Financial Internet Quarterly 2023, vol. 19 / no. 4, p. 115-128
10.2478/fiqf-2023-0030

Financial Internet Quarterly

THE DYNAMIC RELATIONSHIP BETWEEN BTC WITH BIST AND NASDAQ INDICES

Cagri ULU [1]

Abstract

The significance of digital investment has grown substantially, enabled by advancing technology, which provides digital monitoring of investment instruments. Consequently, analyzing these instruments has become imperative. In particular, investors are inclined to compare new investment opportunities with well-established global stock markets, seeking to capitalize on their advanced financial literacy. This study aims to employ econometric analysis to explore the dynamic relationship between Bitcoin and the BIST100 and NASDAQ 100 indices. The time frame for this investigation spans from January 1, 2017, to March 10, 2022. Stationarity was confirmed through unit root tests (ADF, PP, KPSS, ZA, FADF, and FFFFF ADF) for the subsequent utilization of Autoregressive Conditional Variance Models. Additionally, Generalized Autoregressive Conditional Variance and Dynamic Conditional Correlation Tests were conducted. Results from the Dynamic Conditional Correlation Test model revealed no statistically significant dynamic conditional correlation between Bitcoin and BIST 100. Conversely, a negative and significant dynamic conditional correlation emerged between Bitcoin and NASDAQ 100. Investors should not only monitor the market but also review academic studies before making investment decisions. In this regard, this study holds significant importance. The study is limited to the BTC, BIST, and NASDAQ indices. Researchers interested in the topic can increase the dataset to further enrich the study.

JEL classification: E00, F3, C58
Keywords: Dynamic Relations, DCC GARCH, Bitcoin, Finance, Stock Market

Received: 19.07.2023 Accepted: 07.09.2023

Cite this:
Cagri U. (2023) The dynamic relationship between BTC with BIST and NASDAQ indices. Financial Internet Quarterly 19(4), pp. 113-126.

[1] Izmir Kavram Vocational School, Türkiye, e-mail: cagri.ulu@kavram.edu.tr, https://orcid.org/0000-0001-5338-2987.

Introduction

Over the years, investment instruments have undergone diversification, and stock exchanges have established a mutually advantageous relationship between consumers and companies. Companies secure short-term financial resources from consumers, in return for which consumers are entitled to a share of the profits from these firms, a practice commonly encountered in traditional trading methodologies. Traditionally, the provision of resources has relied on liquid assets such as bank loans and foreign currency accounts. However, the advent of technology has ushered in a new era of investment tools, among which Bitcoin (BTC) emerges as a prominent contemporary option.

BTC made its first appearance in 2009 through a 9-page manifesto published on bitcoin.org by an individual named Satoshi Nakamoto. This introduction integrated BTC into a "Peer to Peer" system and explained the utilization of blockchain technology for secure transactions (Nakamoto, 2022). Subsequently, BTC has become a subject of discussions and comparisons with other financial investment instruments.

This study analyzes the dynamic relationship between BTC and BIST 100, an index of Borsa Istanbul, and NASDAQ 100, an index of an American stock exchange. As global financial assets are interconnected, investors need to monitor the global market and adjust their investments accordingly.

The time interval for this analysis spans from January 1, 2017, to March 10, 2022. To ensure stationarity, unit root tests (ADF, PP, KPSS, ZA, FADF, and FFFFF ADF) were conducted in the initial stage of analysis. Based on the results of these tests, Autoregressive Conditional Variance Models (ARCH) were employed. Following that, the Generalized Autoregressive Conditional Variance (GARCH-EGARCH) and Dynamic Conditional Correlation Test (DCC GARCH) were performed.

The Literature Review section provides an overview of prior research pertaining to the subject, offering insights into their respective findings. The subsequent section explains the econometric models used in this study. The results derived from these models are comprehensively examined, culminating in the Conclusion section, where the ultimate findings of the study are summarized.

Literature review

Jin and Masih (2017), gathered daily closing price data for five indices, including the FTSE Bursa Malaysia Emas Shari'ah Index, spanning from January 1, 2013, to January 2, 2017. The Bitcoin price index was sourced from Coindesk, recognized as one of the most active Bitcoin exchanges. During this period, the study applied three distinct methodologies: M-GARCH-DCC, Continuous Wavelet Transforms (CWT), and Maximum Overlap Discrete Wavelet Transform (MODWT) - to assess the correlation between Bitcoin and Shari'ah stock indices. The study's findings reveal a notably low and negative correlation between Bitcoin and Shari'ah stock indices, suggesting that Islamic stock investors could gain from diversifying their portfolios with Bitcoin. Furthermore, these results emphasize the potential benefits of further exploration into the fundamentals of cryptocurrencies within Islamic capital markets.

Conrad et al. (2018) conducted a study focusing on the relationship between volatility and stock market movements in cryptocurrencies, specifically Bitcoin (BTC). The research analyzed long-term and short-term volatility using the GARCH-MIDAS model, which extracts the components of long- and short-term fluctuations in cryptocurrencies. The study covered data from May 2013 to November 2017. Results indicated that the volatility of the S&P 500 had a negative and highly significant impact on long-term BTC volatility. Additionally, the S&P 500 volatility risk premium had a significantly positive influence on long-term BTC volatility. Moreover, a strong positive relationship was found between the Baltic exchange rate index and long-term BTC volatility, indicating a close link between BTC volatility and global economic activity.

Naimy and Hayek (2018) conducted a study aiming to predict volatility in BTC. The analysis focused on the BTC/USD exchange rate between April 1, 2013, and March 31, 2016. Different models, including GARCH (1,1), EWMA, and EGARCH (1,1), were compared to determine the most effective in explaining BTC volatility. The study identified EGARCH (1,1) as the most effective model. However, it was noted that early BTC behavior should be closely monitored, as future results may vary.

Gyamerah (2019) analyzed the volatility of BTC returns using sGARCH, iGARCH, and tGARCH models, covering the period from January 01, 2014, to August 16, 2019. The study revealed that the TGARCH-NIG model was the most effective in predicting BTC return series volatility.

Ardia et al. (2019) tested the presence of regime changes in the GARCH volatility dynamics of Bitcoin daily returns using MSGARCH models. They used a dataset of 2355 observations of BTC prices in USD, spanning from August 18, 2011, to March 3, 2018. The study found strong evidence for regime changes in the GARCH process, and MSGARCH models outperformed single regime specifications when estimating VAR.

Segnon and Bekiros (2020) proposed approaches to model the dynamics governing the mean and variance processes of BTC markets. The study used price observations between January 1, 2013, and November 28, 2018. Markov variation multifractal and FIGARCH models were found to outperform other GARCH-type models in estimating BTC return volatility. Combined estimates were observed to improve individual model estimates.

Venter and Maré (2020) used the GARCH model to analyze the pricing performance of BTC. They also evaluated implied volatility indices of BTCUSD and Cryptocurrency Index (CRIX) datasets. Daily data from January 1, 2016, to January 3, 2019, were considered. The study showed that BTCUSD and CRIX volatility indices exhibited a similar course when tested with the GARCH model. Short-term volatility (30 days) was generally lower compared to longer maturities.

Wang (2021) studied the volatility of BTC returns using the GARCH (1,1) model and other asymmetric models, such as TARCH and EGARCH. The analysis covered the period from October 2013 to July 31, 2020. The study revealed that the GARCH (1,1) model exhibited clustering characteristics in BTC volatility and return, with the volatility being a permanent process but decreasing over time. BTC was found to have a revised asymmetric effect between positive and negative shocks, making it suitable for investors to add to their portfolios as a safe-haven asset during economic depressions.

Sui and Elliott (2021) examined the pricing of BTC options, incorporating both conditional varying variance and regime switching in BTC returns. The study employed a nonlinear time series model combining the SETAR model and the GARCH model to model Bitcoin return dynamics. Daily data between July 18, 2010, and May 31, 2018, were used. The GARCH model showed implied volatility skewness for short-term options.

Abar (2020) aimed to make successful predictions in cryptocurrencies, particularly BTC, using the GARCH model and SVM-EKK regression. The study used BTC price series data from January 1, 2017, to February 29, 2020. Both models provided healthy predictions for the cryptocurrency price series.

Ciaian et al. (2021) estimated BTC's transaction demand and speculative demand equations with a GARCH model using high-frequency data covering hourly data from 2013 to 2018. The results showed that both transaction demand and speculative demand had a statistically significant effect on BTC price formation. Additionally, the BTC price reacted negatively to the BTC velocity but positively to the size of the BTC economy.

Akin et al. (2023), conducted data collection from CoinMarketCap on the three largest cryptocurrencies (Bitcoin, Ethereum, and Binance Coin) on a weekly basis, spanning from August 1, 2017, to April 1, 2022. This period constituted the data collection window for the study. Employing the dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model, the study analyzed the CoinMarketCap dataset. The results of the investigation indicated a noteworthy impact of news and events concerning central bank digital currencies (CBDCs) on Bitcoin returns. Both the CBDC uncertainty index and CBDC attention index exhibited a considerable influence on Bitcoin returns, signifying that positive news in this context could yield substantial returns. These findings underscore the notion that investors' future expectations regarding cryptocurrencies are significantly molded by CBDC-related news and events.

Methodology

While working on a time series, it is of great importance that the series be stationary. Depending on the stationarity, the method is selected by which the series will be advanced. Different stationarity tests are used to understand the reliability of the series (Petrica et al., 2017). In this study, first of all, ADF, PP and KPSS tests, which are traditional and do not allow structural break, were performed. Then, ZA, FADF and FFFF ADF unit root tests were carried out, which allow for modern and structural breaks. After the test results, VAR analysis was performed, and ARCH effects were investigated in the series. The study was terminated with the DCC GARCH test to analyze the dynamic relationship between the series.

Unit root test results not considering structural breaks

Stationarity tests were conducted to check the significance of the series. Augmented Dickey-Fuller (ADF), Phillips Perron (PP) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) unit root tests, which do not take into account the structural break, were applied. Stationarity is of great importance in determining the analyses to be made on the time series.

Table 1: ADF, PP and KPSS Unit Root Test Results in Level

Characteristics		ADF		PP		KPSS	
		Intercept	Interceptand Trend	Intercept	Interceptand Trend	Intercept	Interceptand Trend
BTC	Test Statistics	-1.667067	-1.914840	-1.670458	-1.993322	3.269261	0.340945
	1%	-3.435161	-3.965109	-3.435161	-3.965109	0.739000	0.216000
	5%	-2.863552	-3.413266	-2.863552	-3.413266	0.463000	0.146000
	10%	-2.567891	-3.128657	-2.567891	-3.128657	0.347000	0.119000
	Prob.	0.447900	0.646100	0.446100	0.603900		
BIST100	Test Statistics	-0.619607	-1.617013	-0.488347	-1.539903	2.824638	0.704447
	1%	-3.435169	-3.965120	-3.435161	-3.965109	0.739000	0.216000
	5%	-2.863556	-3.413271	-2.863552	-3.413266	0.463000	0.146000
	10%	-2.567893	-3.128660	-2.567891	-3.128657	0.347000	0.119000
	Prob.	0.863700	0.786100	0.890900	0.815500		
NASDAQ 100	Test Statistics	-1.032457	-2.234098	-1.112875	-2.367322	4.045332	0.721599
	1%	-3.435196	-3.965159	-3.435161	-3.965109	0.739000	0.216000
	5%	-2.863568	-3.413290	-2.863552	-3.413266	0.463000	0.146000
	10%	-2.567899	-3.128671	-2.567891	-3.128657	0.347000	0.119000
	Prob.	0.743500	0.469600	0.712700	0.396600		

Note: ***, **, * indicate significance at 1%, 5% and 10% significance levels.

Source: Author's own work.

ADF, PP and tests, which are unit root tests that do not consider structural break, were applied. All tests were examined at the level and it is understood that stationarity could not be achieved because the probability values are greater than 0.05. When the KPSS test results are examined, it is seen that the series are not stationary.

Table 2: ADF, PP and KPSS Unit Root Test Results in 1st Difference

Characteristics		ADF		PP		KPSS	
		Intercept	Interceptand Trend	Intercept	Interceptand Trend	Intercept	Interceptand Trend
BTC	Test Statistics	-36.94505	-36.949500	-36.97179	-36.972170	0.13498	0.103774
	1%	-3.43517	-3.965115	-3.43517	-3.965115	0.73900	0.216000
	5%	-2.86355	-3.413269	-2.86355	-3.413269	0.46300	0.146000
	10%	-2.56789	-3.128659	-2.56789	-3.128659	0.34700	0.146000
	Prob.	0.00000	0.000000	0.00000	0.000000		
BIST100	Test Statistics	-22.97963	-22.980120	-36.46394	-36.460150	0.13504	0.080503
	1%	-3.43517	-3.965120	-3.43517	-3.965115	0.73900	0.216000
	5%	-2.86356	-3.413271	-2.86355	-3.413269	0.46300	0.146000
	10%	-2.56789	-3.128660	-2.56789	-3.128659	0.34700	0.119000
	Prob.	0.00000	0.000000	0.00000	0.000000		
NASDAQ 100	Test Statistics	-11.80934	-11.813670	-44.35551	-44.350220	0.07610	0.073464
	1%	-3.43520	-3.965159	-3.43517	-3.965115	0.73900	0.216000
	5%	-2.86357	-3.413290	-2.86355	-3.413269	0.46300	0.146000
	10%	-2.56790	-3.128671	-2.56789	-3.128659	0.34700	0.119000
	Prob.	0.00000	0.000000	0.00010	0.000000		

Note: ***, **, * indicate significance at 1%, 5% and 10% significance levels.

Source: Author's own work.

The same tests were applied again by taking the first differences of the series. Since the probability values for ADF and PP are less than 0.05 in all series, it can be said that stationarity is achieved. When the KPSS test results are examined, it is seen that stationarity is provided. At the 1% significance level, all tests are significant.

Unit root test results considering structural breaks

Unit root tests are essential in increasing reliability. After the traditional models, modern unit root tests started to be applied to the series.

For this study, Zivot Andrews (ZA), Fractional Augmented Dickey Fuller (FADF) and Fractional Frequency Flexible Fourier Form Augmented Dickey-Fuller (FFFFADF) tests, which allow structural break, were applied.

Table 3: ZA Unit Root Test Results

Characteristics		Model A (Intercept)	Model B (Trend)	Model C (Intercept and Trend)
BTC	Test Statistics	-2.870013	-2.206822	-3.431682
	1%	-5.340000	-4.800000	-5.570000
	5%	-4.930000	-4.420000	-5.080000
	10%	-4.580000	-4.110000	-4.820000
	Break Point	10.19.2020	11.19.2019	01.08.2018
BIST100	Test Statistics	-3.720117	-3.864384	-3.953157
	1%	-5.340000	-4.800000	-5.570000
	5%	-4.930000	-4.420000	-5.080000
	10%	-4.580000	-4.110000	-4.820000
	Break Point	4.20.2018	3.11.2020	2.18.2020
NASDAQ100	Test Statistics	-4.388460	-2.872674	-3.644380
	1%	-5.340000	-4.800000	-5.570000
	5%	-4.930000	-4.420000	-5.080000
	10%	-4.580000	-4.110000	-4.820000
	Break Point	4.03.2020	12.17.2018	10.04.2018

Source: Author's own work.

According to Table 3 when the statistical values of the series and the critical values are compared, it is understood that stability cannot be achieved for the BTC, BIST and NASDAQ indices. The absolute values of the test statistics are greater than the critical value.

Table 4: FADF and FFFF ADF Unit Root Test Results

Series	Min. KKT	k	FADF
BTC	3.270491	1.0	3.198692 (10)
BIST 100	0.276864	1.0	3.290393 (12)
NASDAQ 100	0.273501	1.0	3.357170 (12)
			Fractional FADF
BTC	3.268545	1.4	2.892659 (10)
BIST 100	0.275422	0.1	7.044294 (12)
NASDAQ 100	0.272455	0.5	4.595373 (12)

Source: Author's own work.

Based on the results of the FADF Unit Root Test, the application of the FADF for analysis is rejected because the F constraint value was lower than the F table value in all series. To increase the reliability of the stationarity analysis, the FFFFF ADF test was conducted.

The FFFFF ADF test results indicate that the F table value is greater than the actual fractional FADF values in all series. Therefore, the appropriate unit root analysis for the series is the ADF Unit Root Test, which takes into account the structural break.

Upon analyzing the results of the ADF unit root test, it is observed that the series become I(1) stationary when the first difference is taken. In I(1) stationary series, ARCH and GARCH effects are chosen as suitable modeling approaches for capturing volatility and dynamics in the data.

Autoregressive conditional variable variance models

After unit root tests for the variables, appropriate ARMA models should be determined. The ARMA models for the series and the number of alternative GARCH models after the ARCH effect were estimated as follows.
BTC – ARMA (3,3) and GARCH (1,1)
BIST100 – ARMA (3,3) and GARCH (1,1)
NASDAQ100 – ARMA (4,4) and EGARCH (1,1)

BTC Index

According to the significance of the coefficients and the minimum Akaike and Schwarz information criteria, which are the model selection criteria, the ARMA(3,3) model was determined as the appropriate model for the BTC return variable. The results are given in Table 5.

Table 5: ARMA(3,3) Model Result on BTC Index Return

Variable	Coefficient (Std. Error)	t-Statistics	Prob.
Constant Term	0.00276000 (0.00192700)	1,431.969	0.1524
AR(1)	0.81941800 (0.14335000)	5,716.197	0.0000***
AR(2)	-0.69738700 (0.15441200)	-4,516.406	0.0000***
AR(3)	0.79733400 (0.11020600)	7,234.958	0.0000***
MA(1)	-0.85103100 (0.14375600)	-5,919.970	0.0000***
MA(2)	0.74547700 (0.15730600)	4,739.035	0.0000***
MA(3)	-0.79002000 (0.11588500)	-6,817.280	0.0000***
SIGMASQ	0.00250700 (0.00000517)	4,850.710	0.0000***
Akaike	-3.13855900		
Schwarz	-3.10678200		

Note: ***, **, * indicate significance at 1%, 5% and 10% significance levels

Source: Author's own work.

When the table is examined, the AR(1) coefficient (0.819418) expresses the value of BTC index return one period ago. The coefficient AR(2) (-0.697387) represents its value two periods ago, and the coefficient AR (3) (0.797334) represents its value three periods ago. In other words, an increase in the BTC return that occurred a period ago has an increasing effect on the current return of BTC. An increase in the return of two periods ago affects the current return negatively. An increase in the return of three periods ago affects the return positively in the current period. The MA coefficient represents the shocks to the system. In other words, it shows the error term. Looking at the MA(1) (-0.851031) coefficient, it is seen that a shock that occurred a period ago has a decreasing effect on the BTC return in the current period. Looking at the MA(2) (0.745477) coefficient, it was observed that a shock that occurred two periods ago increased the BTC return in the current period, and looking at the MA(3) (-0.790020) coefficient, it is possible to say that a shock that occurred three periods ago reduced the return in the current period. When the AR and MA coefficients are examined from the table, it is seen that they are significant according to the 1% significance level.

Table 6: ARCH Effect in ARMA(3,3) Model of BTC Index

Q Statistics		Prob.
ARCH(5)	13.83629	0.0167
Q(10)	3.67910	0.4510
Q2(10)	17.41300	0.0660

Source: Author's own work.

When analyzing the results in the table, it was determined that there is no autocorrelation problem in the ARMA(3,3) model according to the Q(10) statistic for the 10th delay. However, the Q2(10) statistic is significant, indicating that the model has a different variance, implying an ARCH effect.

The ARCH(5) value of 13.83629 with a corresponding probability value of 0.0167 shows the presence of an ARCH effect in the ARMA(3,3) model at the 5% significance level.

Due to the presence of the ARCH effect in the ARMA(3,3) model, the modeling continued with autoregressive conditional heteroskedasticity (ARCH) models. Different GARCH-type models were tried for BTC, and the most suitable (minimum) model for BTC was determined to be ARMA(3,3) - GARCH(1,1) based on assumptions, significance of coefficients, and minimum Akaike and Schwarz information criteria.

Upon examining the results in the last table for the ARMA(3,3) - GARCH(1,1) model, the coefficients α (0.148011) and β (0.598011) were found to be positive and statistically significant at the 1% significance level. The non-negativity condition for variance coefficients was satisfied.

In the GARCH model, α indicates the initial effect of the shock, and β indicates the persistence of the shock in the system. With a β coefficient of 0.598011, it can be interpreted that the shock to the system is not permanent, as the coefficient is close to 1. The half-life shock value was calculated to determine the duration of the shock in the system. However, the specific formulation for calculating the half-life shock value is not provided in the given text.

Half-life Shock

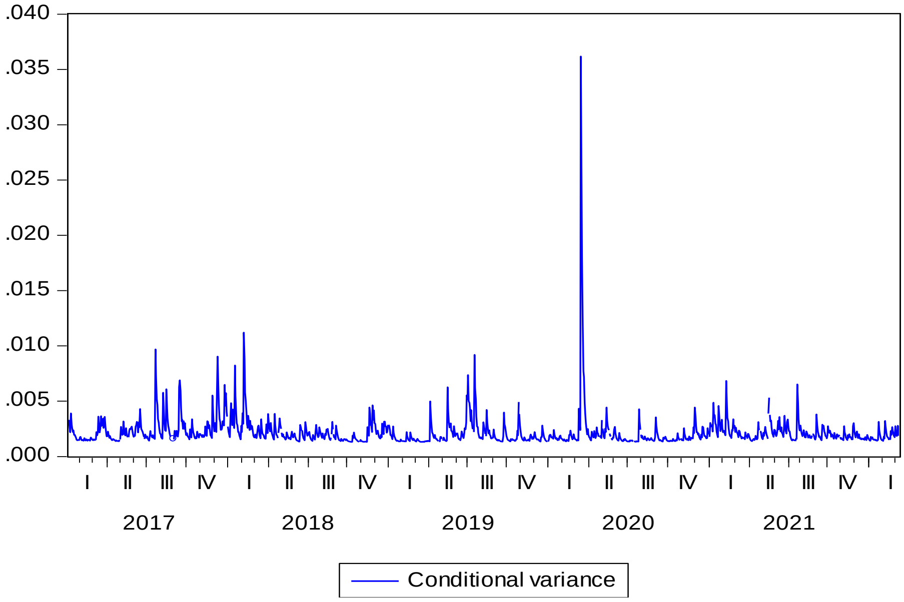
$$-\frac{\ln(0.5)}{\ln(a+b)} = -\frac{\ln(0.5)}{\ln(0.1480+0.5998)} = 2.86 \qquad (1)$$

According to the value obtained, the shock to the system regarding the BTC index return stays in the system for an average of 3 days. From this point of view, it is seen that the shock to the system is not permanent.

To determine whether there is an ARCH effect in the residues obtained from ARMA(3,3) - GARCH(1,1) model, ARCH(5) statistics were examined and the obtained value was found as 5.493894 and the probability value as 0.3586. Therefore, the ARCH effect is eliminated in the model. In addition, looking at the Q(10) statistics, it is seen that there is no autocorrelation problem in the model.

The following figure shows the conditional variance graph obtained from the ARMA(3,3) - GARCH(1,1) model.

Figure 1: Conditional Variance Chart for BTC Return



Source: Own elaboration with using the EViews package program.

BIST 100 index

Alternative ARMA(p,q) models have been tried for the BIST 100 index return. The significance of the coefficients was determined as the ARMA(3,3) model as the appropriate model for the BIST 100 return variable according to the minimum Akaike and Schwarz information criteria, which are the model selection criteria. The results are as in the table below:

Table 7: ARMA(3,3) Model Result on BIST100 Index Return

Variable	Coefficient	T-Statistics	Prob.
Constant Term	0.00074000 (0.00046200)	1.600027	0.1098
AR(1)	-0.31207000 (0.10665500)	-2.925940	0.0035***
AR(2)	-0.25749000 (0.07437900)	-3.461840	0.0006***
AR(3)	-0.76769000 (0.07899300)	-9.718440	0.0000***
MA(1)	0.30009800 (0.10457300)	2.869748	0.0042***
MA(2)	0.33213000 (0.06745900)	4.923416	0.0000***
MA(3)	0.80202800 (0.07991300)	10.036280	0.0000***
SIGMASQ	0.00021100 (0.00000446)	47.260720	0.0000***
Akaike	-5.61514600		
Schwartz	-5.58336900		

Note: ***, **, * indicate significance at 1%, 5% and 10% significance levels

Source: Author's own work.

When the table is examined, the AR(1) coefficient (-0.31207) represents the value of the BIST 100 index return a period ago. The coefficient AR(2) (-0.25749) represents its value two periods ago, and the coefficient AR(3) (-0.76769) represents its value three periods ago. In other words, an increase in the BIST 100 return that occurred a period ago has a reducing effect on the current return of BIST 100. An increase in the return from two periods ago affects the current return negatively. It can be said that an increase in the return of three periods ago affects the return negatively in the current period. The MA coefficient represents the shocks to the system. Looking at the MA(1) (0.300098) coefficient, it is seen that a shock that occurred a period ago has an increasing effect on the BIST 100 return in the current period. Looking at the MA(2) (0.33213) coefficient, it is observed that a shock that occurred two periods ago increased the BIST 100 return in the current period, and looking at the MA(3) (0.802028) coefficient, it is possible to say that a shock that occurred three periods ago increased the return in the current period. When the AR and MA coefficients are examined from the table, it is seen that they are significant according to the 1% significance level.

The Q and Q2 statistics of the ARMA(3,3) model and ARCH statistics were examined to determine whether the model has an ARCH effect.

Table 8: ARCH Effect on the ARMA(3,3) Model of the BIST 100 Index

Q Statistics		Prob.
ARCH(5)	78.30416	0.000
Q(10)	5.49580	0.240
$Q^2(10)$	129.71000	0.000

Source: Author's own work.

Upon examining the results in the table, it is evident that there is no autocorrelation problem in the ARMA(3,3) model based on the Q(10) statistic for the 10th delay. However, the Q2(10) statistic is significant, indicating a different variance in the model. Additionally, the ARCH(5) value is 78.30416 with a corresponding probability value of 0.000, confirming the presence of an ARCH effect in the ARMA(3,3) model at the 1% significance level.

Due to the identified ARCH effect in the ARMA(3,3) model, the modeling process proceeds with autoregressive conditional variance (GARCH) models. Various GARCH-type models were tested for BIST 100, and the most suitable (minimum) model was determined to be ARMA(3,3) - GARCH(1,1) based on the assumptions, significance of coefficients, and minimum Akaike and Schwarz information criteria. The results for this model are presented in the last table.

Examining the last table, we find that the α (0.149861) and β (0.599861) coefficients are positive and statistically significant at the 1% significance level, satisfying the non-negativity condition for variance coefficients. In the GARCH model, α represents the initial effect of the shock, while β indicates the persistence of the shock in the system. With a β coefficient of 0.5998, we can conclude that the shock to the system is not permanent.

The half-life shock value, which measures how long the shock to the system lasts, is calculated using a specific formulation. However, the formulation is not provided in the given text.

Half Life Shock

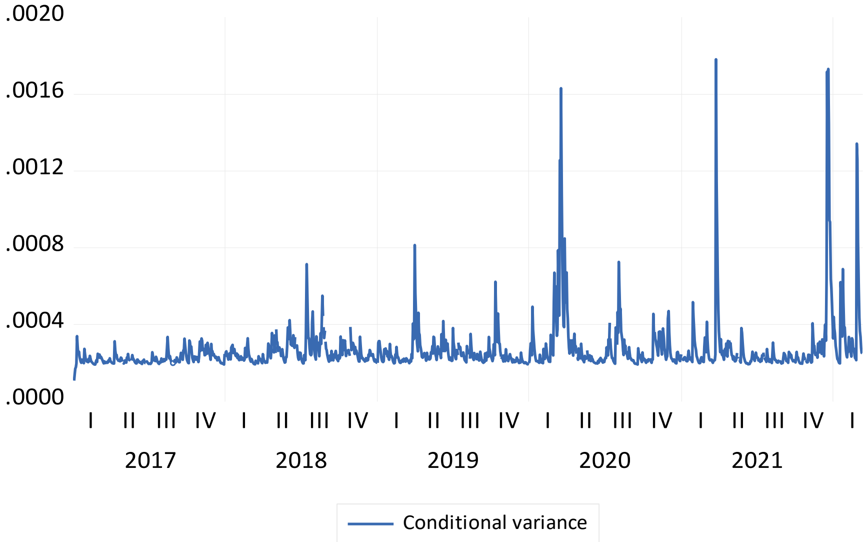
$$\frac{\ln(0.5)}{\ln(a+b)} = -\frac{\ln(0.5)}{\ln(0.1491+0.5998)} = 2.39 \qquad (2)$$

According to the value obtained, the shock to the system regarding the BIST 100 index return stays in the system for an average of 2.5 days. If the GARCH parameter was close to 1, it could be said to have a permanent effect on the system, but the β coefficient was 0.59 and was less than 1. Therefore, it is not possible to talk about its permanent effect on the system.

To determine whether there is an ARCH effect in the residues obtained from ARMA(3,3) - GARCH(1,1) model, ARCH(5) statistics were examined and the obtained value was found as 3.517340 and the probability value as 0.6208. Therefore, the ARCH effect is eliminated in the model. In addition, looking at the Q(10) statistics, it is seen that there is no autocorrelation problem in the model.

The following figure shows the conditional variance graph obtained from the ARMA(3,3) - GARCH(1,1) model.

Figure 2: Conditional Variance Chart for BIST 100 Return



Source: Own elaboration with using the EViews package program.

NASDAQ 100 Index

According to the significance of the coefficients and the minimum Akaike and Schwarz information criteria, which are the model selection criteria, the ARMA(4.4) model was determined as the appropriate model for the NASDAQ 100 return variable. The results are shown in the table below.

Table 9: ARMA(4.4) Model Result for NASDAQ 100 Index Return

Variable	Coefficient	T-Statistics	Prob.
Constant term	0.00076700 (0.00037000)	2.074435	0.0382***
AR(1)	-2.70751800 (0.04919100)	-55.040960	0.0000***
AR(2)	-3.47726500 (0.11334200)	-30.679350	0.0000***
AR(3)	-2.41629600 (0.11152800)	-21.665330	0.0000***
AR(4)	-0.79038900 (0.04514900)	-17.506090	0.0000***
MA(1)	2.55696100 (0.05866200)	43.587910	0.0000***
MA(2)	3.12193500 (0.13125500)	23.785210	0.0000***
MA(3)	2.03757400 (0.12722800)	16.015130	0.0000***
MA(4)	0.60099300 (0.05145700)	11.679520	0.0000***
SIGMASQ	0.00018900 (0.00000045)	42.057840	0.0000***
Akaike	-5.71957500		
Schwarz	-5.67985400		

Note: ***, **, * indicate significance at 1%, 5% and 10% significance levels

Source: Author's own work.

When the results are analyzed, the coefficients AR (1) (-2.707518), AR(2) (-3.477265), AR(3) (-2.416296) and AR(4) (-0.790389) show the NASDAQ 100 index returns as one, two, three and four, respectively. represent their previous values. In other words, an increase in the NASDAQ 100 return that occurred one, two, three and four periods ago has a decreasing effect on the current return of the NASDAQ 100. The MA coefficients represent the shocks to the system. According to in the system in four periods increased the NASDAQ 100 return in the current period. When the AR and MA coefficients are examined from the table, it is seen that they are significant according to the 1% significance level.

In the table below, the Q and Q2 statistics of the ARMA(4.4) model and ARCH statistics are examined to determine whether there is an ARCH effect in the model.

Table 10: ARCH Effect in ARMA(4.4) Model for NASDAQ 100 Index

Q Statistics		Prob.
ARCH(5)	304.0880	0.000
Q(10)	1.7172	0.424
$Q^2(10)$	873.8600	0.000

Source: Author's own work.

When the table is examined, the presence of the ARCH effect was determined according to the 1% significance level according to the ARMA(4.4) model. The ARCH (5) coefficient was 304.0880 and the probability value was 0.000. When Q and Q2 are examined, it is understood that there is no autocorrelation problem in the ARMA(4.4) model. With the ARCH effect, the modeling should be continued with autoregressive conditional variance models. Alternative GARCH type models have been tried. The EGARCH (1,1) model from these models has been estimated since it meets the necessary conditions (minimum Akaike and Schwarz criteria) and the results are shown in the last table.

The last table shows the ARMA(4.4) - EGARCH(1.1) model estimation result for the NASDAQ100 return. The α, β and γ coefficients are statistically significant at the 1% significance level. In the EGARCH model, the asymmetry coefficient γ is negative and statistically significant at the 1% significance level. There is an asymmetry (γ) effect in the model. Therefore, it can be said that the effect of negative shocks on the conditional variance of the NASDAQ100 index is greater than that of positive shocks. In other words, negative shocks have an increasing effect on the volatility of the NASDAQ100 index compared to positive shocks. In the model, the beta coefficient was obtained as 0.9666. Since this value is close to 1, the shock to the system is permanent. In the EGARCH model, the half-life shock is calculated according to the following formulation.

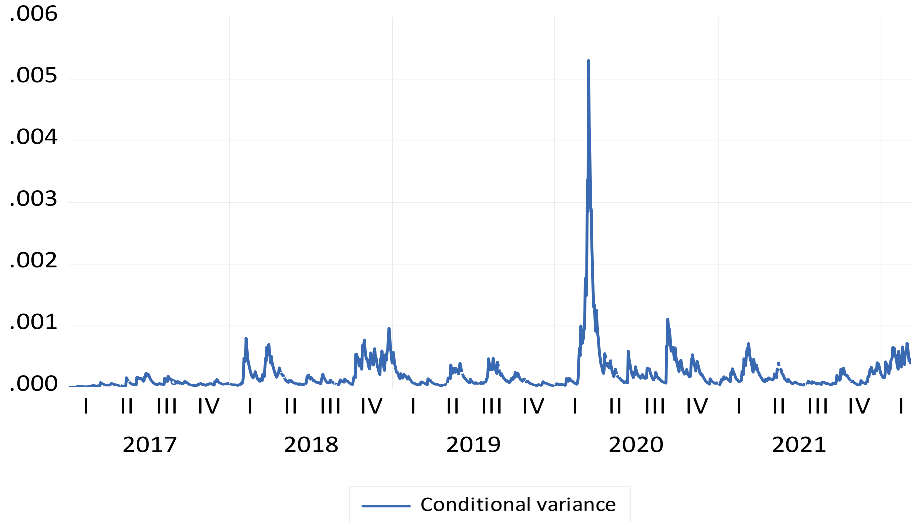
Half-Life Shock

$$-\frac{\ln(0.5)}{\ln(b)} = -\frac{\ln(0.5)}{\ln(0.9669)} = 20{,}592 \qquad (3)$$

According to the result above, a shock to the NASDAQ index remains in the system for an average of 21 days.

The following figure shows the conditional variance graph obtained from the ARMA(4.4) - EGACRH(1,1) model for the NASDAQ 100 index.

Figure 3: Conditional Variance Chart for NASDAQ 100 Return



Source: Own elaboration with using the EViews package program.

Table 11: GARCH and EGARCH Results According to Appropriate ARMA Models for Data

Variable	BTC	BIST100	NASDAQ100
ARMA Equation			
Constant term	0.003102 (0.001456)	0.0013170 (0.0005430)	0.001290 (0.000194)
AR(1)	-0.010225 (0.148000)	-0.3826500 (0.0650799)	-1.887870 (0.332712)
AR(2)	-0.147530 (0.133689)	-0.3121400 (0.0712070)	-0.912530 (0.766489)
AR(3)	0.847426 (0.142471)	-0.8812300 (0.0660550)	0.419741 (0.724689)
AR(4)			0.340404 (0.282115)
MA(1)	0.049025 (0.159618)	0.3657310 (0.0577020)	1.847940 (0.326041)
MA(2)	0.147159 (0.148325)	0.3523590 (0.0564910)	0.825444 (0.740675)
MA(3)	-0.838227 (0.154863)	0.9089430 (0.0565310)	-0.507270 (0.698372)
MA(4)			-0.380390 (0.273415)

Variable	BTC	BIST100	NASDAQ100
Variance Equation			
Constant term	0.000524 (0.000108)	7.53E-05 (1.93E-05)	-0.461020 (0.077349)
α	0.148011 (0.032488)	0.1498610 (0.0385490)	0.219221 (0.036503)
β	0.598011 (0.069650)	0.5998610 (0.0880850)	0.966978 (0.007262)
γ			-0.150020 (0.024969)
ARCH(5)	5.493894 (0.358600)	3.5173400 (0.6208000)	1.064345 (0.957200)
Q(10)	6.114000 (0.191000)	5.8253000 (0.2130000)	4.744900 (0.093000)
$Q^2(10)$	7.311000 (0.696000)	6.2817000 (0.7910000)	4.939900 (0.895000)
Akaike	-3.271966	-5.7329000	-6.234410
Schwarz	-3.228192	-5.6891000	-6.178663

Note: The numbers in parentheses in the GARCH (1,1) model indicate standard errors. The numbers in parentheses for ARCH, Q and Q2 Statistics represent probability values.

Source: Own elaboration.

Analysis of dynamic relationship between variables

While the GARCH models look at the volatility, the DCC GARCH model looks at the volatility spread of the dynamic relationship between two variables. The table below shows the results of variance causality among the variables used in the study.

Table 12: DCC GARCH Model Estimation Results Between Variables

Variables	BTC - BIST	BTC - NASDAQ
γ_{12}	0.025618 (0.046637)	-0.974280*** (0.021882)
α	0.006015 (0.003773)	0.039558*** (0.014669)
β	0.986373*** (0.011058)	0.960432*** (0.015052)
dF	4.346441*** (0.264170)	3.626931*** (0.158930)
Diagnostic Tests		
Hosking (20)	39.372700 [0.241200]	59.617900 [0.967600]
Hosking(50)	39.372700 [0.408200]	195.143000 [0.544000]
Li-McLeod (20)	21.791600 [0.241300]	59.746400 [0.938100]
Li-McLeod(50)	219.401000 [0.141800]	194.794000 [0.551000]

Note: The numbers in round brackets show the standard error values, and the numbers in square brackets show the probabilities. ***, **, * indicate significance at 1%, 5% and 10% significance levels, respectively.

Source: Own elaboration.

In the table, the γ12 coefficient represents the dynamic conditional correlation between Bitcoin and the selected indices. The α coefficient indicates the effect of lagged quadratic shocks on conditional volatility, while the β coefficient represents the persistence of shocks, where a value approaching 1 indicates that incoming shocks are permanent.

The DCC-GARCH model proposed by Engle (2002) was utilized to examine the volatility spread between Bitcoin and the chosen indices. This model offers the advantage of determining possible changes in conditional correlations and the variation of conditional correlations over time for time-varying volatility.

The estimation of the model was initially performed between Bitcoin and BIST 100. According to the table, there is no statistically significant volatility spread at the 5% significance level between Bitcoin and the BIST 100 index, as the γ12 coefficient is statistically insignificant. Additionally, the probability values (shown in square brackets) for the Hosking and Li-McLeod values are greater than 0.05, indicating no issue with the model. The β coefficient suggests that the shock to the system is permanent, and when there is a volatility spread between Bitcoin and BIST 100, a shock to the system permanently affects the volatility spread.

Next, the model was estimated between Bitcoin and NASDAQ 100. The γ12 coefficient indicates a strong correlation, being close to 1 with a negative correlation. A statistically significant volatility spillover at the 1% significance level is observed between Bitcoin and the NASDAQ market. This implies that an increase in Bitcoin volatility has negatively affected the NASDAQ market. The α coefficient is significant and positive, indicating that an increase in lagged quadratic shocks increases the current value of conditional volatility. The β coefficient is close to 1, indicating a permanent volatility spread between Bitcoin and NASDAQ.

When examining the Hosking and Li-McLeod coefficients, it is evident that the model is estimated correctly, and there is no ARCH effect in the squares anymore. This means that the residuals of the established model have no ARCH effect, making the model accurate and meaningful.

Conclusion

The study discusses the dynamic relationship between Bitcoin and selected indices (BIST 100, NASDAQ 100) and analyzes the impact of shocks on the financial market, especially during the Covid-19 outbreak.

When examining the conditional variance graphs of the returns of the studied series, it is observed that significant shocks have occurred, and the Covid-19 epidemic has had a major impact on all variables. Besides Covid-19, the Central Bank's interest rate decisions have also caused significant shocks in the BIST 100 return. Similar results are observed in the conditional variance graphs of NASDAQ 100 and Bitcoin returns, indicating the financial impact of the Covid-19 outbreak on both indices.

Furthermore, the permanence of the shocks in the system is crucial. The shocks regarding the Bitcoin index return last for an average of 3 days, suggesting that the shock is not permanent. The shocks for the BIST 100 index return last for an average of 2.5 days, indicating a non-permanent effect. However, the shocks for the NASDAQ 100 return persist on average for 21 days, suggesting a more permanent impact.

In conclusion, domestic policy decisions in Turkey are effective in the formation of shocks compared to the selected global stock market indices. However, the Covid-19 epidemic has significant effects on all series. The dynamic relationship analysis reveals that there is no dynamic conditional correlation between Bitcoin and BIST 100, but there is a dynamic conditional correlation between Bitcoin and NASDAQ 100, with a negative relationship between them. This suggests that Bitcoin's impact on the Turkish stock market as a developing country and on NASDAQ indices from developed countries can be understood.

In light of the findings presented in this study, it becomes evident that our research builds upon and extends the existing body of knowledge in the field of cryptocurrency-market interactions. Previous research, as exemplified by the works of Jin and Masih (2017) and Conrad et al. (2018), has explored the correlation between Bitcoin and various stock market indices, shedding light on potential diversification opportunities for investors. Moreover, studies like that of Sui and Elliott (2021) have delved into the pricing dynamics of Bitcoin options, offering insights into derivative markets. Our study, which examines the relationship between Bitcoin and select indices (BIST 100 and NASDAQ 100) during the Covid-19 pandemic, contributes by revealing the differential impact and persistence of shocks on these variables.

In particular, our analysis echoes the earlier findings of Gyamerah (2019) and Ardia et al. (2019), highlighting the presence of regime changes and the importance of dynamic conditional correlations. While we concur with the observation that domestic policy decisions in Turkey significantly influence shocks in the BIST 100 index, we extend the narrative by demonstrating the remarkable impact of the Covid-19 pandemic on both domestic and international financial markets. Moreover, our study reaffirms the dynamic relationship between Bitcoin and global indices, especially the NASDAQ 100, with a negative dynamic conditional correlation, in line with the findings of Naimy and Hayek (2018), and Segnon and Bekiros (2020).

In summary, our research not only underscores the continued relevance of cryptocurrency analysis in the context of global financial markets, but it also underscores the evolving nature of these relationships, particularly during times of significant economic disruption such as the Covid-19 pandemic. By delving into the dynamics of Bitcoin's interaction with both emerging and developed market indices, we provide a nuanced perspective on the evolving role of cryptocurrencies in the modern financial landscape.

References

Abar, H. (2020). GARCH Modeli ve DVM – EKK Regresyonu ile Kripto Para Fiyat Öngörüsü: Bitcoin Fiyatı Üzerine Bir Uygulama, Turkish Studies-Economics, Finance, Politics, 15(2), 705-725.

Akin, I., Khan, M.Z., Hameed, A., Chebbi, K. & Satiroglu, H. (2023). The ripple effects of CBDC-related news on Bitcoin returns: Insights from the DCC-GARCH model. Research in International Business and Finance, 66, 102060.

Ardia, D., Keven B. & Maxime R. (2019). Regime Changes in Bitcoin GARCH Volatility Dynamics, Finance Research Letters, (29), 266-271.

Bağcı, E. (2019). Merkez Bankası Politika Faiz Oranı ve Döviz Kuru İlişkisi: Türkiye Örneği. Adıyaman Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 31, 324-348.

Cho, J.H. & Parhizgari, A.M. (2008). East Asian Financial Contagion under DCC-Garch, International Journal of Banking Accounting and Finance, 6, 17-30.

Ciaian, P., d'Artis K. & Miroslava R. (2021). The Price of Bitcoin: GARCH Evidence from High-frequency Data, Journal of Investment Strategies, 9(4), 1-18.

Conrad, C., Anessa C. & Eric G. (2018). Long- and Short-Term Cryptocurrency Volatility Components: A GARCH-MIDAS Analysis, Journal of Risk and Financial Management 11(2), 1-12.

Gyamerah, S.A. (2019). Modelling the Volatility of Bitcoin Returns Using GARCH Models. Quantitative Finance and Economics, 3(4), 739-753.

Hayek, M.R. & Viviane, N. (2018). Modelling and Predicting the Bitcoin Volatility Using GARCH Models. International Journal of Mathematical Modelling and Numerical Optimisation, 8(3), 197-215.

Jin, L.S. & Masih, M. (2017). Exploring Portfolio Diversification Opportunities in Islamic Capital Markets through Bitcoin: Evidence from MGARCH-DCC and Wavelet Approches, Munich Personal RePEc Archive, No. 79752, https://mpra.ub.uni-muenchen.de/79752/ (Accessed: 10.07.2023).

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. bitcoin.org: https://bitcoin.org/bitcoin.pdf (Accessed: 11.11.2022).

Petrica, A., Stancu, S. & Ghitulescu, V. (2017). Stationarity – The Central Concept in Time Series Analysis, International Journal of Emerging Research in Management & Technology, 6(1), 6-16.

Poyraz, E. & Türkün, K.B. (2020). Politika Faizindeki Değişimlerin Borsa İstanbul 100 Endeksi Üzerindeki Etkisinin Olay Analizi İle İncelenmesi. International Review of Economics and Management, 8(2), 201-220.

Segnon, M. & Stelios B. (2020). Forecasting Volatility in Bitcoin Market, Annals of Finance, 16, 435-462.

Siu, T.K. & Robert, J.E. (2021). Bitcoin Option Pricing with a SETAR-GARCH Model. The European Journal of Finance, 27(6), 564-595.

Venter, P.J. & Eben, M. (2020). GARCH Generated Volatility Indices of Bitcoin. Journal of Risk and Financial Management, 13(6), 121-136.

Wang, C. (2021). Different GARCH Models Analysis of Returns and Volatility in Bitcoin. Data Science in Finance and Economics, 1(1), 37-59.