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Research article

Uncovering Bitcoin's electricity consumption relationships with volatility and price: Environmental Repercussions

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A R T I C L E I N F O

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A B S T R A C T

Bitcoin, a global financial asset, surpassed one trillion USD in November 2021, but its environmental impact may cause a 2 °C temperature rise by 2050. Using causal and connectedness analysis, we uncover non-linear relationships between bitcoin's energy consumption, price, and the Crypto Volatility Index. This study uses 1458 daily observations from several databases from March 31, 2019, to March 30, 2023. The phenomenon was analyzed using the theory of production and value investing theory. While the relationship between bitcoin-based electricity consumption and crypto market volatility is bidirectional, Granger causality tests reveal that bitcoin prices Granger-cause electricity consumption, but the converse is not true. Regarding Diebold-Yilmaz connectedness, the price of bitcoin acts as a net contributor, while bitcoin-based electricity consumption and crypto market volatility act as net receivers of spillover from bitcoin price. Our findings contrast with the traditional theory of production, where cost is supposed to determine price, and we show that some bitcoin miners continue operating according to the value investing theory despite suffering financial losses. Limited discussions around bitcoin pricing and its significant expense—that is bitcoin's electricity consumption—indicate the need to explore this relationship. Policymakers, green investors, and others may find the results relevant to building an efficient, environmentally friendly framework and creating much-required innovative regulations.

1. Introduction

The environmentally harmful effects of bitcoin (Truby, 2018) and similar proof of work (PoW)-based applications are of concern for policymakers and many other stakeholders, including green investors. With every single bitcoin transaction consuming around 800 kilo-watt hours, which is the equivalent of almost a month's energy consumption by the average US household, the overall impact is massive (Digiconomist, 2023). A recent blunt statement by US Senator Ed Markey has sparked a debate among bitcoin stakeholders about its environmental impact:

> "When one year of US bitcoin mining creates as many carbon emissions as 7.5 million gas-powered cars—we have a problem. Today's hearing made that even clearer. The crypto industry is growing, but so is the fight for climate justice. We will hold these companies accountable."[1]

Bitcoin works on an underlying technology called blockchain, which essentially maintains a record of bitcoin transactions in a network (Crosby et al., 2016). Since everybody in the network holds a copy of the transactions, the entire process of storing and validating information is inherently inefficient (Bhushan et al., 2021). Because only one miner in the network gets to win the bitcoin as a reward for block validation, despite many running in the race, there is high consumption by all miners in the network (Ghosh et al., 2020). All the networks participating in a mining race need to solve a mathematical problem that demands substantial amounts of computational resources (De Vries, 2018), which leads to high energy consumption because these systems are

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[1] On March 7, 2023, Senator Ed Markey presided over a meeting of the Committee on Environment and Public Works that was centred on the energy use of mining. After this session, he immediately tweeted the statement, which remains publicly available on the X website (formerly Twitter: https://x.com/SenMarkey/status/1633249925398970369?s=20)..

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powered by electricity.

If bitcoin were a country, it would rank 34th in the world in terms of energy consumption (Digiconomist, 2023). Indeed, the carbon footprint of a single bitcoin transaction is equivalent to 0.9 million VISA credit card transactions (Digiconomist, 2023). Bitcoin has more than 450 billion USD in market capitalization, which went as high as 1.2 trillion USD in November 2021 (Nasdaq, 2023). With such vast market acceptance, bitcoin emissions are a major obstacle to adhering to the Paris Agreement of 2015, including reducing global temperature levels (Mora et al., 2018). It was these environmental implications that led Elon Musk to declare that Tesla would no longer accept bitcoin (Kolodny, 2021).

The complicated relationship between bitcoin as a unique decentralized asset and its impact on the natural environment must be addressed by scholars. Although it can be viewed from political, environmental, social, technological, legal, and economic perspectives (Sapra et al., 2023), the present study considers the literature on the economic aspect to identify a relevant research gap.

In leading mining nations like the United States and Russia, Corbet et al. (2021) examined the relationship between bitcoin returns and electricity prices and found a positive correlation. Derks et al. (2018) discovered that as more participants enter the bitcoin mining race, profits tend to decrease, suggesting a trait of a perfectly competitive market. Additionally, Kristoufek (2020) used the cost of mining a single bitcoin as a variable and found a long-term cointegration between bitcoin price (BTCP) and mining expenses. Interestingly, there have not been many discussions on the correlation between bitcoin pricing and its largest expense, electricity consumption. This may be because, as Maiti (2022) pointed out, that the relationship is not linear. These studies offer intriguing results that spark discussions on the dynamic nature and complexity of the relationship between the price of bitcoin and bitcoin-based electricity consumption.

On the volatility side, investors' herding behavior (overreaction to the market) has been found using the daily returns of six cryptocurrencies (Ajaz & Kumar, 2018). Since volatility is heavily influenced determined by investor sentiment (Bonaparte and Bernile, 2023), it would be interesting to explore whether volatility affects bitcoin's price or if bitcoin mining is proxied by its energy consumption.

On the one hand, the extant literature has delved into the dynamics of BTCP and volatility through the lens of investor behavior, primarily in the realm of financial analysis, while on the other, there is limited research exploring BTCP and bitcoin's energy consumption. We address this crucial gap on the relationship between BTCP and bitcoin's energy consumption in the light of crypto market volatility, which reflects the crucial factors of market sentiments and risk perception. With this notion in mind, we delve deeply into the causal and connectedness relationships between BTCP, its energy consumption (CBECI), and the Cryptocurrency Volatility Index (CVI) that are indicative of market sentiments and risk perception.

The identified research gaps made us ponder whether there is a causal relationship between crypto market volatility, bitcoin's energy consumption, and bitcoin prices [RQ1]. What is the total connectedness between crypto market volatility, bitcoin's energy consumption, and bitcoin prices [RQ2]? Is there a spillover effect? If so, how has the spillover among the above-stated variables progressed over the most volatile periods from 2019 to 2023 [RQ3]?

This article fills the gaps reflected in the research questions by following the Akaike information criterion (AIC) under the Vector Auto-Regression (VAR) framework for determining a nine-day lag in the three variable models: BTCP, Cryptocurrency Volatility Index (reflecting investor and overall market sentiments), and Bitcoin's electricity consumption proxied by CBECI. To answer all three research questions, lag selection using AIC under the VAR framework was foundational when applying both Granger causality and Diebold-Yilmaz (DY) techniques. AIC offers consistency, heuristic value, and model parsimony when compared to other lag selection criteria (Cavanaugh and Neath, 2019). VAR-based lags capture dynamic interactions, making the analysis more robust. VAR framework variables are completely endogenous, so exogenous variables are not needed to explain modeled relationships (Sims, 1980).

RQ1 is answered using VAR (Sims, 1980) based on Granger causality (Granger, 1969), while RQ2 and RQ3 are answered using the DY approach based on VAR (Diebold and Yilmaz, 2012). The findings reveal the presence of bidirectional causality between crypto market volatility and bitcoin's energy consumption. BTCP was found to Granger-cause bitcoin's energy consumption, but no reverse causality was found in this case. For crypto volatility and BTCPs, no causal relationships were found. In the case of connectedness, BTCP turned out to be a net contributor of volatility spillover, while bitcoin-based energy consumption and crypto market volatility were net receivers of volatility. From March 2019 to March 2023, there were two significant high-volatility periods: March 2020 (COVID-19) and July and August 2022 (high interest rates around the world to counter inflation).

Further, the interplay between the theory of production and value investing theory aptly explains the lack of causality between bitcoin's electricity consumption and BTCPs. The present study contributes to the literature by explaining the paradox of bitcoin mining even at a loss (in the traditional view, production should be stopped when revenue is insufficient to cover the variable cost). There have been instances in the market where miners continued to mine, even at a loss, by taking a long position in bitcoin because they believed its value would increase in the future. An excerpt from an interview conducted to substantiate the findings is presented below:

> "What's the harm in mining? We tend to continue with the mining in bust. It might be a little difficult to mine at losses, but this is the right time with fewer miners in the bitcoin mining race. Not only do we get the block validation reward, but also the transaction fees. Less miners means less resources spent to compete and more chances of getting bitcoins."
>
> –Bitcoin miner operating in Bangalore, India

The present study offers suggestions to bitcoin miners that they revamp their operational strategy in times of recession. The interplay between the theory of production and value investing theory suggests that miners may continue operating at a loss, provided they are optimistic regarding the future of bitcoin. The findings of this article are of substantial interest to green investors, policymakers, and other green stakeholders.

In section 2, we discuss the background literature, while section 3 reports the data used and presents a descriptive analysis. Sections 4, 5, and 6 detail the methodology, empirical findings, and discussion to make inferences from the analysis. Finally, we conclude the study and discuss its implications in section 7.

2. Literature review

Since bitcoin uses a significant amount of energy—roughly 0.5% of the world's total energy usage, or about as much as Malaysia or Sweden—it creates turmoil in the investment market from an environmental perspective (Carter, 2021). Even though the average returns provided by cryptocurrencies using PoW consensus protocols and those produced using Proof of Stake consensus protocols are not significantly different (Sapkota and Grobys, 2020), bitcoin remains immensely popular in the market. Since bitcoin could push the global temperature rise beyond 2 °C by 2050 (Mora et al., 2018), it has drawn significant interest from investors, environmental stakeholders, and policymakers. There is a growing debate on green vs. dirty cryptocurrencies, with the former less energy-intensive than the latter (Haq and Bouri, 2022). A number of studies have analyzed bitcoin's safe haven properties as a financial asset (Murty et al., 2022; Urquhart and Zhang, 2019). However, very few have focused on the energy consumption aspect of bitcoin from a financial perspective (Haq and Bouri, 2022).

The advocates of bitcoin mining have argued that if this electricity is sourced from renewable sources, high energy consumption should not be an issue. Alternatively, certain energy efficiency programs can persuade bitcoin miners to use highly energy-efficient cryptocurrency mining devices (Hajiaghapour-Moghimi et al., 2022). But will that solve the problem? Here, De Vries (2019) study highlights that renewable energy cannot solve bitcoin's sustainability problem since it can generate an annualized e-waste equivalent to 10,948 metric tonnes. On the energy front, a rational argument is that even if bitcoin mining is powered by renewable energy, the problem of carbon emissions will persist since that renewable energy could have been used in activities powered by non-renewables like coal and natural gas.

The use of non-renewables, which appears to be the core problem in bitcoin mining, is not only an environmental issue but also has social and governance implications. On the social front, issues like workplace policies, equality, and health effects are major issues, while in terms of governance, investors may be at risk due to secret mining operations, power consolidation, negative indirect economic effects, and issues with tax evasion (De Vries et al., 2021).

Numerous studies conducted in recent years have yielded significant insights into different aspects of financial markets and sustainability. Researchers have employed a number of sophisticated econometric techniques, such as the time-varying wavelet-windowed cross-correlation and time-varying causality and cross-quantilogram approaches, to better comprehend the causal relationships in such complex financial systems (Doğan et al., 2023; Ghosh et al., 2023; Tiwari et al., 2023). On a broader economic and environmental scale, renewable energy consumption has had a more positive effect on economic growth than non-renewable sources (Buhari et al., 2020). In light of these findings, it is imperative that policymakers prioritize the transition to renewable energy sources, including reducing export-oriented industries' reliance on fossil fuels (Dogan et al., 2020). Moreover, the intersection of economic complexity and renewable energy adoption has emerged as a potential solution to environmental degradation issues, especially in member states of the Organization for Economic Co-operation and Development (Doğan et al., 2021).

When it comes to investing, however, investors are rational thinkers whose primary purpose is to get good returns. There is a growing debate around the financial returns vs. sustainable financial returns among investors. With clean energy depicting the potential to be a distinct asset class, there is a growing shift of investors to green opportunities (Ah Mand et al., 2023). The presence of green investors changes the market dynamics and the allied ecosystem because the complex market structure leads to a spillover effect. Green investors can encourage polluting companies (like cryptocurrencies) to change, and socially responsible investing causes polluting companies to receive less investment, which lowers overall investment in the market (Barnea et al., 2005). Because of this close interaction between green and non-green investment markets, the present study is important for all investors. Bitcoin spillovers have been found to have a strong impact on the carbon market, but the carbon market does not Granger-cause changes in BTCP (Di Febo et al., 2021). Table 1 presents the key literature on the relationship between BTCPs and bitcoin's energy consumption.

Along with the carbon market, asymmetric spillover effects have also been found between green commodities, bitcoin, and stock market volatility in the United States (Khalfaoui et al., 2022). A recent study (Kristoufek, 2020) highlighted that BTCPs and electricity expenses in mining are interconnected. Maiti (2022) examined the dynamics of BTCPs and bitcoin's energy consumption, but that analysis is restricted to threshold regression. As an extension to Maiti's work, Bejan et al. (2022) explored that relationship using monthly variables and an artificial neural network technique. We believe daily observations are more appropriate given investors' frequent trading and quick information absorption. To verify claims, scholarly research and econometric methods must unravel the non-linear relationship between bitcoin pricing and energy use. We used VAR-based Granger causality and DY VAR-based connectedness to fill this gap. Similarly, the role of crypto market volatility is considered to capture market sentiments through the Crypto Volatility Index (CVI). Therefore, studying how volatility, bitcoin-based electricity consumption, and prices are interrelated becomes important.

3. Data, variables, and descriptive analysis

We analyze crypto market volatility using the CVI, bitcoin-specific energy consumption using the Cambridge Bitcoin-based Electricity Consumption Index (CBECI) in gigawatt hours, and historical BTCPs in US dollars (see Table 2). With 1458 observations, the analysis ran from March 31, 2019, to March 30, 2023. We chose March 31, 2019, as our start date because CVI data was unavailable before then.

The descriptives in Table 3 provide an overview of the historical

Table 1
Previous Closely Related studies.

Article	Data Frequency	Variables	Period	Methodology	Findings
Maiti et al. (2023)	Monthly	Bitcoin Price and CBECI	Nov 2010 to Oct 2021	Transfer Entropy using Shannon and Renyi Estimates	Statistically Significant Information Flow from Bitcoin Price to Electricity
Chitkasame et al. (2022)	Monthly	Total Renewable Energy and Bitcoin's Trading Volume	July 2010 to Dec 2021	Regime Markov Switching Granger Causality test-based Vector Autoregressive Technique	Bitcoin Trading Volume (BitVol) and Total Renewable Energy Consumption have bidirectional causality
Yuan et al. (2022)	Daily	Bitcoin price, CBECI, Hash Rate, Bitcoin Difficulty and BECI	February 10, 2017 to March 29, 2022	Quantile based Network Connectedness	Bitcoin Hashrate and Bitcoin's Electricity Consumption are the primary sources of risk in the information network of Bitcoin Market.
Karmakar et al. (2021)	Daily	CBECI and Electricity Pricing Returns in three prominent electricity market in US.	Dec 19, 2017 to Jun 18, 2021	Time-Varying Regression GARCHX	Bitcoin energy consumption impacts the returns from the three energy markets in US. The volatility effect is found to be increasing over time.
Maiti (2022)	Monthly	Bitcoin Prices and CBECI	Nov 2010 to Oct 2021	Discrete Threshold Regression	The impact of price changes on Bitcoin's energy usage is broken down into six regimes by the discrete threshold model. The findings suggest that only the upper (4th and 6th) regimes, respectively, exhibit statistically significant effects of total bitcoin energy usage on bitcoin prices.
Bejan et al. (2022)	Monthly	Bitcoin Price and CBECI	Jan 2014 to July 2021	Artificial Neural Network	The data demonstrate that there is a strong association between monthly average BTC price values and electricity consumption for mining. Qualitatively, the forecast is more sensitive (or even equivalent) in a short time frame.

Source: Compiled by Authors

Table 2
Sampled variable Description.

Abbreviation	Used Variable's Description	Source	Units
CBECI	CBECI - The amount of energy that the Bitcoin Network is estimated to use each day.	Cambridge Centre for Alternative Finance	Giga Watts
CVI	Crypto Volatility Index by "Cvi. Finance" represents the volatility of the cryptocurrencies in the market.	Cvi. finance	Number (%)
BTCP	Bitcoin Price - Closing value of Bitcoin prices per day.	Bloomberg	USD

Source- Databases used by the authors.

Table 3
Descriptives, Normality and correlation.

Statistics	CVI	CBECI	BTCP
Mean	84.18	10.16	24,669.40
Median	82.55	9.93	19,548.80
Maximum	170.55	16.33	67,566.83
Minimum	50.32	4.41	4105.40
Std. Dev.	19.21	2.95	16,852.88
Skewness	0.9655	0.0834	0.7053
Kurtosis	4.3262	1.9276	2.2225
Jarque-Bera	333.3481	71.5487	157.6196
Probability	0.0000	0.0000	0.0000
Correlation			
CVI	1		
CBECI	0.1227***	1	
BTCP	0.3106***	0.7537***	1

Note: *** shows significance at 1%, ** shows significance at 5%, and * shows significance at 10%.
Source: Author's calculation.

pattern and distribution of the data. All variables have a high standard deviation, reflecting high individual volatility. To check for the issue of multicollinearity, we referred to the correlation matrix; only one relationship with more than 75% correlation was found between CBECI and BTCP at the level. In the next step, these variables were log-transformed to perform stationarity tests for determining the order of integration (see Table 4).

To begin the analysis after the descriptives, we must determine the order of integration for each variable. A series is referred to as stationary if its mean, variance, and structural properties do not change over time. A non-stationary time series is a stochastic process with unit roots or structural breakdowns, according to the unit root idea. The unit root approach was developed by Dickey and Fuller to assess stationarity (Dickey and Fuller, 1979).

For DY connectedness based on VAR, all the variables should be I (1). Any variable with a second order of integration or different orders of integration will not work for DY VAR-based connectedness, and using different lags or second-order lags would make the results unreliable and biased. We thus apply the traditional augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test to attain stationarity (Phillips and Perron, 1988).

The graphs for individual variables are presented in Fig. 1, which tracks the progression of each variable from March 31, 2019, to March 30, 2023.

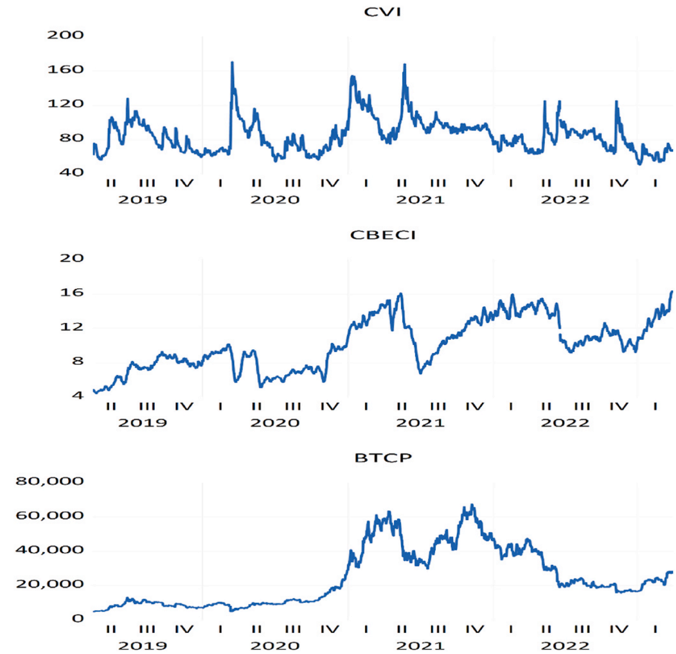

Fig. 1. Multiple Graphs showing the behavior and progression of CVI, CBECI, and BTCP from March 2019 to March 2023.
Source: Created by Authors

4. Methodology

Vector Auto Regression (VAR) is an appropriate econometric model to help analyze the dynamic interplay between CVI, CBECI, and BTCP. We use the VAR model in this study for two purposes: first, to determine the causal relationship among the variables under analysis and second, for the net spillover and connectedness among them. According to Sims (1980), a VAR is a multivariate linear time series model in which the system's endogenous variables are all linear functions of their lagged values.

Let us look at the covariance stationary N-variable *VAR(p)*, $x_t = \sum_{i=1}^{p} \Phi i x_{t-i} + \varepsilon t$, where $\varepsilon \sim (0, \Sigma)$ happens to be the vector of identically and independently distributed disturbances. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the N × N coefficient matrices A_i follow the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, with A_0 being an N × N identity matrix and with $A_i = 0$ for $i < 0$.

The pth order VAR is denoted "VAR(p)" and is sometimes called "a VAR with p lags." A path-order VAR model can be written as

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \ldots\ldots + A_p y_{t-p} + e_t.$$

For our variables, suppose VAR(p = 2),   [VAR Equations]

$$CVI_t = \beta_{10} + \beta_{11} CVI_{t-1} + \beta_{12}\, CVI_{t-2} + \gamma_{11} CBECI_{t-1} + \gamma_{12} CBECI_{t-2} + \theta_{11} BTCP_{t-1} + \theta_{12} BTCP_{t-2} + \varepsilon_{1t}$$

Table 4
Stationarity Results from ADF and PP test.

Variables/Tests	Level ADF	First difference ADF	Level PP	First difference PP	Series
CVI	**−4.2801*** **	-	**−4.7491*** **	-	I (0)
CBECI	−2.7522	**−9.2123*** **	−3.0865	**−28.273*** **	I (1)
Bitcoin Price	−1.5281	**−39.965*** **	−1.544	**−39.924*** **	I (1)

Note: *** at 0.01, ** at 0.05, and * at 0.10 indicate significance.
Source: Author's calculation.

$$CBECI_t = \beta_{10} + \beta_{21}CVI_{t-1} + \beta_{22}\ CVI_{t-2} + \gamma_{21}CBECI_{t-1} + \gamma_{22}CBECI_{t-2} + \theta_{21}BTCP_{t-1} + \theta_{22}BTCP_{t-2} + \varepsilon_{1t}$$

$$BTCP_t = \beta_{10} + \beta_{31}CVI_{t-1} + \beta_{32}\ CVI_{t-2} + \gamma_{31}CBECI_{t-1} + \gamma_{32}CBECI_{t-2} + \theta_{31}BTCP_{t-1} + \theta_{31}BTCP_{t-2} + \varepsilon_{1t}$$

4.1. VAR-based Granger causality

We use the VAR-based Granger causality approach to determine pairwise causal relationships. The Granger technique (Granger, 1969) is a reliable method for checking whether one event leads to another, how much of the second event can be accounted for by its own historical (delayed) values, and how much the historical values of the first event contribute to the explanation. The test's findings establish causation, indicating that one event is Granger-caused by another, or they show no causal relationship. As a result, two-way causality is evaluated.

4.2. Diebold-Yilmaz (DY) connectedness approach

To determine the net spillover and connectedness, we used the DY index approach (Diebold and Yilmaz, 2012) with the generalized VAR framework. This is also called the extended DY spillover index approach, which derives directly from the well-known idea of a variance decomposition associated with an N-variable vector autoregression. It was used to assess the connectivity between variables. We advanced by measuring the directional spillovers in a generalized VAR framework, which eliminates the potential dependence of the results on ordering, as opposed to the original DY spillover index, which uses the simple VAR-based framework and can thus have order-dependent results powered by Cholesky factor orthogonalization (Diebold and Yilmaz, 2012). Unlike the orthogonal innovations required for calculating variance decompositions, the VAR innovations are typically contemporaneously associated. Using the identification approach of Cholesky factorization, we can attain orthogonality, but in this case, variance decompositions depend on the ordering of the variables. To overcome this issue, we use the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), resulting in variance decompositions independent of ordering.

5. Empirical findings

This section reports the pairwise Granger causal relationships based on the VAR framework with the AIC as the appropriate lag selection criterion. We started the analysis with default lags of two; the VAR output was tested for the appropriate number of lags using the lag structure and length criteria. We derived the lag selection table with the AIC, which suggests the maximum number of significant lags [Table 5]. The VAR model selected had nine lags suggested by final error prediction (FPE), AIC, and the Hannan-Quinn (HQ) (Liew, 2004).

The VAR model with nine lags was again estimated and checked for autocorrelation and the AR roots graph. No autocorrelation was found; a linear regression of efficiency (LRE*) statistics of 9.417 was insignificant with a probability value of 0.3996, indicating the acceptance of the null hypothesis and thus no autocorrelation at the selected lag. In addition, if every root has a modulus of less than one and falls inside the unit circle, the computed VAR is stable (Nwafor et al., 2016). The roots of the characteristic polynomial in our analysis do not reside outside the unit circle (Fig. 2).

After ensuring stability and the absence of autocorrelation, we performed the Granger causality test using the VAR-based lag length shown in Table 5; that is, nine lags. The null hypothesis of the Granger causality test is the absence of any causal relationship. The rejection of the null hypothesis suggests causality in the relationships between the variables analyzed. The results are reported in Table 6. To ensure robustness in causal analysis, we chose the VAR framework and determined the appropriate lags after evaluating five different lag selection criteria, as reported in Table 5.

The simple Granger causality tests between two variables evaluate their causal relationship in isolation. By contrast, Granger causality based on VAR simultaneously considers the interactions between multiple variables (H. Toda, 1991). VAR-based Granger causality can assist in determining the direction of causality among system variables. VAR models incorporate time lags for each variable by default, enabling the researcher to determine the lag duration at which causality is most pronounced. Endogeneity issues can be accounted for by VAR models, which depict the simultaneous relationships between variables (Jarociński and Maćkowiak, 2017). Granger causality tests based on VAR are typically more statistically resilient because they consider the behavior of the system as a whole (Toda and Phillips, 1994). This can result in more reliable outcomes, particularly when dealing with noisy or correlated data.

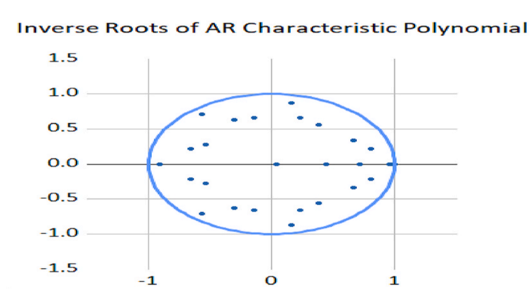

Fig. 2. Stability of the VAR model depicted by the AR Roots Graph.
Source: Generated by Authors

Table 5
Summary of lag selection criteria.

Lag	Likelihood Ratio (LR)	Final Prediction Error (FPE)	Akaike Information Criterion (AIC)	Schwarz Criterion (SC)	Hannan Quinn (HQ)
0	NA	0.000708	1.260639	1.271586	1.264725
1	19,254.16	1.14E-09	−12.07931	−12.03552	−12.06297
2	169.0832	1.03E-09	−12.18437	−12.10774	−12.15577
3	46.11184	1.01E-09	−12.20403	−12.09456	−12.16317
4	59.8867	9.77E-10	−12.23337	−12.09106	−12.18026
5	23.11885	9.73E-10	−12.23709	−12.06194	−12.17172
6	19.6057	9.72E-10	−12.23838	−12.03039	−12.16075
7	11.92207	9.76E-10	−12.23431	−11.99347	−12.14442
8	264.1195	8.20E-10	−12.40773	**−12.13405***	−12.30558
9	50.83369	**8.01e-10***	**−12.43113***	−12.12461	**−12.31673***
10	16.53653	8.02E-10	−12.43037	−12.091	−12.30371
11	**18.11606***	8.02E-10	−12.43075	−12.05854	−12.29183
12	10.16489	8.06E-10	−12.42551	−12.02047	−12.27434

Note: *** at 0.01, ** at 0.05, and * at 0.10 indicate significance.
Source: Calculation by authors

Table 6
Granger Causality among variables.

Causal Relationship	Degree of Freedom	Chi-Square	Relationship at 5% Sig.
CBECI »»» CVI	9	20.51012**	Bidirectional
CVI »»» CBECI	9	22.63482***	
CBECI »»» BTCP	9	15.11611*	Unidirectional
BTCP »»» CBECI	9	40.97005***	
CVI »»» BTCP	9	14.30368	No Causal Relationship
BTCP »»» CVI	9	10.89158	

Note: *** significant at 0.01, ** significant at 0.05, and * significant at 0.10.
Source: Author's calculation using VAR-based lags suggested by FPE, AIC, and HQ criterions

After determining long-term causality using the VAR framework, we used the same framework to determine the connectedness between the CVI, BTCP, and CBECI. Connectedness was operationalized using the volatility spillover table and spillover index (Diebold and Yilmaz, 2012). The rolling window was set to 150 daily observations. A generalized method was adopted for the impulse response function with nine lags, as suggested by the VAR framework, using the lag length criteria determined in Table 5.

The volatility spillover clearly shows that BTCP is a net contributor to tri-connectedness. The market demand and supply forces determine BTCP (Ciaian et al., 2016), which then causes the CBECI to change (YakupSöylemez, 2022) and further leads to a causal impact on CVI as reported by the Granger causal relationship in Table 6. This directional causality from BTCP to CBECI and onward to CVI is validated by the DY-based volatility spillover index reported in Table 7. The connectedness identified among the variables is backed and validated by the Granger causality among relationships, bringing a convergence between the Granger causality and DY-based connectedness. BTCP, as a net contributor, impacts the CBECI and CVI, which are 70% and 30% net receivers of the spillover effect, respectively.

Unlike the article by YakupSöylemez (2022), causality in the present study is not restricted to Hatemi-J (2012) and Toda and Yamamoto (1995). Rather, causality is based on the VAR model with nine lags, as suggested by final error prediction, AIC, and the Hannan-Quinn information criterion. In addition, the connectedness identified by using the DY approach is reported in Table 7 and Fig. 3.

Volatility was clearly higher in March 2020, which may indicate the impact of the COVID-19 crisis (Rooney, 2020). The subsequent significant spikes were observed in July and August of 2022 due to variables including but not restricted to changes in federal rates, soaring inflation, and a bearish crypto market (Kharpal, 2022).

To check the reliability and robustness of the spillover findings, we use different rolling windows as robustness checks. The analysis was re-performed using 120 and 180 rolling windows to compare with the spillover results on a rolling window of 150 observations. As expected, the spillover pattern was indeed closer to the pattern of 150 observations (Fig. 4), despite comparing it with results of rolling windows with a standard deviation of 20% in observations.

After observing the highest volatility spillover connectedness in March 2020, we revisited the connectedness among the chosen variables for the pre- and post-COVID period to better understand the dynamics of the identified relationship (Table 8). To our surprise, the connectedness decreased after COVID from 7.2% to 5.58%.

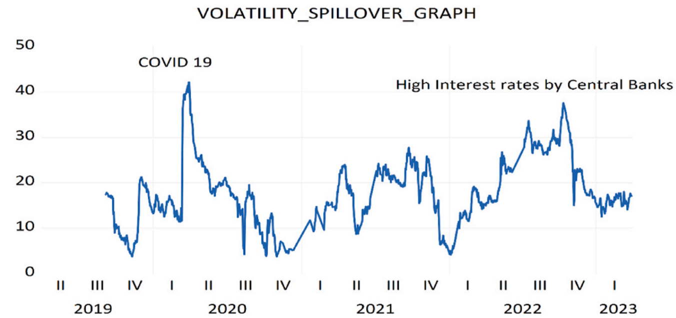

Fig. 3. Volatility spillover from March 31, 2019, to March 30, 2023.
Source: Created by Authors.

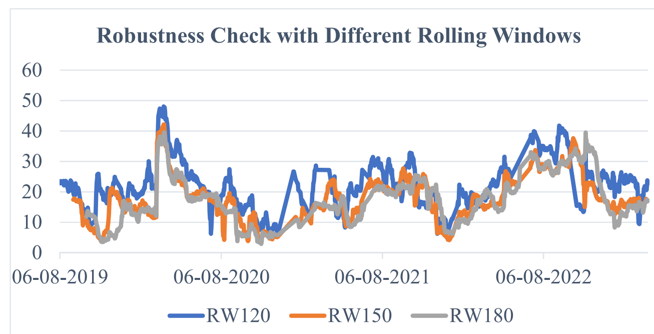

Fig. 4. Spillover comparison at different rolling windows (120,150 and 180 observations).
Source: Created by Authors

It is also worth noting the status of CBECI changing from net contributor to net receiver, which is in line with our observation that BTCP tends to Granger-cause CBECI (in the post-COVID period) and was also highlighted by Derks et al. (2018). COVID-19 is not only relevant because of disruption in the market but also as an event after which the prices of bitcoin rose steadily for a substantial period of time. This price increase could be one reason for spillover and causality running from BTCP to CBECI; it is also explained by De Vries (2018, 2021) and Derks et al. (2018) using zero economic theory.

6. Discussion

The empirical findings of significant causal relationships can be theoretically explained by analyzing them using the theory of production and value investing theory as substantiated by both academic and non-scholarly literature. The causal relationship between CBECI and CVI was found to be bidirectional. This is not an unexpected result, since CBECI can be considered a proxy for bitcoin mining and can be directly associated with crypto volatility—that is, CVI—which is essentially based on the implied volatility of bitcoin and Ethereum (CVI Finance,

Table 7
Volatility Spillover Table (in percentage).

	CVI	CBECI	BTCP	Directional From Others	Net Spillover	Status
CVI	95.96	0.37	3.68	4.04	2.17	Net Receiver
CBECI	0.86	94.06	5.08	5.94	5.26	Net Receiver
BTCP	1.01	0.32	98.68	1.32	−7.43	Net Contributor
Contribution to others	1.87	0.68	8.75	**11.30**		
Directional including own	97.83	94.74	107.43	**3.8%**		

Source: Author's calculation using Diebold-Yilmaz (DY) index.

Table 8
Pre- and Post-Covid Spillover Connectedness Table (in percentages).

Variables	CVI	CBECI	BTCP	Directional From Others	Net Spillover	Status
Pre-Covid (Mar 31, 2019 to Feb 28, 2020)						
CVI	88.43	4.76	6.82	11.573	6.358	Net receiver
CBECI	0.37	95.85	3.78	4.152	−1.652	Net contributor
BTCP	4.84	1.05	94.11	5.889	−4.707	Net contributor
Contribution to others	5.22	5.8	10.6	21.615		
Directional including own	93.64	101.65	104.71	**7.205**		
Post Covid (May 26, 2020 to Mar 31, 2023)						
CVI	96.07	0.43	3.51	3.93	0.76	Net receiver
CBECI	1.04	89.72	9.24	10.28	9.46	Net receiver
BTCP	2.14	0.39	97.47	2.53	−10.22	Net contributor
Contribution to others	3.17	0.82	12.75	16.74		
Directional including own	99.24	90.54	110.22	**5.58**		

Note: NR indicates net receiver status, and NC represents the net contributor status of volatility spillover. All figures are in percentages.
Source: Created by Authors.

2019). Prospect theory and value investing theory also suggest this behavior, where miners would respond to volatility by mining bitcoins. The miners would mine more in a context of greater volatility, leading to high energy consumption in the mining process. This continued mining behavior can align with the behavior suggested by value investing theory (Lee, 2014). Further, that continued mining behavior could signal the market about the prospects of bitcoin in the future (Duggan and Powell, 2022), triggering a loop of causality between CBECI and CVI and leading to enormous amounts of energy consumption. On the other hand, the CBECI Granger causes the CVI to reflect that the cost of mining bitcoins may increase or decrease market volatility through the dynamics of supply and demand. The CBECI is an indicator of the supply of bitcoins entering the market, which leads to volatility in the bitcoin market through price changes that occur as a result of changed supply.

Fig. 5 clearly depicts the Granger causality from BTCPs to bitcoin's mining cost. The BTCPs in the market drive bitcoin mining on the network. Higher prices allow more profit and leave scope to recover the primary cost of mining; that is, the electricity charges paid by the miners to mine bitcoin and validate transactions on the bitcoin network. The theory of production suggests that the price where the miner is unable to recover their variable cost (primarily electricity), mining operations should be stopped. However, some bitcoin miners prefer to keep mining at a loss, anticipating a price rise and thus taking a long position on the bitcoins they generate. This behavior contrasts starkly with the postulates of the theory of production, which is where the theory of value investing comes into the picture. These miners see the value in bitcoins despite their low current prices and are willing to retain them until the price increases or the market corrects itself. The theoretical explanation supports the above Granger causal relationship but also sheds light on how miners may view this relationship in the context of the theory of production and the theory of value investing.

Our finding of unidirectional causality from BTCP to bitcoin-based energy consumption empirically concurs with the explanation given by De Vries (2018, 2021) and Derks et al. (2018). The primary defense is that miners will be profitable if the cost of mining bitcoins is lower than that of a bitcoin. The price of power (energy consumption) and other charges contribute to the cost of bitcoin mining (which also involve mining pool fees, staffing, internet costs, and others). The complex relationship between BTCP and bitcoin-based electricity consumption has yet to be busted. Unlike normal products, BTCPs are market-driven rather than cost-driven. BTCPs derive their value for three key reasons: conspiracy theories (distrust in government), positivity regarding high returns, and fear of missing out (FoMO) (Martin et al., 2022). The prices are determined that if they shoot up due to market forces, they create a gap between the cost of energy consumption in bitcoin mining and bitcoin revenues. If this gap is positive, miners continue mining (Derks et al., 2018). Finally, and notably, the relationship between CVI and BTCP was not found to be significant. Future research may explore the reasons for this result.

On the connectedness front, CVI, bitcoin-based energy consumption, and BTCPs were all found to be connected using the DY VAR-based index. The net contributor status of BTCP accords with the results of VAR-based Granger causality. However, compared to those Granger causality results, BTCP is found to be connected with CVI. This connectedness is expected because of the inherent nature of CVI, which is composed of the 30-day implied volatility of bitcoin and Ethereum (CVI Finance, 2019). Fig. 3 depicts the months of March 2020 and July–August 2022 as periods of unusually high-volatility spillovers.

7. Conclusion and implications

The study concludes by revealing some crucial findings. First, there is the presence of bidirectional causality between CVI) and bitcoin's electricity consumption. Second, as a stark contradiction to cost driving a product's price, BTCPs drive bitcoin mining, which is reflected by the unidirectional Granger causality from BTCPs to bitcoin-based electricity consumption, as proxied by the CBECI. The theory of production and value investing theories have been used as theoretical lenses to demystify the lack of causation from CBECI to BTCPs. The findings may be relevant to policymakers, green investors, and other stakeholders. Third,

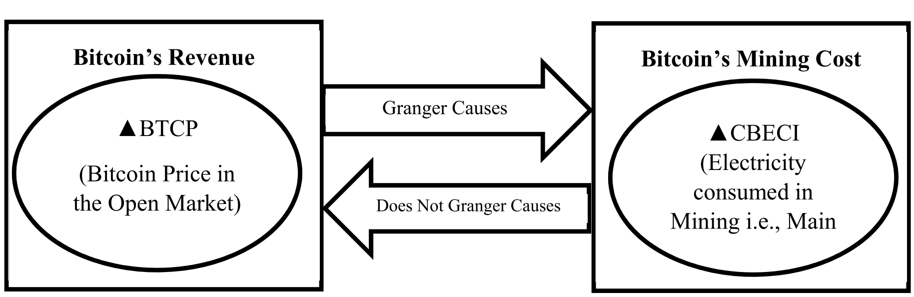

Fig. 5. Granger causal relationship between BTCP and CBECI
Source: Created By Authors

regarding connectedness, bitcoin prices are a net contributor to volatility spillover, whereas cryptocurrency market volatility and bitcoin-based electricity consumption are net receivers of volatility spillover. Our findings that CBECI is a net receiver contrast sharply with those in Yuan et al., 2022a, where CBECI was found to be a net contributor to and transmitter of volatility. Finally, COVID-19 and the increase in interest rates by central banks worldwide were the periods of the highest volatility spillovers from March 31, 2019, to March 30, 2023.

The findings reported here can help investors demystify the complex relationship between cryptocurrency market volatility, BTCPs, and bitcoin-based electricity consumption through the lens of the theory of production. Previous research has suggested that policymakers regulate the cryptocurrency industry with potential mechanisms to lower bitcoin's energy consumption and that miners may be encouraged to use energy from renewable sources by taxing bitcoin those who use non-renewable energy or offering discounts for those who use renewable power to mine bitcoins (Howson and de Vries, 2022).

Howson & de Vries (2022) also emphasize on volatility and credit availability as moderating factors in miners' operating strategy, especially during recessions, unlike prior studies that offered policy suggestions. Access to finance may boost bitcoin mining in recessions. Policymakers may regulate this credit to miners to reduce environmental damage. Policies to regulate or mitigate crypto market volatility can also help limit bitcoin's energy consumption since they are bidirectionally causal. The lack of causality from bitcoin-based electricity consumption to BTCPs is explained using the zero economic profit and value investing theories. In a bitcoin network, everyone can join the network to mine bitcoin (Böhme et al., 2015), with the free entry and exit features indicating a perfectly competitive market; by identifying and instituting policies that discourage investment in PoW cryptocurrencies, their prices and the incentive to mine could both be decreased (Wendl et al., 2023). Since renewable energy helps lower overall carbon dioxide emissions (Yuan et al., 2022b), we may alternatively use renewable energy to mine bitcoin in order to curb its harmful impact on the environment. Given the direct negative relationship between sustainable financing and carbon dioxide emissions (Qin et al., 2022), we recommend readers aim for sustainable financing as it can help achieve carbon neutrality even in the crypto market.

Limitations and future research

Granger causality and connectedness assist in examining variable relationships. However, their limitations may make it difficult to draw strong findings and generalizations, especially regarding causation. These strategies emphasize predictive links, not causal ones. Confounding variables can affect observed relationships, casting doubt on causation. Causality and connectivity may miss endogeneity and missing variables, while omitted variables might misrepresent causality.

Other issues include sample selection bias, especially in observational studies. Data may not adequately represent the population of interest or self-select, skewing the results of causal analysis. Causality and connectedness approaches presume linear relationships between variables, which may not reflect reality. Non-linear and complex interactions make such techniques unsuitable for certain circumstances. Statistical tests may show causality or connectivity, but their practical significance may not. Significant conclusions from small sample sizes or significant variations may not have real-world relevance. In conclusion, causality and connectedness approaches can reveal varied associations, but they should be used with caution.

Future researchers may use additional non-linear causation methodologies to strengthen these results. They can increase the time horizon and use various crypto market volatility proxies. Wavelet quantile correlation, cross-quantilogram, wavelet local multiple regression, partial cross-quantilogram, and other non-linear connectivity approaches can all validate and refine our results. Future studies may also seek to explain the relationship between bitcoin's price and its biggest expense, energy usage, in different time horizons, quantiles, and regimes. The need to study this relationship highlights the possibility of new characteristics and theories around such digital financial assets. In addition, region-wide studies (specifically for countries leading the mining industry) can be taken up in the future to draw robust conclusions.

CRediT authorship contribution statement

Nishant Sapra: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Imlak Shaikh:** Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **David Roubaud:** Conceptualization, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Mehrad Asadi:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft. **Oksana Grebinevych:** Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Ah Mand, A., Ghafoor, A., Sifat, I., 2023. Time-varying price dynamics of clean and dirty energy portfolios. J. Environ. Manag. 337 https://doi.org/10.1016/j.jenvman.2023.117687.

Ajaz, T., Kumar, A.S., 2018. Herding in crypto-currency markets. Annals of Financial Economics 13 (2). https://doi.org/10.1142/S2010495218500069.

Barnea, A., Heinkel, R., Kraus, A., 2005. Green investors and corporate investment. Struct. Change Econ. Dynam. 16 (3), 332–346. https://doi.org/10.1016/j.strueco.2004.04.002.

Bejan, C.A., Bucerzan, D., Crăciun, M.D., 2022. Bitcoin price evolution versus energy consumption; trend analysis. Appl. Econ. https://doi.org/10.1080/00036846.2022.2097194.

Bhushan, B., Sinha, P., Sagayam, K.M., Andrew, J., 2021. Untangling blockchain technology: a survey on state of the art, security threats, privacy services, applications and future research directions. Comput. Electr. Eng. 90, 106897.

Böhme, R., Christin, N., Edelman, B., Moore, T., 2015. Bitcoin: economics, technology, and governance. J. Econ. Perspect. 29 (2), 213–238. https://doi.org/10.1257/jep.29.2.213.

Bonaparte, Y., Bernile, G., 2023. A new "Wall Street Darling?" effects of regulation sentiment in cryptocurrency markets. Finance Res. Lett. 52 https://doi.org/10.1016/j.frl.2022.103376.

Buhari, D.O.Ğ.A.N., Lorente, D.B., Ali Nasir, M., 2020. European commitment to COP21 and the role of energy consumption, FDI, trade and economic complexity in sustaining economic growth. J. Environ. Manag. 273 https://doi.org/10.1016/j.jenvman.2020.111146.

Carter, N., 2021. How Much Energy Does Bitcoin Actually Consume? https://hbr.org/2021/05/how-much-energy-does-bitcoin-actually-consume.

Cavanaugh, J.E., Neath, A.A., 2019. The Akaike information criterion: background, derivation, properties, application, interpretation, and refinements. Wiley Interdisciplinary Reviews: Comput. Stat. 11 (3), e1460.

Chitkasame, T., Rakpho, P., Khiewngamdee, C., 2022. Analyzing structural change and causality between energy consumption and Bitcoin's activity. Energy Rep. 8, 736–743. https://doi.org/10.1016/j.egyr.2022.10.320.

Ciaian, P., Rajcaniova, M., Kancs, d'Artis, 2016. The economics of BitCoin price formation. Appl. Econ. 48 (19), 1799–1815. https://doi.org/10.1080/00036846.2015.1109038.

Corbet, S., Lucey, B., Yarovaya, L., 2021. Bitcoin-energy markets interrelationships - new evidence. Resour. Pol. 70 https://doi.org/10.1016/j.resourpol.2020.101916.

Crosby, M., Pattanayak, P., Verma, S., Kalyanaraman, V., 2016. Blockchain technology: beyond bitcoin. Applied Innovation 2 (6–10), 71.

CVI Finance, 2019. CVI Index - CVI - the Crypto Volatility Index. https://docs.cvi.finance/cvi-index/cvi-index.

De Vries, A., 2018. Bitcoin's growing energy problem. Joule 2 (5), 801–805. https://doi.org/10.1016/j.joule.2018.04.016.

De Vries, A., 2019. Renewable energy will not solve Bitcoin's sustainability problem. Joule 3 (4), 893–898. https://doi.org/10.1016/j.joule.2019.02.007.

De Vries, A., 2021. Bitcoin boom: what rising prices mean for the network's energy consumption. Joule 5 (3), 509–513. https://doi.org/10.1016/j.joule.2021.02.006.

De Vries, A., Gallersdörfer, U., Klaaßen, L., Stoll, C., 2021. The true costs of digital currencies: exploring impact beyond energy use. One Earth 4 (6), 786–789. https://doi.org/10.1016/j.oneear.2021.05.009.

Derks, J., Gordijn, J., Siegmann, A., 2018. From chaining blocks to breaking even: a study on the profitability of bitcoin mining from 2012 to 2016. Electron. Mark. 28 (3), 321–338. https://doi.org/10.1007/s12525-018-0308-3.

Di Febo, E., Ortolano, A., Foglia, M., Leone, M., Angelini, E., 2021. From Bitcoin to carbon allowances: an asymmetric extreme risk spillover. J. Environ. Manag. 298 https://doi.org/10.1016/j.jenvman.2021.113384.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the Estimators for autoregressive time series with a unit root. J. Am. Stat. Assoc. 74 (366), 427–431. https://doi.org/10.2307/2286348.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006.

Digiconomist, 2023. Bitcoin Energy Consumption Index - Digiconomist. https://digiconomist.net/bitcoin-energy-consumption.

Doğan, B., Driha, O.M., Balsalobre Lorente, D., Shahzad, U., 2021. The mitigating effects of economic complexity and renewable energy on carbon emissions in developed countries. Sustain. Dev. 29 (1), 1–12. https://doi.org/10.1002/sd.2125.

Dogan, B., Madaleno, M., Tiwari, A.K., Hammoudeh, S., 2020. Impacts of export quality on environmental degradation: does income matter? Environ. Sci. Pollut. Control Ser. 27 (12), 13735–13772. https://doi.org/10.1007/s11356-019-07371-5.

Doğan, B., Trabelsi, N., Tiwari, A.K., Ghosh, S., 2023. Dynamic dependence and causality between crude oil, green bonds, commodities, geopolitical risks, and policy uncertainty. Q. Rev. Econ. Finance 89, 36–62. https://doi.org/10.1016/j.qref.2023.02.006.

Duggan, W., Powell, F., 2022. Is Bitcoin Mining Profitable in 2022. Forbes Advisor. https://www.forbes.com/advisor/investing/cryptocurrency/is-bitcoin-mining-profitable/.

Ghosh, A., Gupta, S., Dua, A., Kumar, N., 2020. Security of Cryptocurrencies in blockchain technology: state-of-art, challenges and future prospects. J. Netw. Comput. Appl. 163 https://doi.org/10.1016/j.jnca.2020.102635.

Ghosh, S., Tiwari, A.K., Doğan, B., Abakah, E.J.A., 2023. The dynamic relationship between gas and crude oil markets and the causal impact of US shale gas. Comput. Econ. https://doi.org/10.1007/s10614-023-10415-1.

Granger, C.W.J., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37 (3), 424–438. https://doi.org/10.2307/1912791.

Hajiaghapour-Moghimi, M., Azimi Hosseini, K., Hajipour, E., Vakilian, M., 2022. An approach to targeting cryptocurrency mining loads for energy efficiency enhancement. IET Gener., Transm. Distrib. 16 (23), 4775–4790. https://doi.org/10.1049/gtd2.12640.

Haq, I.U.I., Bouri, E., 2022. Sustainable versus conventional cryptocurrencies in the face of cryptocurrency uncertainty indices: an analysis across time and scales. J. Risk Financ. Manag. 15 (10) https://doi.org/10.3390/jrfm15100442.

Hatemi-J, A., 2012. Asymmetric causality tests with an application. Empir. Econ. 43 (1), 447–456. https://doi.org/10.1007/s00181-011-0484-x.

Howson, P., de Vries, A., 2022. Preying on the poor? Opportunities and challenges for tackling the social and environmental threats of cryptocurrencies for vulnerable and low-income communities. Energy Res. Social Sci. 84 https://doi.org/10.1016/j.erss.2021.102394.

Jarociński, M., Maćkowiak, B., 2017. Granger causal priority and choice of variables in vector autoregressions. Rev. Econ. Stat. 99 (2), 319–329.

Karmakar, S., Demirer, R., Gupta, R., 2021. Bitcoin mining activity and volatility dynamics in the power market. Econ. Lett. 209 https://doi.org/10.1016/j.econlet.2021.110111.

Khalfaoui, R., Ben Jabeur, S., Dogan, B., 2022. The spillover effects and connectedness among green commodities, Bitcoins, and US stock markets: evidence from the quantile VAR network. J. Environ. Manag. 306 https://doi.org/10.1016/j.jenvman.2022.114493.

Kharpal, A., 2022. Bitcoin (BTC) Falls as Market Focuses on Celsius Issue, Fed Rate Hike. CNBC. https://www.cnbc.com/2022/06/13/bitcoin-btc-falls-as-market-focuses-on-celsius-issue-fed-rate-hike.html.

Kolodny, L., 2021. Elon Musk Says Tesla Will Stop Accepting Bitcoin for Car Purchases. CNBC. https://www.cnbc.com/2021/05/12/elon-musk-says-tesla-will-stop-accepting-bitcoin-for-car-purchases.html.

Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in non-linear multivariate models. J. Econom. 74 (1), 119–147. https://doi.org/10.1016/0304-4076(95)01753-4.

Kristoufek, L., 2020. Bitcoin and its mining on the equilibrium path. Energy Econ. 85 https://doi.org/10.1016/j.eneco.2019.104588.

Lee, C.M.C., 2014. Value investing: bridging theory and practice. China Accounting and Finance Review 16 (2), 5. https://doi.org/10.7603/s40570-014-0005-3.

Liew, V., 2004. Which lag selection criteria should we employ? Econ. Bull. 3, 1–9.

Maiti, M., 2022. Dynamics of bitcoin prices and energy consumption. Chaos, Solit. Fractals X 9, 100086. https://doi.org/10.1016/j.csfx.2022.100086.

Maiti, M., Vukovic, D.B., Frömmel, M., 2023. Quantifying the asymmetric information flow between Bitcoin prices and electricity consumption. Finance Res. Lett. 57 https://doi.org/10.1016/j.frl.2023.104163.

Martin, B.A.S., Chrysochou, P., Strong, C., Wang, D., Yao, J., 2022. Dark personalities and Bitcoin®: the influence of the Dark Tetrad on cryptocurrency attitude and buying intention. Pers. Indiv. Differ. 188, 111453 https://doi.org/10.1016/j.paid.2021.111453.

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. Nat. Clim. Change 8 (11), 931–933. https://doi.org/10.1038/s41558-018-0321-8.

Murty, S., Victor, V., Fekete-Farkas, M., 2022. Is bitcoin a safe haven for Indian investors? A garch volatility analysis. J. Risk Financ. Manag. 15 (7) https://doi.org/10.3390/jrfm15070317.

Nasdaq, 2023. Bitcoin Market Capitalization. Nasdaq. https://data.nasdaq.com/data/BCHAIN/MKTCP-bitcoin-market-capitalization.

Nwafor, G., Odokp, P., Atsu, J., Esuabana, I., 2016. Modelling and Adequacy of Vector Autoregressive.

Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ. Lett. 58 (1), 17–29. https://doi.org/10.1016/S0165-1765(97)00214-0.

Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75 (2), 335–346. https://doi.org/10.1093/biomet/75.2.335.

Qin, M., Su, C.-W., Zhong, Y., Song, Y., Oana-Ramona, L., 2022. Sustainable finance and renewable energy: promoters of carbon neutrality in the United States. J. Environ. Manag. 324 https://doi.org/10.1016/j.jenvman.2022.116390.

Rooney, K., 2020. Bitcoin Loses Half of its Value in Two-Day Plunge. CNBC. https://www.cnbc.com/2020/03/13/bitcoin-loses-half-of-its-value-in-two-day-plunge.html.

Sapkota, N., Grobys, K., 2020. Blockchain consensus protocols, energy consumption and cryptocurrency prices. Journal of Energy Markets 13 (4), 117–139. https://doi.org/10.21314/JEM.2020.221.

Sapra, N., Shaikh, I., Dash, A., 2023. Impact of proof of work (PoW)-Based blockchain applications on the environment: a systematic review and research agenda. J. Risk Financ. Manag. 16 (4) https://doi.org/10.3390/jrfm16040218.

Sims, C.A., 1980. Macroeconomics and reality. Econometrica 48 (1), 1–48. https://doi.org/10.2307/1912017.

Tiwari, A.K., Abakah, E.J.A., Doğan, B., Ghosh, S., 2023. Sustainable debt and gas markets: a new look using the time-varying wavelet-windowed cross-correlation approach. Energy Econ. 120 https://doi.org/10.1016/j.eneco.2023.106606.

Toda, H., 1991. Vector Autoregression and Causality. Yale University.

Toda, H.Y., Phillips, P.C.B., 1994. Vector autoregression and causality: a theoretical overview and simulation study. Econom. Rev. 13 (2), 259–285.

Toda, H.Y., Yamamoto, T., 1995. Statistical inference in vector autoregressions with integrated processes. J. Econom. 66 (1), 225–250. https://doi.org/10.1016/0304-4076(94)01616-8.

Truby, J., 2018. Decarbonizing Bitcoin: law and policy choices for reducing the energy consumption of Blockchain technologies and digital currencies. Energy Res. Social Sci. 44, 399–410. https://doi.org/10.1016/j.erss.2018.06.009.

Urquhart, A., Zhang, H., 2019. Is Bitcoin a hedge or safe haven for currencies? An intraday analysis. Int. Rev. Financ. Anal. 63, 49–57. https://doi.org/10.1016/j.irfa.2019.02.009.

Wendl, M., Doan, M.H., Sassen, R., 2023. The environmental impact of cryptocurrencies using proof of work and proof of stake consensus algorithms: a systematic review. J. Environ. Manag. 326 https://doi.org/10.1016/j.jenvman.2022.116530.

YakupSöylemez, S., 2022. AN analysis of the causality relationship between bitcoin electricity consumption, price and volume. Journal of Research in Business 7 (1), 103–122. https://dergipark.org.tr/en/pub/jrb/issue/70563/1018901.

Yuan, X., Su, C.-W., Peculea, A.D., 2022a. Dynamic linkage of the bitcoin market and energy consumption: an analysis across time. Energy Strategy Rev. 44 https://doi.org/10.1016/j.esr.2022.100976.

Yuan, X., Su, C.-W., Umar, M., Shao, X., Lobonţ, O.-R., 2022b. The race to zero emissions: can renewable energy be the path to carbon neutrality? J. Environ. Manag. 308 https://doi.org/10.1016/j.jenvman.2022.114648.