market indices.

The results present findings that there is risk and information transmission between the cryptocurrencies market and global stock markets. According to the model results, determining the trend of co-movement between bitcoin and stock markets is an important finding for the portfolio diversification motif. If an investor who goes into portfolio diversification adds bitcoin and S&P500, FTSE100, SSEC and NIKKEI indices to her portfolio, the benefit of portfolio diversification may decrease. Therefore, it will have to either not include these instruments in its portfolio or give a lower weight for the portfolio.

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