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AN ANALYSIS OF THE CAUSALITY RELATIONSHIP BETWEEN BITCOIN ELECTRICITY CONSUMPTION, PRICE AND VOLUME

BİTCOİN ELEKTRİK TÜKETİMİ İLE FİYATI VE HACMİ ARASINDAKİ NEDENSELLİK İLİŞKİSİNİN ANALİZİ

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Abstract

This study aims to analyze the causal relationship between electricity consumption, price and transaction volume of Bitcoin, which is the most important asset of the crypto money market in terms of both market capitalization and transaction volume. In this study, the Bitcoin electricity consumption variable is represented by Cambridge Bitcoin Electricity Consumption Index. As the data set, 1446 days of data between February 2017 and February 2021 were used. The causality relationship between the variables is analyzed using the Hatemi-J (2012) and Toda Yamamoto (1995) tests. In addition, this study is a rare study that examines the relationship between electricity and volume, together with the work done by Schinckus et al. (2020). According to the results of this study, the decrease in Bitcoin electricity consumption causes a decrease in the Bitcoin price. However, a negative relationship is detected Bitcoin electricity consumption and Bitcoin trade volume in this study, like the study by Schinckus et al. (2020), the relationship was found to be very weak.

Keywords: Bitcoin Electricity Consumption, Bitcoin Price and Bitcoin Trade Volume, Asymmetric Causality, Hatemi-J, Toda Yamamoto.
Jel Codes: C32, C58, D53.

Öz

Bu çalışma fiyat ve işlem hacmi açısından kripto para piyasasının en önemli enstrümanı olan Bitcoin'in elektrik tüketimi ile fiyatı ve işlem hacmi arasındaki nedensellik ilişkisini analiz etmeyi amaçlamaktadır. Çalışmada Bitcoin elektrik tüketimi değişkeni Cambridge Bitcoin Elektrik Tüketim Endeksi ile temsil

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"There is no requirement of Ethics Committee Approval for this study."

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edilmektedir. Araştırmada Şubat 2017 ile Şubat 2021 tarihleri arasındaki 1446 günlük veri seti kullanılmıştır. Değişkenler arasındaki nedensellik ilişkisi Hatemi-J (2012) ve Toda Yamamoto (1995) testleri kullanılarak analiz edilmiştir. Ayrıca bu çalışma, Schinckus vd. (2020) tarafından yapılan çalışma ile birlikte Bitcoin elektrik tüketimi ile işlem hacmi asrasındaki ilişkiyi inceleyen ender çalışmalardan biridir. Bu çalışmanın sonuçlarına göre Bitcoin elektrik tüketimindeki düşüş Bitcoin fiyatında düşüşe neden olmaktadır. Ancak bu çalışmada Schinckus vd. (2020) tarafından yapılan çalışmaya benzer olarak zayıf ama negatif bir ilişki tespit edilmiştir.
Anahtar Kelimeler: Bitcoin Elektrik Tüketimi, Bitcoin Fiyatı ve İşlem Hacmi, Asimetrik Nedensellik, Hatemi-J, Toda Yamamoto.
Jel Kodlar: C32, C58, D53.

1. Introduction

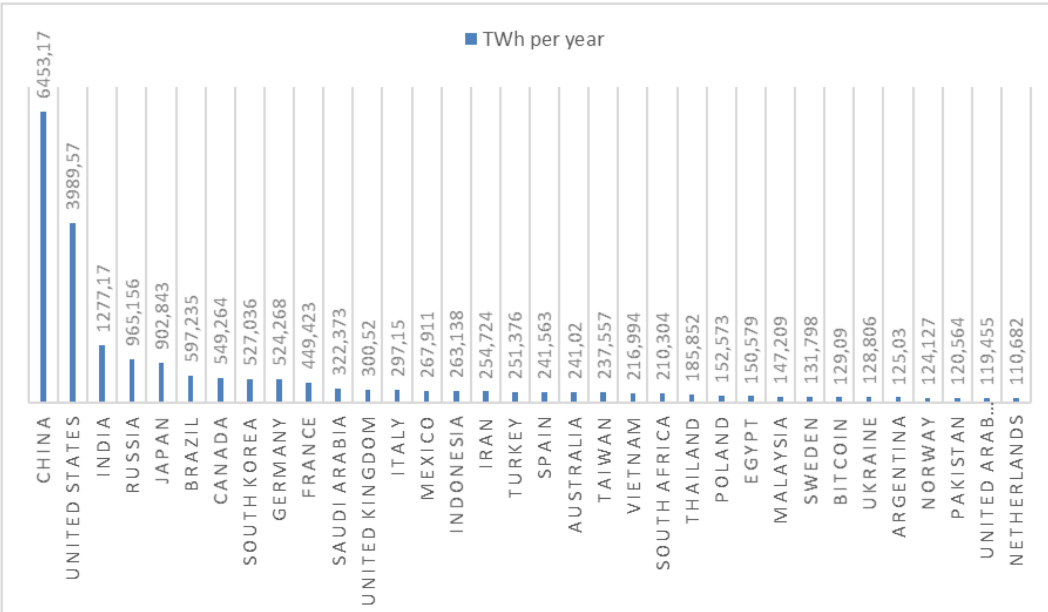
Cryptocurrencies, shown as the most important example of blockchain technology reached significant dimensions in terms of transaction volume and market capitalization. Even though the highest transaction volume of cryptocurrency is Tether, Bitcoin maintains its importance among all cryptocurrencies in terms of market capitalization. Today, while the market capitalization of a total of 4,594 cryptocurrencies is $ 1,451 Billion, the fact that this market capitalization of Bitcoin alone is $ 877.93 Billion provides evidence that it could be take Bitcoin as a basis when examining the crypto money market (Table 1).

Table 1: A Brief of Market Information of the Top 10 Cryptocurrencies

No	Name	Symbol	Market Cap	Total Volume	Total Supply	Consensus Mechanism
1	Bitcoin	BTC	$877.93B	35.84%	18.64M	PoW
2	Ethereum	ETH	$173.72B	16.15%	114.84M	PoW
3	Cardano	ADA	$41.71B	15.09%	31.94B	PoS
4	Binance Coin	BNB	$35.33B	2.16%	170.53M	PoSA
5	Tether	USDT	$35.01B	73.63%	35.66B	n/a
6	Polkadot	DOT	$31.92B	3.52%	1.04B	NPoS
7	XRP	XRP	$20.26B	3.79%	99.99B	Custom
8	Litecoin	LTC	$11.66B	3.95%	67.10M	PoW
9	Chainlink	LINK	$11.08B	1.39%	1.00B	n/a
10	Stellar	XLM	$10.14B	2.10%	105.44B	Custom

Sources: investing.com; coindesk.com; coinmarketcap.com, *Accessed Date: 28.02.2021.*

Studies on Bitcoin focus on issues such as price, volume and volatility. However, the focus of discussions on the sustainability of Bitcoin trading is Bitcoin energy consumption (Taylor, 2018). Today, based on the estimation studies on Bitcoin energy consumption, annual Bitcoin electricity consumption has exceeded the annual electricity consumption of most countries (Figure 1). Moreover, Bitcoin electricity consumption tends to increase over the years (Figure 2). Krause & Tolaymat (2018)'s papers revealed that cryptocurrency mining needs more energy consumption than traditional aluminum, copper, gold, platinum, and rare earth oxide mining. This situation reveals the size of the amount of electricity consumed in cryptocurrency mining. Moreover, Taylor (2018) argues that the increase in electricity consumption is independent of the value of Bitcoin and that an increase in the price of Bitcoin without innovation in mining hardware will increase electricity consumption. Taylor (2018) analyzes this relationship between Bitcoin price and electricity consumption by basing it on the hash rate. However, there are also opinions that the effect of the consensus protocols used on electricity consumption is limited (Sapkota & Grobys, 2019; Zade et al., 2019).



Graph 1: Annual Electricity Consumption (2019-most recent avaliable year) (**Source:** U.S. Energy Information Adminastration)

As stated in this context, various cryptocurrencies that differentiate the electricity consumption spent in cryptocurrency mining use different consensus protocols (Table 1). Among these consensus protocols, especially PoW (Proof of Work) and PoS (Proof of Stake) come to the fore. The PoW protocol consumes more electricity than the PoS protocol (Sedlmeir et al., 2020). Sapkota & Grobys (2019) presented evidence that there is no difference in mining returns between the two protocols. In addition, findings on the research of a hybrid model provides higher average returns compared to the other two models are also presented. However, in a study on the effect of differences in equipment used on energy consumption, Zade et al. (2019) encountered limited effect. Therefore, it can be concluded that the consensus mechanism is important in cryptocurrency mining, but it does not cause a serious differentiation in energy demand and efficiency.

Graph 2: Bitcoin Electricity Consumption (Source: Cambridge Center for Alternative Finance)

However, due to the hardware used in Bitcoin mining activities, the computational algorithms are quite complex, and it is necessary to bear high costs due to significant energy consumption (Cocco et al., 2017; de Vries, 2020; Giungato et al., 2017; Küfeoğlu & Özkuran, 2019; Taylor, 2018). In addition, it is evaluated that the CO_2 emissions, especially in the estimations about the size of the energy generated in mining activities, can increase the temperature by 20 ^{0}C in thirty years (Mora et al., 2018). However, Sedlmeir et al. (2020) have obtained evidence that there is no direct link between energy consumption and transaction volume, and therefore Bitcoin electricity consumption will not have a significant impact on climate change. Despite the excess of energy consumption, Bitcoin trading volume is expanding due to the opportunities it provides. Considering that one of the most important factors affecting Bitcoin electricity consumption is miner income (Das & Dutta, 2020), the necessity of using cheap energy sources emerges. Therefore, it is necessary to focus on alternatives such as green energy (Bastian-Pinto et al., 2021; Baur, 2019; Das & Dutta, 2020; Mir, 2020). It is estimated that 98% of Bitcoin in the markets will be produced by 2028. This situation also reveals the importance of evaluations on this issue (Küfeoğlu & Özkuran, 2019). In this context, this study fills the gap in the literature by analyzing the causality relationship between Bitcoin electricity consumption, Bitcoin prices and transaction volume.

The calculation of Bitcoin energy consumption, which is used as the main data of this study, is extremely hard due to the difficulties in predicting the future value of Bitcoin prices and the constant development of the hardware used (Küfeoğlu & Özkuran, 2019). Studies predicting the Bitcoin electricity consumption have been the subject of extensive research due to increasing importance of Bitcoin (de Vries, 2020; Küfeoğlu & Özkuran, 2019). Although it should be considered that the literature is heavily focused on Bitcoin, other cryptocurrencies constitute 1/3 of the total energy demand (Gallersdörfer et al., 2020). However, it is also seen that even Bitcoin energy demand is not sufficiently associated with the Bitcoin market. Moreover, the diversity of other cryptocurrencies makes it difficult to reveal meaningful relationships.

It has been provided that the hash algorithm is effective in estimating the energy consumption of cryptocurrencies and determining their efficiency (Li et al., 2019; Stoll et al., 2019; Taylor, 2018). However, the hash rate is not the only variable in the estimation studies on Bitcoin electricity consumption. In this study, Cambridge Bitcoin Electricity Consumption Index (CBECI) was used as Bitcoin electricity consumption data (https://cbeci.org, Accessed Date: 03.05.2021).

CBECI has compiled more than 60 different application-specific integrated circuits (ASIC) models since October 2014. It uses various mining equipment types and features within the framework of these compiled models. The mining efficiency for each type of machine used is expressed in Joules per Gigahash (J/Gh). CBECI develops the manufacturer specifications of these machines with the help of experts to measure the actual power usage. The model developed by CBECI assumes that miners will operate the equipment as long as they remain economically profitable. Various variables are used to determine the period that a particular type of equipment stays in the profit. These variables are the economic life of each machine, the total miner revenues, the total network hash rate, the energy efficiency of the hardware, and the electricity price per kWh that miners have to pay (Table 2). This situation can be expressed mathematically as in Formula 1:

$$\vartheta * P_{el} \leq SR_{ev} \tag{1}$$

where ϑ – energy efficiency of mining hardware [J/h]

P_{el} – electricity cost per joule [USD/J]

SR_{ev} – mining revenue per hash [USD/h]

CBECI does not consider capital expenditures (such as acquisition and depreciation costs) and operational activities (such as maintenance and labor costs) in its profitability calculations, but only considers the electricity costs incurred during the operation of the machines. The most important assumption when making all calculations is that electricity prices are stable over time and equal to 0.05 USD/kWh. Accordingly, the profitability threshold (θ) can be expressed as in Formula 2:

$$\theta = \frac{SR_{ev}}{P_{el}} \tag{2}$$

where θ – profitability threshold [J/h]

P_{el} – electricity cost per joule [USD/J]

SR_{ev} – mining revenue per hash [USD/h]

Ultimately, this index establishes a link between the profitability of mining equipment and the energy efficiency of the equipment. The model uses the latest profitable equipment when none of the equipment is profitable. The link between profitability and efficiency can be expressed as in Formula 3.

$$Eq_{prof}(P_{el}) = \{\vartheta_1, \vartheta_2, \dots\} \tag{3}$$

Eq_{prof} (P_{el}) – set of profitable hardware given electricity price P_{el}

ϑ_i – energy efficiency of mining hardware [J/h]

CBECI considers the scenario where it uses the most efficient energy equipment as the lower bound estimation (E_{lower}). In this case, electricity consumption is the lowest, and miner profitability is at the highest level. In other words, the lower bound assumes that the most efficient equipment is used by all miners. Under this assumption, miners will change their equipment if they find more efficient equipment. Another variable used in the calculations is the concept of power usage efficiency (PUE), which expresses data center energy efficiency. While determining the lower limit, the PUE value is determined as 1.01. Considering that this value is 1.11 for Google (https://www.google.com/about/datacenters, Accessed Date: 15.05.2021), the size of the power usage activity can be evaluated for the lower limit. The mathematical relationship for the estimation of the minimum amount of electricity consumed in Bitcoin mining is as shown in Formula 4.

$$E_{lower}(P_{el}) = \min\left(Eq_{prof}(P_{el})\right) * H * PUE * 3.16 * 10^7 \tag{4}$$

where E_{lower} – lower bound power consumption [W]

min (Eq_{prof}(P_{el})) – energy efficiency of the most efficient hardware [J/h]

H – hashrate [h/s]

PUE – power usage effectiveness

The lower limit in Bitcoin energy consumption refers to the situation where energy efficiency is at the highest level. This situation is calculated under various assumptions and can turn into useful information at a certain level. However, it should be noted that the lower bound calculations are not realistic. The reasons for this are not all miners are using the most efficient equipment, not considering the installation time of newly released equipment, hardware supply shortages, and an optimistic PUE assumption. For all these reasons, lower bound calculations were not used in our study.

CBECI also calculates the upper bound (E_{upper}) using a more complex calculation technique. The basic assumption in the upper bound calculation is that miners work with the least efficient hardware. Least efficient hardware refers to the least efficient option where miners are in profit. Because miners will not continue their activities when they are at a loss. Another assumption in the calculation of the upper limit is that the PUE value is assumed to be 1.20. Within the framework of all these explanations, the upper limit can be expressed mathematically as stated in Formula 5:

$$E_{upper}(P_{el}) = \max\left(Eq_{prof}(P_{el})\right) * H * PUE * 3.16 * 10^7 \tag{5}$$

where E_{upper} – upper bound power consumption [W]

max ($Eq_{prof}(P_{el})$) – energy efficiency of the least efficient but still profitable hardware [J/h]

H – hashrate [h/s]

PUE – power usage effectiveness

The upper bound calculations of Bitcoin electricity consumption give a measurable limit but are not realistic for various reasons. These reasons: Miners' demand for efficient equipment is not taken into account, their old equipment is often refurbished, and they do not take into account operational expenses such as cooling and maintenance costs. For all these reasons, upper limit values are not used in our study.

$$E_{estimated}(P_{el}) = \frac{\sum_{i=1}^{N} \vartheta_i}{N} * H * PUE * 3.16 * 10^7 \tag{6}$$

$E_{estimated}$ – best guess power consumption [W]

$\frac{\sum_{i=1}^{N} \vartheta_i}{N}$ – average energy efficiency of profitable hardware [J/h]

H – hashrate [h/s]

PUE – power usage effectiveness

Table 2: CBECI Model Parameters

Parameter	Description	Measure/Unit	Source
Network hashrate, mean daily	The mean rate at which miners are solving hashes that day	Exahashes per second (Eh/s)	Dynamic: https://coinmetrics.io/
Bitcoin issuance value, daily	The sum USD value of all bitcoins issued that day	USD	Dynamic: https://coinmetrics.io/
Miners fees, daily	The sum USD value of all fees paid to miners that day	USD	Dynamic: https://coinmetrics.io/
Difficulty, mean daily	The mean difficulty of finding a new block that day	Dimensionless	Dynamic: https://coinmetrics.io/

Bitcoin market price	The fixed closing price of the asset as of 00:00 UTC that day	USD	Dynamic: https://coinmetrics.io/
Network hashrate, real-time estimate	The real-time estimate of the rate at which miners are solving hashes	Exahashes per second (Eh/s)	Dynamic: https://www.blockchain.com/
Mining equipment efficiency	Measures the energy efficiency of a given mining hardware type	Joules per Gigahash (J/Gh)	Static: hardware specs from 60+ equipment types, taken from various sources
Electricity cost	Average electricity cost incurred by miners	USD per kilowatt-hour ($/kWh)	Static: estimate (assumption)
Data centre efficiency	Measures how efficiently energy is used in a data centre: expressed via power usage effectiveness (PUE)		Static: estimate (assumption)

Source: https://cbeci.org/cbeci/methodology, *Accessed Date: 05.01.2021.*

2. Literature Review

Measurements of the relationship between the Lightning Network (LN), a blockchain-based payment protocol, and market dynamics can be used to explain the effects of market conditions on payment protocols. However, it is considered that market dynamics do not have a significant effect on the topological configuration of the LN (Martinazzi et al., 2020).

The relationship between Bitcoin and asset classes such as gold, currency, commodities, stock indices, and bond indices has been frequently evaluated in the literature (Bhuiyan et al., 2021; Corbet et al., 2020; Jang et al., 2019; Jareño et al., 2020; Kang et al., 2020; Elsayed et al., 2020; Lahmiri & Bekiros, 2020; Maghyereh & Abdoh, 2020; Rehman & Apergis, 2019; Umar et al., 2021; Title, 2019). Some of these studies provide evidence that Bitcoin prices generally move independently and allow global investors to diversify (Bhuiyan et al., 2021; Lahmiri & Bekiros, 2020; Maghyereh & Abdoh, 2020). Moreover, there is evidence in the literature that investors can use Bitcoin to optimize their investments in environments of global economic uncertainty (Qin et al., 2021; Su, Qin, Tao, & Umar, 2020). This situation also shows that economic uncertainty processes can be predicted by taking advantage of Bitcoin returns. Corbet et al., (2020) argue that there is a stronger relationship between Bitcoin and financial assets than previously thought.

When the relationships between bitcoin returns and volatility spillover are examined, negative and significant relationships are observed between the variables (Jareño et al., 2020; Lahmiri & Bekiros, 2020). Similarly, there are studies in the literature that have found significant relationships between geopolitical risks and Bitcoin prices (Jiang et al., 2020; Su et al., 2020). Gozgor et al., (2019) found that Bitcoin returns were significantly affected by US trade policy uncertainties. Wang et al., (2019) provide evidence that Bitcoin returns are not affected by economic uncertainty and volatility indices. The study evaluates that Bitcoin can be a haven for investors in times of economic uncertainty. Besides, there are studies (Gürsoy, 2021) in which there is no causal relationship with monetary policy uncertainties.

Some studies have found a strong and positive relationship between bitcoin prices and gold prices (Bhuiyan et al., 2021; Corbet et al., 2020; Kang et al., 2020; Jareño et al., 2020; Kang et al., 2019; Su et al., 2020). However, some studies provide evidence that there is no causal relationship between precious metals and cryptocurrencies and that cryptocurrencies can provide diversification opportunities for portfolios of precious metals (Lahmiri & Bekiros, 2020; Maghyereh & Abdoh, 2020; Rehman & Vinh Vo, 2020). However, studies have found significant and negative relationships between other financial assets such as oil prices, bond prices, and Bitcoin prices (Kang et al., 2020; Su et al., 2020).

Corbet et al. (2020) examined the relationship between Bitcoin prices and energy market returns and returns of energy firms. In the study, it has been determined that the use of cryptocurrencies has a significant effect on the returns of some firms. Corbet et al. (2020) state that the environmental effects of the increase in the use of cryptocurrencies should be analyzed in their study. In the literature, some studies examine the relationships between Bitcoin returns, volatility and transaction volume. Studies have presented evidence of a relationship between volume and Bitcoin returns (Balcilar et al., 2017; Gemici & Polat, 2019; Sahoo et al., 2019). A similar situation was encountered when the causal relationships between cryptocurrencies were examined (Elsayed et al., 2020; Keskin & Aste, 2019).

The only study in the literature examining the relationship between energy consumption and Bitcoin data was conducted by Schinckus et al., (2020). In the study, besides the Bitcoin trade volume, buying and selling volumes of cryptocurrencies were also included in the analysis. The study found a positive relationship between the buying and selling volumes of cryptocurrencies and their energy consumption. The study provides evidence of an increasing correlation between cryptocurrency transaction volumes and energy consumption. However, the study conducted by Schinckus et al., (2020) covers the data between 2014-2017. Considering that the period in which the cryptocurrency transaction volume reached significant measures was the 2018-2021 period, it becomes important to reanalyze the relationship between energy consumption and transaction volume. In addition, our study expands the study by adding price data to energy consumption and transaction volume data. In this respect, our study also fills the gap in the literature by analyzing the relationships between Bitcoin transaction volume, price, and energy data.

3. Methodology

This study investigates the relationship between bitcoin prices, the energy consumption of bitcoin, and bitcoin transaction volume. Then, Hatemi-J (2012) Asymmetric Causality and Toda and Yamamoto (1995) tests were run using daily data (1466) observations between February 2017 and February 2021. In the study, econometrical models are established to evaluate all variables in equations. The data belonging to the 3 variables used in this study were obtained from different sources, a wide range of data available was selected. Bitcoin energy consumption data was obtained from digiconomist.net, the data of the bitcoin price and bitcoin transaction volume were obtained from investing.com, which includes the total data of 7 major crypto exchanges (Binance, GDAX, Bitfinex, BitStamp, Kraken, Poloniex, itBit). In addition, the abbreviations of the variables in the study are used for bitcoin energy consumption (BENERG), bitcoin price (BPRICE), and bitcoin transaction volume (BTRANS). First, the unit root tests of the data are performed, and the Zivot-Andrews Unit Root Test, which considers the structural breaks, is used for this test.

Many tests have been developed to investigate the relationship between two variables in time series. These tests are sometimes built based on an economic theory between variables, or they search for a hidden relationship. In asymmetric causality analysis tests, it is argued that there is a hidden relationship between two-time series, which cannot be correlated at first glance, and that there is no relationship between them, and that these hidden relationships can only be found by considering the asymmetry between the components. The asymmetric causality test, which was first introduced to the literature by Granger and Yoon (2002), was developed by Hatemi-J (2012), examines the variables by separating them into positive and negative components. Causality analysis aims to find hidden relations that will help to understand the dynamics of the series and allow to development of possible predictions for the future. Causality relationship of two integrated variables y_{1t} and y_{2t} can be written as follows (Hatemi-J, 2012: 449-450).

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{10} + \sum_{i=1}^{t} \varepsilon_{1i} \qquad ve \qquad y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{20} + \sum_{i=1}^{t} \varepsilon_{2i} \tag{7}$$

Here, $t = 1,2,...T$, denotes the constant terms, y_{1t} and y_{2t} denotes initial values, ε_{1i} and ε_{2i} error terms. Positive and negative shocks are expressed as in equation (8).

$$\varepsilon_{1i}^{+} = \max\ (\varepsilon_{1i}, 0)\,, \varepsilon_{2i}^{+} = \max\ (\varepsilon_{2i}, 0), \varepsilon_{1i}^{-} = \min\ (\varepsilon_{1i}, 0)\ \ ve\ \ \varepsilon_{2i}^{-} = \min\ \ (\varepsilon_{2i}, 0) \tag{8}$$

Error terms are expressed as $\varepsilon_{1i} = \varepsilon_{1i}^{+} + \varepsilon_{1i}^{-}$ ve $\varepsilon_{2i} = \varepsilon_{2i}^{+} + \varepsilon_{2i}^{-}$ Based on these, it is possible to rewrite equations (7) and (8) as follows:

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{1,0} + \sum_{i=1}^{t} \varepsilon_{1i}^{+} + \sum_{i=1}^{t} \varepsilon_{1i}^{-}, \tag{9}$$

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{2,0} + \sum_{i=1}^{t} \varepsilon_{2i}^{+} + \sum_{i=1}^{t} \varepsilon_{2i}^{-}. \tag{10}$$

Lastly, the positive and negative shocks in each variable are expressed in cumulative form as

$$y_{1t}^{+} = \sum_{i=1}^{t} \varepsilon_{1i}^{+}, \qquad y_{1t}^{-} = \sum_{i=1}^{t} \varepsilon_{1i}^{-}, \qquad y_{2t}^{+} = \sum_{i=1}^{t} \varepsilon_{2i}^{+}, \qquad y_{2t}^{-} = \sum_{i=1}^{t} \varepsilon_{2i}^{-}, \tag{11}$$

Then, assuming that is $y_t^{+} = y_{1t}^{+}, y_{2t}^{+}$, the causality relationship between the positive components is tested through the p delayed vector autoregressive model (VAR). VAR (p) model is expressed as in equation (12).

$$y_t^{+} = v + A_1 y_{t-1}^{+} + \cdots + A_p y_{t-1}^{+} + u_t^{+} \tag{12}$$

Here, y_t^+ indicates a variable vector of size 2x1, v is constant variable vector of size 2x1, u_t^+ is error term size of 2x1, and A_p is expressed as a parameter matrix of "p" order, which is determined using 2x2 size delay length information criteria. The following equation is used to determine the optimal lag lengt:

$$HJC = \ln(|\widehat{\Omega}_j|) + j\left(\frac{n^2 lnT + 2n^2 \ln(\ln T)}{2T}\right), \qquad j = 0,\ldots,p \tag{13}$$

$(|\widehat{\Omega}_j|)$ shows j length of the lag of the estimated VAR model's error term is variance-covariance matrix, n is the number of equations in the VAR model, and T is the number of observations.

After the lag length is determined, the Wald statistic is used to test the H_0 fundamental hypothesis, which indicates the absence of Granger-causality between series. The VAR model equation created to obtain the Wald statistics is as follows.

$Y = DZ + \delta$ the equation is more clearly expressed.

$$Y: = (y_1^+, y_2^+, \ldots, y_T^+)$$

$$D: = (v, A_1, A_2, \ldots, A_p)$$

$$Z_t := \begin{bmatrix} 1 \\ y_t^+ \\ y_{t-1}^+ \\ \vdots \\ y_{t-p+1}^+ \end{bmatrix} \tag{14}$$

$$Z: = (Z_0, Z_1, \ldots, Z_{T-1})$$

$$\delta: = (u_1^+, u_2^+, \ldots, u_T^+)$$

According to equation (14): it refers to matrixes of different sizes *Y : (n x T)*, *D : (n x (1+np))*, Z_t*: ((1+np) x 1)*, *Z: ((1+np) x T)* and $\delta: (n\ x\ T)$.

The basic hypothesis $(H_0: C\beta = 0)$ which states that there is no Granger causality is tested with the Wald statistic. The Wald statistics can be calculated with the help of the following equation.

$$Wald = (C\beta)'[C((Z'Z)^{-1} \otimes S_U)C']^{-1}(C\beta) \tag{15}$$

Equation (15) is in the form of $\beta = vec(D)$ and indicates the column clustering operator. $\otimes$ Kronecker, *C* represents the indicator function including constraints. The variance-covariance matrix calculated for the unconstrained VAR model is expressed as $S_U = \frac{\widehat{\delta}'_U \widehat{\delta}_U}{T-q}$. And here, the *q* represents the number of lags in the VAR model.

In the research, four hypotheses have been established to test the existence of a causality relationship between the variables. These hypotheses established for study are as follows.

H_0: There is no causal relationship between BENERG and BPRICE, BTRANS.

H_1: There is causal relationship between BENERG and BPRICE, BTRANS.

Another method, developed by Toda and Yamamoto (1995), take the Granger causality test to a higher level. In addition, the model tries to enhance some of the problems that occur in the Granger causality test. To be able to test Granger causality for time series, the series must first become stationary and stabilize at the same level. However, once this condition has been met, co-integration must also occur to demonstrate a long-term relationship between stationary series at the same level. In other words, only the Granger causality test can be performed between the series that are stable at the same level and have a cointegration relationship between them. However, the Toda-Yamamoto test revealed that time series, which are at different levels of stability, may have causality between them, and even causality testing can be done without the need for a stationary test. This model can also be tested whether there is a co-integration between the series, regardless of co-integration (Toda and Yamamoto, 1995: 246).

In the case of the performing Toda and Yamamoto (1995) test, the appropriate lag length *(k)* is determined by the VAR model. In the second stage of the analysis, the degree of integration (d_{max}) of the variable, which has the highest degree of integration, is added to the lag length *(k)* of the model. In the last stage, the VAR model is estimated according to the lags with series level values ($k + d_{max}$). The VAR model is applied with the help of the following equations (Toda and Yamamoto, 1995: 230)

$$Y_t = a_0 + \sum_{i=1}^{k+d_{max}} a_{1i} Y_{t-i} + \sum_{i=1}^{k+d_{max}} a_{2i} X_{t-i} + u_t \tag{16}$$

$$X_t = \beta_0 + \sum_{i=1}^{k+d_{max}} \beta_{1i} X_{t-i} + \sum_{i=1}^{k+d_{max}} \beta_{2i} Y_{t-i} + v_t \tag{17}$$

For the Toda and Yamamoto (1995) The hypotheses established for study are as follows.

H_0: *The X variable is not the Granger cause of the Y variable.*

H_1: *The X variable is the Granger cause of the Y variable.*

4. Findings and Discussions

The Zivot-Andrews Unit Root Test (1992), which allows for structural break, was used to test the stationarity of the time series in this study. This test is a new unit root test that does not find Perron's (1989) external breakpoint assumption rational and allows an estimated break in the under-trend function against the basic hypothesis versus the alternative hypothesis. Zivot and Andrews (1992) criticized Perron's external breakpoint assumption and developed a new unit root test method under the alternative hypothesis that allows an estimated break in the trend function using the data used by Perron. Since structural break is accepted as intrinsic in Zivot-Andrews test, Zivot-Andrews test is considered to be superior to Perron test. For this reason, Zivot-Andrews test is preferred in this study.

According to the intercept and trend-breaking model C results obtained from the Zivot-Andrews unit root test, it was determined that the BENERG and BTRANS variables are stationary at the I (0) level. However, the BPRICE variable is not stable at the level, but it is found to be stationary at the I (1) level. In addition, when the break dates obtained from the ZA unit root test were examined, it was observed that the movements in the ordinary political and economic policies that occurred on these dates caused the breaks.

Table 3: The results of Zivot-Andrews Unit Root Test

	Zivot-Andrews (Model C)					
Variables	**I(0) Test Statistic**	**I(0) Breaking Date**	**Critical Values**	**I(1) Test Statistic**	**I(1) Breaking Date**	**Critical Values**
BENERG	-5.459**	05.12.2020	-5.08	-	-	-5.08
BPRICE	-2.674	09.07.2020	-5.08	-10.039	09.07.2020	-5.08
BTRANS	-8.539	14.08.2018	-5.08	-	-	-5.08

***: It is significant at 5% level.*

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In this part of the study, the causality between the bitcoin prices, energy consumption of the bitcoin, and bitcoin transaction volume are analyzed by the asymmetric causality test introduced into the literature by Hatemi-J (2012). Hatemi-J asymmetric causality test was performed with the help of the Gauss 10 econometric analysis package program. The findings related to the analysis are given with the (+) and (-) symbols in a way that positive and negative causality can be seen. In addition, both variables included in the model were examined as both dependent and independent variables.

According to the results of the Hatemi-J asymmetric causality test (Table 4), which investigates the causality relationship between the cumulative positive and negative changes of the variables, it was found that there were two-way partial causality relationships among the BENERG, BPRICE and BTRANS at the 5% significance level.

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Table 4: The results of Hatemi-J Asymmetric Causality Analysis

Direction of Causality	Wald Statistics	Bootstrap Critical Values		
		%1	%5	%10
BENERG (+) > BPRICE (+)	5.985	18.109	9.892	6.935
BENERG (-) > BPRICE (-)	11.036**	17.391	9.974	7.100
BPRICE (+) > BENERG (+)	16.039**	17.183	9.680	7.004
BPRICE (-) > BENERG (-)	16.122**	16.879	9.855	6.866
BENERG (+) > BTRANS (+)	3.309	21.262	10.376	6.961
BENERG (-) > BTRANS (-)	3.305	19.743	10.271	6.880
BTRANS (+) > BENERG (+)	5.121	18.903	10.014	6.929
BTRANS (-) > BENERG (-)	5.156	18.083	10.257	7.210
BTRANS (+) > BPRICE (+)	8.328**	12.853	8.301	6.494
BTRANS (-)> BPRICE (-)	7.084	12.954	8.245	6.404
BPRICE (-)> BTRANS (+)	6.164	12.473	8.029	6.263
BPRICE (-) > BTRANS (-)	7.561	12.382	8.194	6.508

*** It is significant at 5% level.*

According to the results of the Hatemi-J asymmetric causality test, which investigates the causality relationship between the cumulative positive and negative changes of the variables, it was found that there were two-way partial causality relationships among the BENERG, BPRICE and BTRANS at the 5% significance level.

According to the results of the equation in which a positive causality relationship was tested from the BENERG to the BPRICE, the Wald test statistic value (5.985) was found to be not significant because it was less than the bootstrap critical value (9.892). H_0 hypothesis was accepted and the H_1 hypothesis was rejected. Also, in another equation where negative causality is tested for the same variables, the Wald test statistic value (11.036) is found while the bootstrap critical value is 9.974. It is significant because Wald test statistic value is higher than the bootstrap critical value. According to the results of the equation in which a positive-negative causality relationship is tested from the BPRICE to BENERG was observed that both a positive and a negative causality relationship. It was found that BPRICE affected BENERGY at a 5% significance level. H_0 hypothesis was rejected, H_1 hypothesis was accepted.

On the other hand, according to the results of the equation in which a positive and negative causality relationship is tested from the BENERG to BTRANS was tested, the Wald test statistic values less than bootstrap critical values. It couldn't be reached the 5% significance level. From BTRANS to BENERGY. H_0 hypothesis was accepted, H_1 hypothesis was rejected. The findings indicate that there is no one-way or two-way causality relationship between BTRANS and BENERGY.

However, a partial causality relationship has been identified between BTRANS and BPRICE. Only one causality effect was determined from the 4 equations established between BTRANS and BPRICE. In the equation where positive causality was tested from the BTRANS to BPRICE the Wald test statistic value (8.328) is found while the bootstrap critical value is 8.301. It was found significant because Wald test statistic value is higher than the bootstrap critical value. H_0 hypothesis was rejected, H_1 hypothesis was accepted. Apart from this, the causality relationship could not be determined for other equations established from BPRICE to BTRANS.

Another method, which used in this study, is the Toda-Yamamoto test, the basic hypothesis and alternative hypothesis can be discussed as follows.

H_0: The X variable is not the Granger cause of the Y variable.

H_1: The X variable is the Granger cause of the Y variable.

The success of the Toda-Yamamoto causality test is directly related to the correct determination of the value of the series (d_{max}) and *(k)* in the model.

Table 5. Toda-Yamamoto Causality Test Results

Dependent Variable	Independent Variable	dmax	k	Chi-Square Test Statistics	Probability	Causality and Direction
BPRICE	**BENERGY**	9		17.69205	0.0389	BENERGY => BPRICE
BTRANS		9		6.534878	6.534878	BENERGY ≠> BTRANS
BENERGY	**BPRICE**	9		30.72404	0.0003	BPRICE => BENERGY
BTRANS		2		0.072714	0.9643	BPRICE ≠> BTRANS
BENERGY	**BTRANS**	9		5.730869	0.7665	BTRANS ≠> BENERGY
BPRICE		2		4.459055	0.1076	BTRANS ≠> BPRICE

**: It is significant at 5% level.

The optimal lag length was determined according to the criterion SC, dmax = the maximum stationarity level according to the unit root test of Lee Strazicich, k = VAR denotes the lag length. All variables are evaluated in equations as both dependent and independent variables.

At the end of the analysis, it was obtained partial meaningful relations in all. The causality relationship with a 5% significance level was realized from the BPRICE to BENERGY. It was found the causality relations from BENERGY to BPRICE. It is seen that the H_0 hypothesis is rejected, H_1 hypothesis is accepted. However, there was no causality relationship in the rest of the equation. It was seen that the established H_1 hypothesis is accepted. The H_0 hypothesis is rejected.

5. Conclusion

The 21st century has been a period of anxiety regarding the use of traditional currencies due to their sustainability. Many reasons cause the emergence of this situation. Especially these reasons can be counted as technological developments, differentiation of the needs of today's people and globalization. But most of all, with the strengthening of the dominant currencies in the global markets, the currencies of other countries, especially the developing countries, rapidly lose their competitiveness. Based on these and similar reasons, the use of cryptocurrency has become increasingly common. The first and most popular of these cryptocurrencies is Bitcoin. Since it is an energy-based creation process, unlike traditional money, it is closely related to energy consumption. Therefore, in this study, bitcoin energy consumption, bitcoin price, and transaction volume were investigated. In this direction, analysis was carried out using 2 different causality tests using daily data between 2017 February-2021 February.

According to the findings obtained from the study conducted, it was seen that the results of both causality tests confirm each other. According to the Hatemi-J Asymmetric causality test results, while positive shocks in bitcoin energy consumption do not have a significant effect on positive shocks of bitcoin price, negative shocks are significantly effective. In other words, while increasing energy consumption for bitcoin does not affect the price, the decrease in energy consumption has a causal effect on the decrease in prices. In the equations investigating the relationship between bitcoin energy consumption and bitcoin price, Toda-Yamamoto Causality Test results revealed two-way causality between bitcoin energy consumption and bitcoin prices. On the other hand, no causality relationship has been found between bitcoin energy consumption and bitcoin transaction volume. This result was the same in every test performed. Although not supported by the Toda-Yamamoto test results, according to the Hatemi-J asymmetric causality test results, it has been observed that the positive change in bitcoin transaction volume affects the positive change in bitcoin prices weakly.

This research is the causal relationship between Bitcoin electricity consumption and price in the literature. This study finds evidence of a relationship between the Cambridge Bitcoin Electricity Consumption Index and price. This evidence shows that when Bitcoin electricity consumption decreases, there will be a price decrease. Therefore, market actors will be able to use electricity consumption as a leading indicator in their investment analysis. On the other hand, a significant relationship was found between Bitcoin electricity consumption and transaction volume, similar to the study of Schinckus et al. (2020). Since this relationship is quite weak, it does not contain sufficient data for analysis.

Author Contrubition

CONTRUBUTION RATE	EXPLANATION	CONTRIBUTORS
Idea or Notion	Form the research idea or hypothesis	Author 1 & Author 2
Literature Review	Review the literature required for the study	Author 1
Research Design	Designing method, scale, and pattern for the study	Author 1 & Author 2
Data Collecting and Processing	Collecting, organizing, and reporting data	Author 2
Discussion and Interpretation	Taking responsibility in evaluating and finalizing the findings	Author 1 & Author 2

Conflict of Interest

No conflict of interest was reported by the authors.

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References

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, *64*(March), 74–81. https://doi.org/10.1016/j.econmod.2017.03.019.

Bastian-Pinto, C. L., Araujo, F. V. d. S., Brandão, L. E., & Gomes, L. L. (2021). Hedging renewable energy investments with Bitcoin mining. *Renewable and Sustainable Energy Reviews*, *138*(September 2020). https://doi.org/10.1016/j.rser.2020.110520.

Baur, D. G. (2019). *The (Un –) Sustainability of Bitcoin Investments*. 1–19.

Bhuiyan, R. A., Husain, A., & Zhang, C. (2021). A wavelet approach for causal relationship between bitcoin and conventional asset classes. *Resources Policy*, *71*(May 2020), 101971. https://doi.org/10.1016/j.resourpol.2020.101971.

Cocco, L., Pinna, A., & Marchesi, M. (2017). Banking on blockchain: Costs savings thanks to the blockchain technology. *Future Internet*, *9*(3), 1–20. https://doi.org/10.3390/fi9030025.

Corbet, S., Katsiampa, P., & Lau, C. K. M. (2020). Measuring quantile dependence and testing directional predictability between Bitcoin, altcoins and traditional financial assets. *International Review of Financial Analysis*, *71*(April), 101571. https://doi.org/10.1016/j.irfa.2020.101571.

Corbet, S., Lucey, B., & Yarovaya, L. (2020). Bitcoin-energy markets interrelationships – New evidence. *Resources Policy*, *June*, 101916. https://doi.org/10.1016/j.resourpol.2020.101916.

Das, D., & Dutta, A. (2020). Bitcoin's energy consumption: Is it the Achilles heel to miner's revenue? *Economics Letters*, *186*, 108530. https://doi.org/10.1016/j.econlet.2019.108530.

de Vries, A. (2020). Bitcoin's energy consumption is underestimated: A market dynamics approach. *Energy Research and Social Science*, *70*(February), 101721. https://doi.org/10.1016/j.erss.2020.101721.

Gallersdörfer, U., Klaaßen, L., & Stoll, C. (2020). Energy Consumption of Cryptocurrencies Beyond Bitcoin. *Joule*, *4*(9), 1843–1846. https://doi.org/10.1016/j.joule.2020.07.013.

Gemici, E., & Polat, M. (2019). Relationship between price and volume in the Bitcoin market. *Journal of Risk Finance*, *20*(5), 435–444. https://doi.org/10.1108/JRF-07-2018-0111.

Giungato, P., Rana, R., Tarabella, A., & Tricase, C. (2017). Current trends in sustainability of bitcoins and related blockchain technology. *Sustainability (Switzerland)*, *9*(12). https://doi.org/10.3390/su9122214.

Gozgor, G., Tiwari, A. K., Demir, E., & Akron, S. (2019). The relationship between Bitcoin returns and trade policy uncertainty. *Finance Research Letters*, *29*(March), 75–82. https://doi.org/10.1016/j.frl.2019.03.016.

Granger, C. W., & Yoon, G. (2002). "Hidden cointegration". U of California, Economics Working Paper, (2002-02).

Gürsoy, S. (2021). The effect of the monetary policy uncertainty of US and Japan on Bitcoin price. *Journal of Yalova Social Scientific*, 11(1), 7-16.

Hatemi-J, A. (2012). Asymmetric causality tests with an application. *Empirical Economics*, 43(1), 447-456.

Jang, S. M., Yi, E., Kim, W. C., & Ahn, K. (2019). Information flow between bitcoin and other investment assets. *Entropy*, *21*(11), 1–8. https://doi.org/10.3390/e21111116.

Jareño, F., González, M. de la O., Tolentino, M., & Sierra, K. (2020). Bitcoin and gold price returns: A quantile regression and NARDL analysis. *Resources Policy*, *67*(February). https://doi.org/10.1016/j.resourpol.2020.101666.

Jiang, Y., Wang, G.-J., Wen, D.-Y., & Yang, X. (2020). Business conditions, uncertainty shocks and Bitcoin returns. *Evolutionary and Institutional Economics Review*, *17*(2), 415–424. https://doi.org/10.1007/s40844.020.00172-3.

Kang, S. H., McIver, R. P., & Hernandez, J. A. (2019). Co-movements between Bitcoin and Gold: A wavelet coherence analysis. *Physica A: Statistical Mechanics and Its Applications*, *536*, 120888. https://doi.org/10.1016/j.physa.2019.04.124.

Kang, S. H., Yoon, S. M., Bekiros, S., & Uddin, G. S. (2020). Bitcoin as Hedge or Safe Haven: Evidence from Stock, Currency, Bond and Derivatives Markets. *Computational Economics*, *56*(2), 529–545. https://doi.org/10.1007/s10614.019.09935-6.

Keskin, Z., & Aste, T. (2019). Information-theoretic measures for non-linear causality detection: application to social media sentiment and cryptocurrency prices. *ArXiv*. https://doi.org/10.1098/rsos.200863.

Krause, M. J., & Tolaymat, T. (2018). Quantification of energy and carbon costs for mining cryptocurrencies. *Nature Sustainability*, *1*(11), 711–718. https://doi.org/10.1038/s41893.018.0152-7.

Küfeoğlu, S., & Özkuran, M. (2019). Bitcoin mining: A global review of energy and power demand. *Energy Research and Social Science*, *58*(August), 101273. https://doi.org/10.1016/j.erss.2019.101273.

Lahmiri, S., & Bekiros, S. (2020). Renyi entropy and mutual information measurement of market expectations and investor fear during the COVID-19 pandemic. *Chaos, Solitons and Fractals*, *139*, 110084. https://doi.org/10.1016/j.chaos.2020.110084.

Li, J., Li, N., Peng, J., Cui, H., & Wu, Z. (2019). Energy consumption of cryptocurrency mining: A study of electricity consumption in mining cryptocurrencies. *Energy*, *168*, 160–168. https://doi.org/10.1016/j.energy.2018.11.046.

Maghyereh, A., & Abdoh, H. (2020). Tail dependence between Bitcoin and financial assets: Evidence from a quantile cross-spectral approach. *International Review of Financial Analysis*, *71*(June), 101545. https://doi.org/10.1016/j.irfa.2020.101545.

Martinazzi, S., Regoli, D., & Flori, A. (2020). A tale of two layers: The mutual relationship between bitcoin and lightning network. *Risks*, *8*(4), 1–18. https://doi.org/10.3390/risks8040129.

Mir, U. (2020). Bitcoin and its energy usage: Existing approaches, important opinions, current trends, and future challenges. *KSII Transactions on Internet and Information Systems*, *14*(8), 3243–3256. https://doi.org/10.3837/tiis.2020.08.005.

Mora, C., Rollins, R. L., Taladay, K., Kantar, M. B., Chock, M. K., Shimada, M., & Franklin, E. C. (2018). Bitcoin emissions alone could push global warming above 2°C. *Nature Climate Change*, *8*(11), 931–933. https://doi.org/10.1038/s41558.018.0321-8.

Qin, M., Su, C. W., & Tao, R. (2021). BitCoin: A new basket for eggs? *Economic Modelling*, *94*(February 2020), 896–907. https://doi.org/10.1016/j.econmod.2020.02.031.

Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. *Econometrica* 57:1361-1401.

Rehman, M. U., & Apergis, N. (2019). Determining the predictive power between cryptocurrencies and real time commodity futures: Evidence from quantile causality tests. *Resources Policy*, *61*(July 2018), 603–616. https://doi.org/10.1016/j.resourpol.2018.08.015.

Rehman, M. U., & Vinh Vo, X. (2020). Cryptocurrencies and precious metals: A closer look from diversification perspective. *Resources Policy*, *66*(April), 101652. https://doi.org/10.1016/j.resourpol.2020.101652.

Sahoo, P. K., Sethi, D., & Acharya, D. (2019). Is bitcoin a near stock? Linear and non-linear causal evidence from a price–volume relationship. *International Journal of Managerial Finance*, *15*(4), 533–545. https://doi.org/10.1108/IJMF-06-2017-0107.

Sapkota, N., & Grobys, K. (2019). Blockchain Consensus Protocols, Energy Consumption and Cryptocurrency Prices. *SSRN Electronic Journal*, 1–29. https://doi.org/10.2139/ssrn.3403983.

Schinckus, C., Nguyen, C. P., & Ling, F. C. H. (2020). Crypto-currencies trading and energy consumption. *International Journal of Energy Economics and Policy*, *10*(3), 355–364. https://doi.org/10.32479/ijeep.9258.

Sedlmeir, J., Buhl, H. U., Fridgen, G., & Keller, R. (2020). The Energy Consumption of Blockchain Technology: Beyond Myth. *Business and Information Systems Engineering*, *62*(6), 599–608. https://doi.org/10.1007/s12599.020.00656-x.

Stoll, C., Klaaßen, L., & Gallersdörfer, U. (2019). The Carbon Footprint of Bitcoin. *Joule*, *3*(7), 1647–1661. https://doi.org/10.1016/j.joule.2019.05.012.

Su, C. W., Qin, M., Tao, R., Shao, X. F., Albu, L. L., & Umar, M. (2020). Can Bitcoin hedge the risks of geopolitical events? *Technological Forecasting and Social Change*, *159*(June), 120182. https://doi.org/10.1016/j.techfore.2020.120182.

Su, C. W., Qin, M., Tao, R., & Umar, M. (2020). Financial implications of fourth industrial revolution: Can bitcoin improve prospects of energy investment? *Technological Forecasting and Social Change*, *158*(June), 120178. https://doi.org/10.1016/j.techfore.2020.120178.

Taylor, D. (2018). *An Analysis of Bitcoin and the Proof of Work Protocols Energy Consumption, Growth, Impact and Sustainability*. http://www.esru.strath.ac.uk/Documents/MSc_2018/Taylor.pdf.

Umar, Z., Trabelsi, N., & Alqahtani, F. (2021). Connectedness between cryptocurrency and technology sectors: International evidence. *International Review of Economics and Finance*, *71*(May 2019), 910–922. https://doi.org/10.1016/j.iref.2020.10.021.

Unvan, Y. A. (2019). Impacts of Bitcoin on USA, Japan, China and Turkey stock market indexes: Causality analysis with value at risk method (VAR). *Communications in Statistics – Theory and Methods*, *0*(0), 1–16. https://doi.org/10.1080/03610.926.2019.1678644.

Wang, G. J., Xie, C., Wen, D., & Zhao, L. (2019). When Bitcoin meets economic policy uncertainty (EPU): Measuring risk spillover effect from EPU to Bitcoin. *Finance Research Letters*, *31*(November 2018), 489–497. https://doi.org/10.1016/j.frl.2018.12.028.

Zade, M., Myklebost, J., Tzscheutschler, P., & Wagner, U. (2019). Is bitcoin the only problem? A scenario model for the power demand of blockchains. *Frontiers in Energy Research*, *7*(MAR). https://doi.org/10.3389/fenrg.2019.00021.

Zivot, E. and Andrews, D. W. K. 1992. Further Evidence on the Great Crash, the Oil Price Shock, and the Unit-Root Hypothesis. Journal of Business & Economic Statistics 10(3):251-270.

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