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THE CAUSALITY RELATIONSHIP BETWEEN BITCOIN AND DOLLAR, GOLD AND BIST100 INDEX

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ABSTRACT

This study investigates the causal relationships between Bitcoin and the US Dollar (USD), Gold, and BIST100 Index as alternative investment instruments. Employing Hong's variance causality test, the research explores spillover effects in mean and volatility. Using daily data from September 17, 2014, to October 13, 2023, the study reveals a one-way average causality from Bitcoin to BIST100 and the USD. Variance test results show a two-way volatility spillover between Bitcoin and USD, Gold, and BIST100. Hacker-Hatemi-J symmetric causality test detects a one-way causality from Bitcoin to the USD, while Hatemi-J asymmetric test reveals a unidirectional causality from positive Bitcoin shocks to negative shocks of BIST100 and Gold, and bidirectional causality with USD's negative shocks. Additionally, a bidirectional causality exists from Bitcoin's negative shocks to Gold's positive shocks and a unidirectional causality to USD's negative shocks. Recognizing Bitcoin as a financial asset sheds light on its interaction with traditional markets, aiding investors in refining strategies. In summary, this study enhances comprehension of cryptocurrency's role by emphasizing the causal link between Bitcoin and the USD.

Keywords: Hong's causality test, Hatemi-J causality test, Bitcoin, USD, BIST100 index.

1 INTRODUCTION

Bitcoin (BTC) is the first virtual or cryptocurrency designed to operate on a distributed computer network, beyond the control of any individual, group, or entity, serving as both a currency and a means of payment [1,2]. Introduced by its creator Satoshi Nakamoto in 2008, BTC's genesis involved the registration of the bitcoin.org domain in August 2008. In October of the same year, Nakamoto published the seminal paper titled "Bitcoin: A Peer-to-Peer Electronic Cash System," meticulously detailing the system required to create an "electronic system for transactions without relying on trust" [3,4]. The inaugural Bitcoin block, known as the genesis block (or block 0), was mined on January 3, 2009.

The primary goal behind the emergence of cryptocurrencies was to establish a unique digital payment system allowing unlimited financial transactions without the need for intermediaries such as banks or governments. This would eliminate the involvement of third parties in financial transactions. The distributed architecture provided by blockchain technology, coupled with cryptographic techniques, makes Bitcoin highly resistant to attacks and fraud [2]. Moreover, the transparency facilitated by blockchain technology ensures that transactions are recorded on the publicly accessible Bitcoin network, constituting one of Bitcoin's major advantages [5].

While digital currencies have recently gained prominence, the roots of blockchain technology trace back to 1982. Computer scientist, cryptographer, and inventor David Lee Chaum is recognized as the creator of digital currency. His 1982 thesis titled "Computer Systems Established, Maintained, and Trusted by Mutually Suspicious Groups" is the earliest known proposal for blockchain protocol [6,7].

Today, BTC stands undoubtedly as the most well-known and valuable digital currency. Initially traded for less than $1 in its early years (2010), it quickly soared to over $65,000 in a relatively short time (2021). With over 20,000 cryptocurrencies existing today, the emergence of new digital currencies is partly attributed to the fame of BTC. Furthermore, the proliferation of cryptocurrency exchanges and their increasing use for payments and transfers have transformed various digital currencies, including BTC, into significant investment instruments.

2 LITERATURE REVIEW

Sarker et al. [8] employed the nonlinear ARDL method and Granger causality test to investigate the impact of climate policy uncertainty and changes in energy prices on Bitcoin prices. Using data from October 1, 2013, to December 1, 2021, they analyzed monthly climate policy uncertainty (CPU), global energy price index (GPEI), and Bitcoin prices. Their findings showed that increases in climate policy uncertainty and decreases in the global energy price index positively affected Bitcoin in the short term. They highlighted those changes in climate policy uncertainty and the global energy price index had significantly higher effects on Bitcoin in the long term. The Granger causality test revealed a bidirectional causality between Bitcoin and climate policy uncertainty, while a unidirectional causality from the global energy price index to Bitcoin was observed.

Fasanya et al. [9] explored the relationship between Bitcoin and gold markets in uncertainty caused by infectious diseases using jump and causality tests. Analyzing daily data from July 19, 2010, to May 26, 2020, encompassing Bitcoin, gold, and the Infectious Diseases Uncertainty (EMV-ID) index, their spillover tests suggested a low-level connection between the two markets. They emphasized that gold markets acted as a clear volatility transmitter, while Bitcoin markets acted as receivers of shocks. Moreover, during downward market movements, Bitcoin and gold markets were reported to be less correlated.

Tunçel et al. [10] investigated the causality relationship between Bitcoin prices and the BIST100 index. Using daily data from July 19, 2010, to January 10, 2020, they conducted Lee-Strazicich unit root tests, indicating that the Bitcoin variable stabilized at level I(0), while the BIST100 variable stabilized at level I(1). Employing the Toda-Yamamoto causality test, they identified a bidirectional causality relationship between the variables at a 5% significance level.

Kaymak and Koç [11] examined the causality relationship between Bitcoin and Borsa Istanbul based on transaction volumes. Covering the period from January 1, 2017, to December 1, 2021, they conducted ADF and PP unit root tests to ascertain the stationarity of the series. The results indicated stationarity after taking the first differences. Contrary to expectations, the Toda-Yamamoto causality test suggested no causality relationship between Bitcoin and Borsa Istanbul variables during the identified period.

Li et al. [12] investigated the causality relationship between Bitcoin and crude oil markets under extreme and non-extreme shocks such as terrorist attacks, political issues, or financial crises. Utilizing weekly closing prices for Bitcoin and crude oil, their findings suggested that the interaction between the variables varied over time, with stronger causal connections during periods of significant movements in oil returns. Asymmetric causal connections were identified during extreme shocks.

Özmerdivanlı [13] explored the relationship between Covid-19 pandemic indicators and various financial markets representing Turkey, including gold, BIST100, Bitcoin, and the US dollar. Using daily data from March 11, 2020, to July 31, 2021, they applied the Johansen cointegration test, revealing long-term cointegration among the variables. The VECM-based causality test indicated long-term causality relationships in models where Bitcoin, interest rates, oil, and gold variables were dependent. In the short term, a unidirectional causality relationship was identified only between the US dollar and BIST100.

Kubar and Toprak [14] examined the relationship between Bitcoin and other top 10 cryptocurrencies (Ethereum, Tether, Ripple, etc.) during the period from August 21, 2020, to January 7, 2021. Employing Granger causality tests with daily closing prices in USD, they found a positive strong relationship between Bitcoin and all cryptocurrencies except Tether (USDT). Bidirectional causality was identified between Bitcoin and Ethereum, while unidirectional causality was observed between Bitcoin and other cryptocurrencies.

Soyaslan [15] investigated the short and long-term relationships and causality between Bitcoin and BIST100, BIST Banks, and BIST Technology variables. Using daily closing prices from April 21, 2011, to February 11, 2020, ADF and PP unit root tests indicated the removal of unit roots when first differences were taken. The Johansen cointegration test revealed a balanced relationship between Bitcoin and the BIST100 index, while no relationship was identified with BIST Banks and BIST Technology indices. Granger causality test results showed no causality relationship between Bitcoin and BIST100, BIST Banks, and BIST Technology indices in the short term.

3 MATERIAL AND METHOD

This study examines the causality relationship between Bitcoin (BTC) and the USD, Gold and BIST100 index using daily data between September 17, 2014 and October 13, 2023. Bitcoin and Gold prices are obtained from Yahoo Finance [16] database in US Dollars. The exchange rate is taken from the Central Bank of the Republic of Turkey (CBRT) [17] database as the USD/TL effective selling rate and BIST100 as the index value based on closing prices. Dates when the series are not traded are excluded from the analysis. All series subject to analysis are transformed into logarithmic return series $\left(log\, Y_{i,t} = log(X_{i,t}/X_{i,t-1})x100\right)$.

In the study, firstly, the outlier values of the series converted into logarithmic return series were calculated and the outlier values were corrected by taking the average of 10 observations as suggested by Bodart and Candelon. After the correction of the outliers, the stationarity levels of the series were investigated with Augmented-Dickey Fuller and Phillips Perron unit root tests. After determining the stationarity levels of the series, the appropriate ARMA (p,q) models are examined within the framework of Akaike Information Criterion. After determining the appropriate ARMA(p,q) models, the ARCH test was applied to the series to investigate whether there is an ARCH effect in the series. The ARCH effect is tested under the null hypothesis of no ARCH effect and the alternative hypothesis of an ARCH effect. The rejection of the null hypothesis of no ARCH effect at the 1%, 5% and 10% significance levels indicates that the series are suitable for Generalized Autoregressive Conditional Variance (GARCH) model structure. The series with the appropriate GARCH(p,q) model are estimated using GARCH, EGARCH, GJR-GARCH, IGARCH, APARCH, FIEGARCH and FIAPARCH models and the most appropriate GARCH(p,q) model is determined according to the model selection criteria.

In this study, the causality relationship between Bitcoin and USD, Gold and BIST100 index was estimated with the mean and variance causality tests developed by Hong [18] and calculated with the help of Generalized Autoregressive Conditional Variance with Variance (GARCH) models, and the cross-correlations between the squares of the standardized error terms obtained from the most appropriate GARCH model were calculated. Unlike classical causality tests (e.g. Granger [19]; Toda-Yamamoto [20]), the Hong [18] test for causality in variance proposes an asymptotic N (0,1) test procedure to measure volatility spillovers between two time series where the error terms are not constant variance and the two variables exhibit conditional variance and may have infinite conditional variance. This test procedure is based on the Cheung and Ng [21] test for causality in variance. Cheung and Ng [21] defined the condition for Y_t to be the cause of X_t in variance in two stationary and conditional variance series such as X_{t+1} and Y_t with information sets $I_t = \{X_{t-j}, J\} \geq 0$ and $J_t = \{X_{t-j}, Y_{t-j}, J\} \geq 0$, where $\mu_{x,t+1}$ is the conditional mean of X_{t+1} conditional on information set I_t through equation (1):

$$E\left\{\left(\left(X_{t+1} - \mu_{x,t+1}\right)^2 | I_t\right)\right\} \neq E\left\{\left(\left(X_{t+1} - \mu_{x,t+1}\right)^2 | J_t\right)\right\} \tag{1}$$

In order to test for causality in variance, the univariate GARCH (p,q) model must first be calculated. h_{it}^0 GARCH (p,q) equation is calculated from equation (2) to define the conditional variance calculated from the GARCH model:

$$h_{it}^0 = \omega_i^0 + \sum_{j=1}^{q} \alpha_{ij}^0 \, \varepsilon_{it-j}^2 + \sum_{j=1}^{p} \beta_{ij}^0 \, h_{it-j}^0 \tag{2}$$

For $i = 1,2$ in equation (2), it is defined as $\varepsilon_{it} = Y_{it} - \mu_{it}^0$ and $\varepsilon_{it} = Y_{it} - \mu_{it}^0$. Parameters $E(\varepsilon_{it}|I_{it-1}) = 0$and $E(\varepsilon_{it}^2|I_{it-1}) = h_{it}^0$ represent the conditional variance of ε_{it}^2.

Under the assumption that parameters $\omega_i^0 > 0$; α_{ij}^0 and β_{ij}^0 ensure the strict positivity of h_{it}^0, the squared standardized errors for series X_t and Y_t are calculated with the help of the equations in equation (3):

$$\hat{u}_t = \left\{\frac{\left(Y_{it} - \mu_{it,Y}\right)^2}{\hat{h}_{it,Y}}\right\} \text{ and } \hat{v}_t = \left\{\frac{\left(X_{it} - \mu_{it,X}\right)^2}{\hat{h}_{it,X}}\right\} \tag{3}$$

Following Chung and Ng [21], Hong [18] defines the cross-correlation formulation between $\hat{u}_t$ and $\hat{v}_t$ as the following equation, where T is the sample size, parameter $\hat{\rho}_{uv}(J)$ is the cross-correlations of $\hat{u}_t$ and $\hat{v}_t$ at lag J, and parameters $\hat{C}_{uu}(0)$ and $\hat{C}_{vv}(0)$ are the sample variances of $\hat{u}_t$ and $\hat{v}_t$:

$$\hat{\rho}_{uv}(J) = \{\hat{C}_{uu}(0)\hat{C}_{vv}(0)\}^{-\frac{1}{2}} C_{uv}(J) \tag{4}$$

Equation (4) imposes two conditions on the calculation of the cross-correlations of $\hat{u}_t$ and $\hat{v}_t$ at lag J. When $\hat{C}_{uu}(0) = T^{-1}\sum_{t=1}^{T}\hat{u}_t^2$ and $\hat{C}_{vv}(0) = T^{-1}\sum_{t=1}^{T}\hat{v}_t^2$, this condition is expressed by equation (5).

$$\hat{C}_{uv}(J) = \left\{\begin{matrix} T^{-1}\sum_{t=j+1}^{T} \hat{u}_t\hat{v}_{t-j}, J \geq 0 \\ T^{-1}\sum_{t=-j+1}^{T} \hat{u}_{t+j}\hat{v}_t, J < 0 \end{matrix}\right\} \tag{5}$$

Hong [18] improves the Chung and Ng [21] variance causality test and uses a weighting function of $k(\bullet)$to calculate the variance causality relationship between X_t and Y_t, where M is a positive integer and the number of lags is defined. This weighted function is defined through kernel functions such as Bartlett, Daniell, Parzen and Tukey-Hanning [22]. In this context, based on $k(\bullet)$weighting functions, the Hong [18] test for causality in variance is calculated through equation (6), which shows $C_T(k) = \sum_{J=1}^{T-1}(1-\frac{J}{T})k^2(\frac{J}{M})$ mean equations and $D_T(k) = \sum_{J=1}^{T-1}(1-\frac{J}{T})\left\{1-\frac{(j+1)}{T}\right\}k^4(\frac{J}{M})$ variance equations:

$$Q = \frac{\left\{T\sum_{J=1}^{T-1} k^2(\frac{J}{M)\hat{\rho}_{uv}^2(J) - C_T(k)}\right\}}{2D_T(k)^{\frac{1}{2}}} \tag{6}$$

In the study, the causality relationship between these variables is also investigated with the Hacker-Hatemi-J [23] and Hatemi-J [24] symmetric and asymmetric causality tests, which allow the effects of positive and negative shocks on the series to be observed. Under the assumption that the causality relationship between the two series defined as y_{1t} and y_{2t} is investigated, the equations for series y_{1t} and y_{2t} will be formed as follows [25-27]:

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{1,0} + \sum_{i=1}^{i} \varepsilon_{1i} \quad \text{and} \quad y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{2,0} + \sum_{i=1}^{i} \varepsilon_{2i} \tag{7}$$

$y_{1,0}$ and $y_{2,0}$ are the initial values, ε_{1i} and ε_{2i} are the error terms, and the positive and negative shocks in the error terms are the white noise error terms consisting of the sum of the positive and negative shocks of the error terms expressed as $\varepsilon_{1i}^{+} = max(\varepsilon_{1i}, 0)$, $\varepsilon_{1i}^{-} = min(\varepsilon_{1i}, 0)$ and $\varepsilon_{2i}^{+} = max(\varepsilon_{2i}, 0)$, $\varepsilon_{2i}^{-} = min(\varepsilon_{2i}, 0)$ $(\varepsilon_{1i} = \varepsilon_{1i}^{+} + \varepsilon_{1i}^{-}, \varepsilon_{2i} = \varepsilon_{2i}^{+} + \varepsilon_{2i}^{-})$. In the Hatemi-J causality test, the positive and negative shocks in the variables with causality relationship are defined as $y_{1t}^{+} = \sum_{i=1}^{t} \varepsilon_{1i}^{+}$, $y_{1t}^{-} = \sum_{i=1}^{t} \varepsilon_{1i}^{-}$, $y_{2t}^{+} = \sum_{i=1}^{t} \varepsilon_{2i}^{+}$, $y_{2t}^{-} = \sum_{i=1}^{t} \varepsilon_{2i}^{-}$ in cumulative form. Under the assumption that the positive cumulative variable is equal to $(y_t^{+} = (y_{1t}^{+}, y_{2t}^{+}))$ and the negative cumulative variable is equal to $(y_t^{-} = (y_{1t}^{-}, y_{2t}^{-}))$, the causality relationship is tested through the following model with the help of p. Lagged VAR(p) model:

$$y_t^{+} = \alpha + A_1 y_{t-1}^{+} + \cdots + A_p y_{t-1}^{+} + u_t^{+} \tag{8}$$

In equation (8), y_t^{+} is the vector of variables, α is the fixed variable and u_t^{+} is the error term vector. The Hacker-Hatemi-J [23] causality test allows estimating the causality relationship with boostrap simulation when the error terms are not normally distributed and there is an ARCH effect. In the application of Hacker-Hatemi-J [23] and Hatemi-J [24] causality tests, Akaike (AIC), Schwarz (SC) and Hannan-Quinn (HQ) information criteria can be used. However, in response to the fact that different results may emerge in models solved with SIC and HQ information criteria, Hatemi-J [24] developed the HJC information criterion based on the average of SIC and HQ information criteria. The HJC information criterion is defined as follows:

$$HJC = ln(|\hat{\Omega}_j|) + \mathrm{j}\left(\frac{n^2 \ln T + 2n^2 \ln(\ln T)}{2T}\right) \tag{9}$$

$j = 0,1,\ldots,p$ In equation (9), parameter $\hat{\Omega}_j$ is the variance-covariance matrix of the error term of the VAR(p) model estimated at lag, n is the number of VAR model equations, and T is the number of observations [25,26]. After determining the appropriate lag length for the application of Hacker-Hatemi-j [23] and Hatemi-J [24] symmetric and asymmetric causality tests, the null hypothesis H0: There is no Granger causality relationship between variables and the alternative hypothesis H1: There is a Granger causality relationship between variables are tested at 1%, 5% and 10% significance levels according to the calculated Wald test results. If the results obtained from the Wald test are greater than the critical values determined at the 1%, 5% and 10% significance levels, the null hypothesis is rejected and the causality relationship between the variables is accepted.

4 RESULTS AND DISCUSSION

The study first investigated the outlier values of the variables converted into return series. Accordingly, it is determined that there are 5 deviant observation values for BTC series, 36 for BIST100 series, 21 for USD series and 15 for Gold series. These deviant observation values were corrected by taking the average of 10 observations as suggested by Bodart and Candelon [28]. Graphs of the adjusted return series are presented in Figure 1. According to Figure 1, the years 2020 and 2022 indicate the periods with the highest volatility in the BIST100, USD and Gold series. When the said situation is evaluated daily BTC series, it is seen that the periods with the highest increase in volatility are 2017 and 2019.

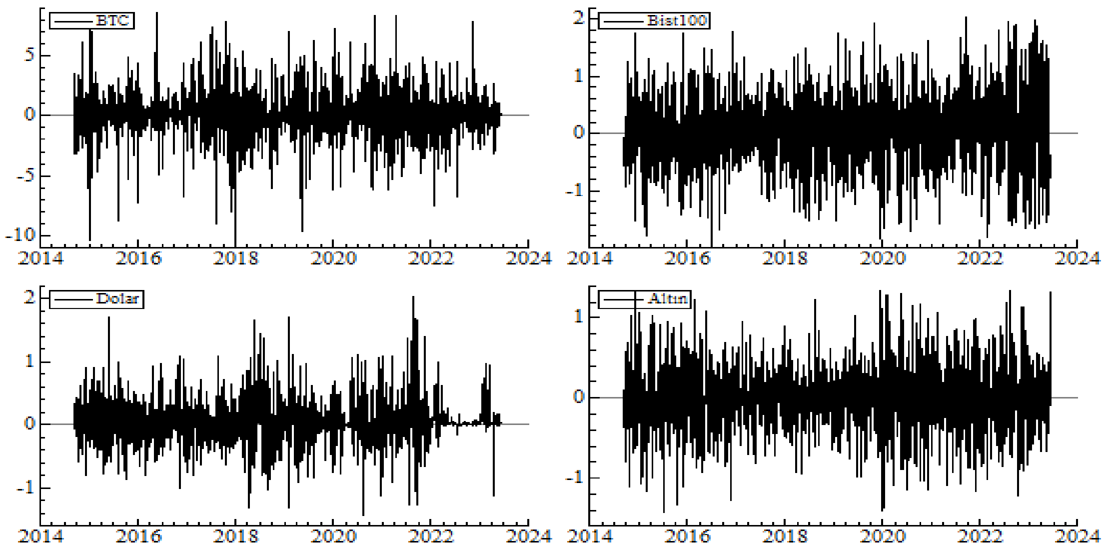

Figure 1. Adjusted series of BTC, BIST100, USD and Gold variables.

Table 1 presents descriptive statistics, ARCH(p,q) estimation results and Augmented-Dickey Fuller (ADF) and Phillips-Perron (PP) unit root test results. Table 1 shows that the mean of the BTC series is higher than the other series. The standard deviation value, which is a measure of volatility, is higher in the BTC series compared to other series. The standard deviation values of the BIST100 and USD series are higher than those of the Gold series. The skewness coefficient indicates that the BTC, BIST100 and Gold series are left skewed while the USD series is right skewed. The kurtosis coefficient indicates that all series have a steep structure. Jarque-Bera test statistic results indicate that all series are not normally distributed. ARCH test results reveal that all series exhibit conditional variance characteristics. Box-Pierce autocorrelation test results daily series and their squares indicate the presence of ARCH effect. ADF and PP unit root test results indicate that all series are stationary at their level values.

Table 1. Descriptive statistics.

	BTC	BIST100	USD	GOLD
Average	0.0789	0.0588	0.0491	0.0084
Minimum	-10.368	-1.9616	-1.4153	-1.4320
Maximum	8.6277	2.0206	2.0402	1.3493
Std.Error	1.842	0.580	0.345	0.368
Kurtosis	7.320	3.766	6.606	4.366
Skewness	-0.2361	-0.0490	0.5669	-0.0422
J-Bera	1787.454 [0.000]	56.436 [0.000]	1352.375 [0.000]	177.477 [0.000]
ARCH(5)	16.617 [0.000]	10.880 [0.000]	110.48 [0.000]	6.8536 [0.000]
Q(50)	65.422 [0.0704]	71.2512 [0.025]	248.519 [0.097]	54.338 [0.312]
QS(50)	269.403 [0.000]	387.694 [0.000]	2333.84 [0.000]	220.494 [0.000]
ADF	-46.919***	-46.292***	-39.253***	-48.600***
PP	-46.945***	-46.417***	-41.350***	-48.600***
Number of Observation	2271	2271	2271	2271

Note: *, ** and *** denote stationarity at 10%, 5% and 1% significance levels, respectively. Values in parentheses are p probability values for rejecting the null hypothesis that the series are non-stationary at level values. ARCH(5) stands for LM conditional variance test. Q(50) and QS(50) are the Box-Pierce autocorrelation test results for the series and their squares, respectively. Q(p) values considered in the Box-Pierce autocorrelation test are determined as approximate integer values by taking the square root of the total number of observations i

After determining the stationarity levels of the series, the appropriate ARMA (p,q) models were determined within the framework of the Akaike Information Criterion. ARMA(2,2) model for BTC, ARMA (3,3) for BIST100, ARMA (2,3) for USD series and ARMA (2,2) for Gold series were determined as the most appropriate ARMA(p,q) models. After determining the appropriate ARMA(p,q) models, ARCH test was applied to the series and the null hypothesis of no ARCH effect was rejected at the 1%, 5% and 10% significance levels. This indicates that the series are suitable for the GARCH model structure. The conditional variance equations of the series with ARCH(p,q) model are analyzed with the help of GARCH models. Accordingly, FIEGARCH(2,2) for BTC series, GARCH(3,3) for BIST100 series, FIEGARCH(2,3) for USD series and IGARCH(2,2) for Gold series are determined as the most appropriate models. Since the Jarque-Bera test results indicate that the series are not normally distributed, student-t distribution is used in GARCH model estimations. GARCH volatility estimation results for the series are presented in Table 2.

Table 2. Volatility model results.

Periods	ω	ν	α	β	d	θ_1	θ_2	Ø	t	Log(L)	Q(50)	$Q_S(50)$
BTC	0.068 [0.000]	2.026 [0.020]	-	0.750 [0.000]	0.667 [0.000]	0.053 [0.020]	0.317 [0.000]	-0.475 [0.013]	2.505 [0.000]	- 4178.218	71.059 [0.111]	30.851 [0.974]
BIST100	0.059 [0.000]	0.002 [0.204]	0.033 [0.002]	0.959 [0.000]	-	-	-	-	8.629 [0.000]	- 1901.555	46.567 [0.367]	36.917 [0.877]
USD	0.010 [0.000]	-2.138 [0.020]	-	-0.937 [0.000]	0.713 [0.000]	0.037 [0.346]	0.698 [0.000]	1.005 [0.000]	3.192 [0.000]	34.905	64.940 [0.057]	78.019 [0.903]
GOLD	0.009 [0.128]	0.000 [0.149]	0.0243 [0.003]	0.975 [-]	-	-	-	-	4.652 [0.000]	-847.171	43.756 [0.566]	37.3745 [0.865]

Note: Values in parentheses are probability values. ω is the constant term for the variance equation, v is the constant term for the mean equation, α and β are the ARCH-GARCH parameters denoting the asymmetric effect of shocks on volatility and persistence in the volatility set, respectively, and d is the long memory parameter for volatility. The parameters θ_1 and θ_2 denote the leverage effect. Ø is the ARCH parameter, t is the Student distribution parameter, Log(L) is the maximum likelihood, (50) and QS(50) are the Box-Pierce autocorrelation test results for the series and their squares, respectively. In the IGARCH (2,2) model calculated for the gold series, the β parameter is calculated by the (1- α) method. Therefore, the probability value is not observed.

According to the results presented in Table 2, the coefficient β, which expresses the persistence in volatility, is statistically significant at 1% significance level in the estimated BTC, BIST100 and USD models. This result indicates that the persistence of shocks in volatility is high. In the FIEGARCH models calculated for BTC and USD series, which include the leverage effect, the coefficients θ_1 and θ_2 are positive and statistically significant at 1% significance level. According to this result, good news in the market increases volatility more than bad news. In the models estimated for BTC and USD series, the d parameter, which indicates the presence of long memory in volatility, is positive and statistically significant at 1% significance level. The $d > 0.5$ condition of this parameter, which is defined as continuously stationary under the $0 < d < 0.5$ condition, indicates that the persistence of shocks in volatility lasts longer, in other words, shocks in volatility are effective for a longer period of time.

Following the appropriate GARCH model estimations, the causality relationship between BTC, BIST100, USD and Gold series in the mean and variance were estimated using the squares of the standardized error terms obtained from the GARCH model estimations. According to the mean causality test results presented in Table 3, a unidirectional causality relationship was found from BTC to BIST100 at 5% and 1% significance levels, respectively, and from BTC to USD at 10% significance level.

Table 3. Causality test results at the mean.

Direction of Causality	M1	M2	M3	M4	M5
BIST100=>BTC	-0.080 [0.532]	-0.164 [0.565]	-0.323 [0.627]	-0.396 [0.654]	-0.621 [0.733]
BTC=>BIST100	-0.419 [0.662]	0.862 [0.194]	2.182** [0.015]	2.616*** [0.004]	2.916*** [0.002]
USD=>BTC	0.026 [0.490]	0.245 [0.403]	0.735 [0.231]	1.074 [0.142]	1.168 [0.121]
BTC=>USD	0.239 [0.405]	0.011 [0.496]	0.069 [0.473]	0.052 [0.479]	-0.042 [0.517]
GOLD=>BTC	-0.754 [0.774]	-0.712 [0.762]	-0.961 [0.832]	-0.879 [0.810]	-0.847 [0.801]
BTC=>GOLD	-0.463 [0.678]	0.563 [0.287]	1.346* [0.089]	1.575* [0.058]	1.643* [0.052]

Note: *, ** and *** denote 10%, 5% and 1% significance levels, respectively. Values in parentheses are p probability values. M is the maximum number of lags. Daniell Kernel function is used in the estimation of causality analysis.

Table 4 shows the variance causality test results between BTC, BIST100, USD and Gold series. In the light of the information presented in the Table, it is seen that there is a bidirectional causality relationship between BTC and BIST100, USD and Gold series at 1% significance level. This result also indicates that there is a strong volatility spillover between BTC and the BIST100, USD and Gold markets, which are defined as alternative investment instruments. This result shows that the BTC market has gained an important place in Turkey and that the development of financial technologies and information has led to a high level of pass-through among all the markets subject to the study. The high volatility spillovers observed in BTC and other alternative investment instruments not only increase the likelihood of unexpected losses for investors, but also point to the existence of excessive risk in the markets.

Following the tests for causality in the mean and variance, the symmetric and asymmetric causality relationship between BTC and the BIST100, USD and Gold series were analyzed. Table 5 presents the results of the Hacker-Hatemi-J causality test. As a result of VAR(p) model estimation, the appropriate lag length was determined as 2 according to the Akaike Information Criterion. Since all variables subject to the analysis were found to be stationary at their level values, no lag length was added and the model was tested with the HJC information criterion considering the appropriate lag length. The results of the causality test indicate that the null hypothesis of no causality from BTC to USD is rejected at the 10% significance level and there is a unidirectional causality relationship from BTC to USD when the variables are not divided into positive and negative shocks. Apart from the causality relationship in question, no causality relationship was detected between the other variables subject to the study for all levels of significance.

Table 4. Causality test results for variance.

Direction of Causality	M1	M2	M3	M4	M5
BIST100=>BTC	3.484 [0.000]	6.062 [0.000]	8.153 [0.000]	10.013 [0.000]	11.143 [0.000]
BTC=>BIST100	4.957 [0.000]	7.501 [0.000]	9.923 [0.000]	11.928 [0.000]	12.225 [0.000]
USD=>BTC	24.865 [0.000]	25.899 [0.000]	25.744 [0.000]	25.659 [0.000]	24.732 [0.000]
BTC=>USD	4.307 [0.000]	5.831 [0.000]	7.034 [0.000]	8.257 [0.000]	8.249 [0.000]
GOLD=>BTC	9.535 [0.000]	9.929 [0.000]	9.580 [0.000]	9.812 [0.000]	10.638 [0.000]
BTC=>GOLD	7.212 [0.000]	9.673 [0.000]	12.151 [0.000]	13.638 [0.000]	14.433 [0.000]

Note: *, ** and *** denote 10%, 5% and 1% significance levels, respectively. Values in parentheses are p probability values. M is the maximum number of lags. Daniell Kernel function is used in the estimation of causality analysis.

Table 5. Hacker-Hatemi-J bootstrap causality test results.

Null Hypothesis (H_0)	W Test Statistics	1%	5%	10%
BTC≠>GOLD	0.921	6.704	3.740	2.237
GOLD≠>BTC	0.289	4.563	2.867	2.227
BTC≠>BIST100	0.066	5.305	3.226	2.552
BIST100≠>BTC	0.045	6.740	3.590	2.773
BTC≠>USD	3.448*	5.082	3.644	2.454
USD≠>BTC	1.779	6.206	4.832	3.778

Note: ***, ** and * indicate that the coefficient is significant at 1%, 5% and 10% significance levels, respectively. The optimal lag length is set as 1 based on k+dmax. HJC information criterion is chosen as the information criterion. Bootstrap number is taken as 1000.

The results of the Hatemi-J asymmetric causality test are presented in Table 6. According to the calculated Wald test results, there is a unidirectional Granger causality relationship from the positive shocks of BTC to the negative shocks of BIST100 and Gold, and a bidirectional Granger causality relationship to the negative shocks of USD. It is concluded that there is a bidirectional Granger causality relationship from the negative shocks of BTC to the positive shocks of Gold and unidirectional Granger causality relationship towards the negative shocks of Gold, while there is a unidirectional Granger causality relationship from the negative shocks of BTC to the negative shocks of USD.

Table 6. Hatemi-J asymmetric causality test results.

Null Hypothesis (H_0)	W Test Statistics	1%	5%	10%
$BTC^{+} \neq> BIST100^{+}$	1.268	6.764	6.204	4.778
$BIST100^{+} \neq> BTC^{+}$	193.583***	16.367	5.511	4.891
$BIST100^{-} \neq> BTC^{-}$	0.729	11.611	5.768	4.311
$BTC^{-} \neq> BIST100^{-}$	208.500***	10.680	8.436	5.278
$BIST100^{+} \neq> BTC^{-}$	150.680 ***	10.901	6.739	4.687
$BTC^{-} \neq> BIST100^{+}$	2.447	11.730	6.920	4.273
$BIST100^{-} \neq> BTC^{+}$	0.812	7.916	6.030	4.471
$BTC^{+} \neq> BIST100^{-}$	141.333***	9.471	6.242	5.066
$GOLD^{+} \neq> BTC^{+}$	280.801***	10.670	5.845	4.367
$BTC^{+} \neq> GOLD^{+}$	2.411	10.172	7.286	6.064
$GOLD^{-} \neq> BTC^{-}$	1.759	8.727	5.176	3.982
$BTC^{-} \neq> GOLD^{-}$	253.702***	9.154	5.870	4.482
$GOLD^{+} \neq> BTC^{-}$	173.613***	7.482	6.084	5.264
$BTC^{-} \neq> GOLD^{+}$	4.202*	10.617	5.255	4.068
$GOLD^{-} \neq> BTC^{+}$	3.979	14.954	8.675	5.828
$BTC^{+} \neq> GOLD^{-}$	151.294***	13.743	8.355	6.690
$USD^{+} \neq> BTC^{+}$	189.302***	8.147	7.209	5.722
$BTC^{+} \neq> USD^{+}$	5.444	9.455	8.005	6.754
$USD^{-} \neq> BTC^{-}$	1.266	7.178	5.389	4.565
$BTC^{-} \neq> USD^{-}$	117.011***	11.073	7.413	5.687
$USD^{+} \neq> BTC^{-}$	357.211***	11.352	8.005	5.076
$BTC^{-} \neq> USD^{+}$	0.011	9.446	5.485	4.708
$USD^{-} \neq> BTC^{+}$	7.412*	12.654	8.478	6.410
$BTC^{+} \neq> USD^{-}$	382.851***	10.483	7.176	4.950

Note: ***, ** and * indicate that the coefficient is significant at 1%, 5% and 10% significance levels, respectively. The optimal lag length is set as 2 based on k+dmax. HJC information criterion is chosen as the information criterion. The number of bootstraps is taken as 1000. + sign indicates positive shocks and – sign indicates negative shocks.

5 CONCLUSION AND SUGGESTIONS

This study examines the causal relationships between Bitcoin (BTC), the BIST100 index, the US Dollar (USD), and gold using daily data spanning from September 17, 2014, to October 13, 2023. To analyze both symmetric and asymmetric causal interactions among these financial instruments, the study employs Hong's mean and variance causality tests [18], as well as the symmetric (Hacker-Hatemi-J [23]) and asymmetric (Hatemi-J [24]) causality tests.

The empirical findings reveal various causality relationships among the examined variables. The results from the mean causality test indicate a weak unidirectional causality from BTC to USD, whereas variance causality tests identify significant volatility spillover effects across all four financial instruments. The asymmetric causality test further detects a unidirectional causality from BTC's positive shocks to the negative shocks of the BIST100 and gold, along with a bidirectional causality between BTC's positive shocks and USD's negative shocks.

These results align with previous studies investigating the interactions among these financial assets. Prior research by Sarker et al. [8], Li et al. [12], and Fasanya et al. [9] highlights Bitcoin's heightened sensitivity to external shocks, such as economic uncertainty and commodity price fluctuations, corroborating our findings on volatility spillovers. Similarly, Özmerdivanlı [13] identifies a long-term relationship between Bitcoin and major financial indicators, reinforcing the strong connection observed between BTC and USD. The literature also indicates that Bitcoin interacts with traditional financial assets, particularly during periods of economic instability. However, some studies present divergent findings. For instance, Kaymak and Koç [11] assert that BTC does not exhibit significant causality with Borsa Istanbul transaction volumes, contradicting our findings on volatility spillovers with the BIST100. Additionally, studies by Bouri et al. [14] and Dyhrberg [15] suggest that Bitcoin operates largely independently of traditional financial assets, functioning primarily as a speculative asset rather than an integrated investment instrument. These perspectives indicate that Bitcoin's price dynamics may be structurally distinct from those of conventional financial markets.

The findings of this study underscore the interconnectedness of Bitcoin, the BIST100, the US dollar, and gold within financial markets. The observed volatility spillovers suggest that price movements in these assets can influence one another, emphasizing the need for investors to consider these interdependencies when constructing diversified portfolios. Furthermore, the growing prominence of Bitcoin and its increasing interactions with traditional financial instruments necessitate enhanced regulatory oversight in the development of monetary policies and risk management strategies. Future research could extend this analysis by incorporating macroeconomic variables to further elucidate these relationships, as well as employing advanced econometric and machine learning methodologies to improve predictive accuracy. Comparative studies across various financial markets could provide additional insights into the differential impacts of these instruments. The significant volatility spillovers identified among BTC, USD, gold, and the BIST100 highlight the importance of further research on risk management strategies for cryptocurrency-inclusive portfolios.

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Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics

Artificial Intelligence (AI) Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the authors.

Contributions of the Authors

Hakan KAYA: Literature Review, Data Collection and Model Development, Data Analysis, Interpretation of the Results, Editing.

Batuhan ÖZKAN: Data Collection and Model Development, Methodology, Data Analysis, Interpretation of the Results, Manuscript Writing.

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