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Impact of Bitcoin mining and crypto market determinants on Bitcoin-based energy consumption

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Abstract

Purpose – While Blockchain can serve us, Bitcoin threatens our survival. If Bitcoin is assumed to be a country, it will rank 38th globally for energy consumption. With 90.2 metric million tonnes of carbon dioxide, Bitcoin mining and trading has emerged as an environmental threat. The current study investigates how the trading-specific variables, the prices of Crypto Index and Ethereum, affect bitcoin-based energy consumption. Also, the role of mining-specific variables is analyzed.

Design/methodology/approach – The study uses monthly data from various sources collected from December 2018 to January 2023. The authors used the Autoregressive Distributed Lag (ARDL) Model to determine the short- and long-term relationships between variables. This study uses the Theory of Green Marketing and the Theory of Cross Elasticity of Demand as a theoretical lens.

Findings – The findings show that escalating crypto market index and Ethereum prices with a one-month lag increases bitcoin-specific electricity consumption and carbon emissions. Green investors may shift to cryptocurrencies based on consensus other than of Proof-of-Work. Ethereum behaves like a substitute for Bitcoin, reflected by the long-term positive relationship between Bitcoin's energy consumption and Ethereum prices.

Originality/value – The study analyses how the crypto market index and Ethereum price affect bitcoin-based energy use. The relationships identified are substantiated by the literature to provide suggestions to green investors and policymakers to mitigate the harmful impact of Bitcoin's colossal energy consumption on the natural environment.

Keywords Carbon emission, Cryptocurrency, Environment, Global warming, Proof of work, Sustainable finance

Paper type Research paper

1. Introduction

Bitcoin is the first successful application of blockchain technology, which can serve as the primary fuel for the global network of money transmission (Hashemi Joo *et al.*, 2020). Out of approximately 22,000 cryptocurrencies (Coinmarketcap.com, 2023), the most prominent is the virtual currency known as Bitcoin, which was first introduced to the world in 2008 by an anonymous author (or group of anonymous authors) using the pseudonym Satoshi Nakamoto (2008). "Bitcoin threatens our existence while Blockchain can benefit us" (Truby, 2018). The way Bitcoins are mined severely threatens the environment. With massive energy consumption powered by both renewable and non-renewable sources, it contributes to around 90.2 metric million tonnes of carbon dioxide (De Vries, 2021). However, the Blockchain, which is the underlying technology of Bitcoin, may have many use cases that can benefit the global economy (Porras-Gonzalez *et al.*, 2019).

The tweet on Bitcoin (a Proof-of-Work based blockchain application) by United States Senator Ed. Markey highlights the detrimental impact of such applications on the environment.

JEL Classification — O11, O13, O16, 033, Q01, Q56

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> 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. – Ed Markey on March 07, 2023 [1].

The cryptocurrency market has significantly grown in recent years. When drafting this paper, it is estimated to be around US$ 1.07 trillion, with 22,702 different cryptocurrencies tracked across 552 exchanges (Coinmarketcap.com, 2023). Bitcoin alone holds a market capitalization of more than US$ 450 billion and has gone as high as US$ 1.2 Trillion in November 2021 (Nasdaq, 2023). With such a high market acceptance and involvement, concerns have been raised regarding the Bitcoin's contribution to climate change. Because of the unusual blockchain networks which are based on the Proof of Work (POW) protocol and the associated "mining" activities, both of which have growing carbon footprints (Mora *et al.*, 2018). Bitcoin alone can push global warming above 2 °C (Mora *et al.*, 2018) and can be detrimental to the Paris Agreement 2015, aiming to keep the global temperature rise under 2 °C (UNFCCC, 2015). According to Digiconomist (2023), Bitcoin would rank 36th on the Global ranking of energy consumption and is assumed to be an independent country.

Not only this, even the e-waste disposal (hardware components), using a conservative methodology (De Vries, 2019), can be around 44,400 metric tons per annum (Author's calculation) as compared to 16,442 metric tons in 2018 for every 1.5 years of usage [2]. Every 1 Kilo Watt hour (7 GWH per month) of energy powered by coal and petroleum produces 1.025 (7,175 tons) and 1.107 kg (7,750 tons) of Carbon emissions in the United States (EIA, 2021). PoW-based Bitcoin's annual carbon emissions in 2021 could be accountable for around 19,000 deaths in the future (Truby *et al.*, 2022).

Considering the detrimental impact on the environment through intensive energy consumption, carbon emissions, Global warming and loss of lives, the authors decided to delve into the dynamics around Bitcoin as a financial asset catering to investors. It is crucial to keep track of the energy consumed by Bitcoin and try to reduce it wherever possible. Green and sustainable investing is this study's core motivational driver that shall help mitigate the harmful impact on our natural environment.

The environment and Blockchain technology share a complex relationship that can be looked at with different perspectives like Political, Economic, Social, Technological, Legal and Environmental (PESTLE) (Sapra *et al.*, 2023). Despite strongly criticizing proof of work's damaging effect on the environment, some supporters believe that Blockchain technology can help meet sustainable Development Goals (SDGs) (Adams *et al.*, 2018). The advocates of Blockchain technology suggest that its rapid progress can help accelerate the process of carbon neutrality (Qin *et al.*, 2023). While some studies have explored the relationship between Bitcoin prices and Bitcoin's energy consumption, none of them has identified a linear relationship (Kristoufek, 2020; Maiti, 2022). The relationship between Bitcoin's market and Bitcoin's energy consumption has also been explored and found to be positive (Yuan *et al.*, 2022). To the best of our knowledge, no study has analyzed the impact of the Cryptocurrency market and Ethereum prices on Bitcoin's energy consumption. We try to bridge this gap by taking important mining-specific variables, including the average block, hash rate and number of Bitcoin transactions per month.

While evaluating the phenomenon, we use the Theory of Green Investing as the theoretical lens. This theory not only explains the phenomenon but also emphasizes its relevance for green investors and policymakers. Compared to traditional assets, Green assets have delivered high returns in recent years, reflecting unexpected and substantial increases in environmental concerns and not high expectations of returns only (Pástor *et al.*, 2022). Despite significant inter-period variations in return-risk dynamics and substantial downside risk over the long term, green investments offer better overall risk-return optimization (Bhatnagar *et al.*, 2023). This makes the study and its possible outcomes relevant for academicians, professionals, investors and policymakers.

Considering this idea, the study analyzes the impact of factors contributing to this high energy consumption. CIX200 (Crypto Index) market prices representing the major 200 cryptocurrencies (Solactive, 2023) and Ethereum prices are considered trading-specific variables. For mining factors, we have considered Bitcoin average block size, Bitcoin hash rate and Bitcoin number of transactions as the variables for analyzing the impact on Bitcoin-based energy consumption proxied by Cambridge Bitcoin Electricity Consumption Index (Cambridge Centre for Alternative Finance, 2023).

The study aims to fulfill these identified research gaps using the following research objectives and questions.

- *RO1.* Identifying the market and mining-specific factors responsible for enormous bitcoin-based energy consumption.
- *RQ1.* What are the significant mining and trading variables leading to increased Bitcoin-based energy consumption?
- *RQ2.* How are these factors identified in RQ1 related to Bitcoin's energy consumption?
- *RO2.* Suggesting possible measures for reducing the vast energy consumption by Bitcoin.
- *RQ3.* What measures can policymakers or investors take to mitigate the harmful impact on the environment? [Findings of ARDL analysis substantiated by literature]

The findings show that on the mining side, the average size of the block on the Bitcoin network, hash rate and the number of transactions validated have a positive relationship with the bitcoin-based energy consumption in the short run using both OLS and ARDL. While the hash rate relationship is already established (De Vries, 2018), the logical relationship between the average size of the block and number of transactions and Bitcoin energy consumption are validated in this empirical study by quantifying the impact. As trading variables are concerned, the Cix200 (Crypto market index without Bitcoin) is positively associated. At the same time, Ethereum prices are negatively related in the current period. However, they are positively related at a lag of one month to bitcoin-based energy consumption as per the results of this study, with monthly variables ranging from December 2018 to January 2023.

All five variables turn out to be significantly impacting Bitcoin's energy consumption, with all variables positively affecting it, except for Ethereum, which has a negative relationship in the short run but a positive relationship in the long run.

To the best of our knowledge, no research has been conducted to evaluate the impact of crypto market performance on Bitcoin-based energy consumption and analyze its relationship with the prices of Ethereum, which is the closest substitute to Bitcoin for people wanting to trade or mine Ethereum (Hooson, 2022). The study's findings are relevant not only to green investors, cryptocurrency dealers and academicians but also to social stakeholders having environmental concerns.

Section 2 discusses the background literature, followed by Data & Descriptive Analysis in Section 3. The Methodology, Empirical Findings and Discussion are provided in Sections 4, 5 and 6, respectively. After summarizing the results and their relevance through the Conclusion and Implications in section 7, we declare the Limitations and suggest Future areas in section 8.

2. Literature review

At the beginning of 2009, the distributed, open, peer-to-peer Bitcoin network went live. Anyone can join this network and provide their computer hardware, such as CPUs, GPUs or specialized application-specific integrated circuits, to help build new blocks containing transactions for the Blockchain of Bitcoin (Küfeoğlu and Özkuran, 2019). The network offers an incentive for adding a new block to the Blockchain network. The Bitcoin system makes it computationally difficult to create a block, encouraging network users to act honestly. To produce blocks that meet specific criteria, participants must spend resources, such as time and electricity, to run their hardware. The entire proof-of-work process of adding new blocks is called "mining."

The PoW protocol was first used by Bitcoin (Nakamoto, 2008) and then by Ethereum after a few years (Buterin, 2014). The node with the right to add the next block to the chain in PoW consensus is selected by solving a cryptographic puzzle (officially, a "zero-knowledge proof"), which is a riddle that is difficult to solve but simple to check. "Mining" is a common word for adding a new block, and miners are the nodes that perform this task. Miners that successfully mine a new block are rewarded with a certain amount of the native coin (or a portion of it). The nodes are in a race to make the next block. The decision is based only on computer power, not on what makes sense (Zhang and Lee, 2020). When a node finishes a block, the information is sent to the other nodes in the network. The nodes check that the block was made correctly and add it to the (block)chain, proving that it fits in with the history of transactions (Bouraga, 2021). In practice, it has become exponentially harder to solve the puzzle over time. Now, one needs special hardware (called ASICs or application-specific integrated circuits), a group of computers called "mining pools," and a lot of energy (Küfeoğlu and Özkuran, 2019).

On the mining front, energy consumption depends on network power usage (generally represented by Hash rate), Cooling Cost, Expected Electricity consumption and Bitcoin Miner Device Production (De Vries, 2018). With more competitors, more hash rate comes into the picture and further energy consumption (De Vries, 2020). On the other hand, trade factors such as Bitcoin price have been found to drive mining expenses rather than the other way around (Kristoufek, 2020). The per coin climate damages from Bitcoin had been increasing from 2016 to 21 rather than decreasing with industry maturation. Even worse, during specific periods, the bitcoin climate damages exceeded the price of each coin created (Jones *et al.*, 2022). Instead of cost determining the price, the bitcoin price determines the mining cost miners can afford to mine profitably and trade bitcoin prices. Since the bitcoin market behaves like a perfect competition market, the Economic theory predicts the profits to reach zero with more competitors entering the bitcoin market with a single homogeneous good. Therefore, the high energy cost makes Bitcoin less profitable (Derks *et al.*, 2018).

As far as the trading part is concerned, out of the entire crypto-market, Bitcoin and Ethereum have a combined market share of approximately 60% (CoinMarketCap, 2022). Cocco *et al.* (2019) emphasize how Bitcoin's core technology, in particular, is a "safe haven" for addressing contemporary environmental concerns better than gold. When it comes to the valuation of Bitcoin (or any other such crypto), it is determined by three prominent factors – acceptance as a medium of exchange, cost of cryptocurrency mining and speculative factors (Pakhnenko *et al.*, 2022).

Much has been spoken about in the Literature about Bitcoin energy consumption which depends on the mining-specific variables like those discussed above. On the trading side, profit is the central area of focus for the literature in the Finance domain. However, there is a dearth of literature that caters to green investors and policymakers by informing them about the impact of crypto market activities on Bitcoin's energy consumption.

After thoroughly going through the literature, we could not find empirical studies dealing with energy consumption and prices of trading specific variables like crypto index like CIX200 and Ethereum prices. In addition, we found no significant literature on the relationship between the average block size and transaction count and bitcoin-based energy consumption. We attempt to fill this crucial research gap by achieving the research objectives and the questions mentioned in the introduction section of this study.

To find the answers to the targeted research questions, the authors went ahead with the data collected from various sources and attempted to quantify this relationship. The following hypothesis was developed to meet our first research question.

The following hypothesis has been tested in the empirical analysis:

H1. The size of the block on the Bitcoin network significantly impacts Cambridge Bitcoin Electricity Consumption Index (CBECI).

The block size on the Bitcoin blockchain is directly proportional to the amount of energy consumed by Bitcoin mining hardware. As the number of blocks increases, so does the amount of energy required to validate each block, resulting in a greater demand for computational power and an increase in energy consumption (Bouraga, 2021; Zhang and Lee, 2020). In 2017, the average block size on the Bitcoin blockchain was 1 MB, and the anticipated annual energy usage of the Bitcoin network was 35 Terra-Watt hour (Krause and Tolaymat, 2018). However, energy usage has also climbed significantly with the increasing block size and rising popularity of Bitcoin. The literature speaks about the number of blocks and energy consumption. However, it is relatively silent on the size of the block, which is one of our independent variables in this study. Thus, the relationship between the block size on the Bitcoin blockchain and the energy consumption of Bitcoin mining machines is an essential factor that must be continuously monitored and adjusted to ensure the network's stability. We plan to empirically understand the relevance and relationship between the size of the block and Bitcoin's energy consumption.

H2. The number of Bitcoin transactions has a significant impact on CBECI.

As the volume of transactions increases, so should the computer power needed to validate them, leading to an increase in energy usage. Also, the Bitcoin network's energy usage per transaction has increased with time. In February 2023, the average energy consumption per transaction was estimated to be 842 kWh which can power around 566 thousand visa transactions (Digiconomist, 2023). The literature talks about the crucial role of Bitcoin transactions in the huge energy consumption for reaching consensus in recording these transactions on the Bitcoin network (Bouraga, 2021; de Vries, 2019; Sedlmeir *et al.*, 2020). We test the impact of the number of transactions on the bitcoin-based energy consumption proxied by CBECI.

H3. The Price of the CIX200 (crypto market Index) and Ethereum (closest substitute) significantly impact CBECI.

There is currently a dearth of literature analyzing the impact of changes in prices of crypto market indices on the bitcoin's energy consumption. Using this analysis, we attempt to identify and quantify this relationship. With crypto volatility and energy volatility having connectedness in the long and short run (Le, 2023), the debate on how the changes in the crypto market affect bitcoin-based electricity consumption has been triggered. The nature of the relationship can help draft suitable strategies to reduce bitcoin-based energy consumption. Ethereum and Bitcoin are decentralized cryptocurrencies that rely on blockchain technology to verify and record transactions. Ethereum ranks second in terms of market capitalization next to Bitcoin (Coinmarketcap.com, 2023). Even though Ethereum and Bitcoin have some similarities, they are not suitable direct substitutes for each other. They have different features and ways to use them. However, for investors, Ethereum and Bitcoin are cryptocurrencies that behave like financial assets.

For meeting the second research question, we use the results of RQ1 and RQ2 substantiated with literature to make suggestions for mitigating this massive bitcoin-based energy consumption and further reducing the carbon emissions moderated by the non-renewables as the source of power generation.

3. Data, variables and descriptive analysis

We used CBECI in Gigawatt hours to analyze the bitcoin-based energy consumption as a proxy. The independent variables are bifurcated into mining and trading-specific variables. The Bitcoin average block size, bitcoin hash rate and bitcoin number of transactions were categorized into mining-specific variables. While the prices of CIX200 & Ethereum fell into trading-specific variables. We used data from December 2018 to January 2023 (50 monthly observations) from the Cambridge Centre for Alternative Finance, Nasdaq and Yahoo Finance (Table 1) for the regression analysis.

The study also attempts to capture the relationship between Bitcoin's energy consumption and the Crypto market for which CIX200 is considered. The historical data for CIX200 is maintained from its launch date, i.e. 31st December 2018 (Solactive, 2019). Since the data for the cix200 was unavailable before December 2018, we took the starting period to December 2018. Additionally, the year 2018 happens to be a significant year post which the crypto market started attracting substantial investments, evident from its market capitalization (Coinmarketcap, 2023). The month-end closing prices or values were considered. Wherever necessary, a month's opening prices were considered the previous month's ending price to make the analysis free from biases or frequency mismatches.

We first look at the descriptives in Table 2, where 6.99 Gigawatt hour is the average monthly bitcoin-based electricity consumption, and the maximum consumption is 10.67 Gigawatt per hour. Similar parameters are available for the independent variables. Except for the prices of the Cix200 Index and Ethereum, all the variables were found to be normally distributed at the level. The only variables with more than 75% of correlation are Cix200 and Ethereum prices at the level. However, these are transformed for the analysis post the determination of integration order using stationarity results from Table 3.

After the descriptives, we start by identifying the order of integration for each variable to proceed with the analysis. If a series' mean, variance and structural characteristics remain constant across time, it is said to be stationary. According to the unit root concept, a non-stationary time series is a stochastic process having unit roots or structural breaks.

Abbreviation	Variable description
CBECI_GW	CBECI – The daily estimated guess value of electricity the Bitcoin Network consumes
BT Avg. Block size	Bitcoin Average Block Size – Records the block size on the Blockchain where Bitcoin transactions are stored
BT Hash Rate	Hash Rate – It refers to the number of hashes or guesses that can be made to crack the algorithm puzzle for generating bitcoin as mining rewards
BT No of Transactions	Bitcoin No. of Transactions – The total number of transactions in the Bitcoin network taking place in a month, including mined and exchanged bitcoins
CIX 200	CMC200 index by Solactive represents the top 200 cryptocurrencies in the market except for the bitcoin, which may impact its dominance
Eth P	Ethereum Price – The closing value of Ethereum Prices per day

Source	Units
The Cambridge Centre for Alternative Finance	Gigawatts
Nasdaq	MB
Nasdaq	Tera Hash
Nasdaq	Nos
Yahoo Finance	USD$
Yahoo Finance	USD$

Source(s): Reported Databases by Authors

Table 1. Sampled variable description

Statistics	CBECI	Avg. Block size	Hash rate	No of trans	Cix200	Ethereum price
Mean	6.994	1.185	141,275,015	292,201	536.24	1,334
Median	6.849	1.182	129,529,450	289,808	407.70	1,132
Maximum	10.670	1.539	316,782,326	381,652	1522.08	4,631
Minimum	2.978	0.816	43,291,797	207,348	89.59	107
Std. Dev.	2.270	0.158	68,077,209	42,983	411.69	1,263
Skewness	0.0291	−0.2077	0.5138	0.0698	0.8035	0.8406
Kurtosis	1.9902	2.6158	2.5966	2.4235	2.4260	2.6665
Jarque–Bera	2.1315	0.6670	2.5386	0.7331	6.0661	6.1197
Probability	0.3445	0.7164	0.2810	0.6931	*0.0482*	*0.0469*
Correlation						
CBECI	1					
Avg. Block Size	0.4645***	1				
Hash Rate	0.7277***	0.2358*	1			
No of Transactions	−0.4611***	0.0264	−0.3998***	1		
Cix200	0.6814***	0.3511**	0.3616***	−0.4934***	1	
Ethereum Price	0.6995***	0.2895**	0.4567***	−0.5390***	*0.9547****	1

Note(s): *** significant at 0.01, ** significant at 0.05, and * significant at 0.10
Source(s): Calculations reported by authors using Eviews V12

Table 2.
Descriptives, normality and correlation

Variables/Tests	L.ADF	F.ADF	L.PP	F.PP	Series
CBECI_GW	−2.3063	*−6.0680*	−2.3063	*−6.0583*	I(1)
BT Avg. Block Size	*−5.1305*	NA	*−5.1298*	NA	I(0)
BT Hash Rate	−2.9682	*−7.4855*	−2.7103	*−10.1082*	I(1)
BT No of transactions	*−6.0765*	NA	*−6.0715*	NA	I(0)
Cix200	−1.1698	*−6.3602*	−1.2239	*−6.3604*	I(1)
Ethereum Price	−1.0433	*−6.6274*	−1.1073	*−6.6239*	I(1)

Source(s): Author's calculation

Table 3.
Stationarity results from ADF and PP test

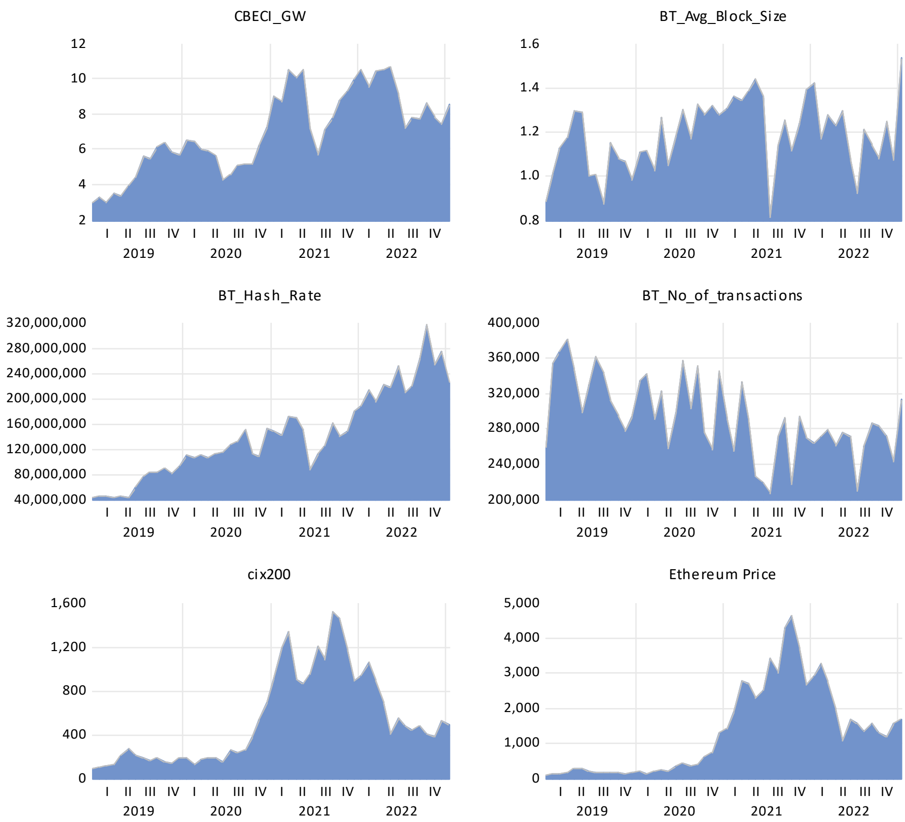
Unit roots, however, are critical non-stationary sources. When a time series is non-stationary, it is indicated by the presence of a unit root, but when it is stationary, it is assumed by the absence of a unit root. Dickey and Fuller (Dickey and Fuller, 1979) established the unit root method for testing stationarity.

For ARDL, all the variables should be I(0) or I(1). Any variable with the second order of integration will not work for the ARDL model making the results unreliable and biased. Pre-testing for unit roots is not required when using the ARDL cointegration approach. However, stationary conditions must be checked for all series as the first step of model estimation to keep the ARDL model from crashing when there is an integrated stochastic trend of I. (2). In order to achieve stationarity; we use the conventional Augmented Dickey–Fuller (ADF) test and the Phillips–Perron test (Phillips and Perron, 1988).

The graph for individual variables is provided below in Figure 1, which tracks the progression of each variable from December 2018 to January 2023.

4. Methodology

We have used the simple Ordinary Least Square (OLS) regression and Autoregressive Distributed Lag (ARDL) model for analyzing the short-run relationship, followed by the



Source(s): Authors own creation

Figure 1.
Multiple Graphs depicting the behavior and progression of each variable from December 2018 to January 2023

ARDL method for the long-term relationship among the variables. According to Greene (2008), the ARDL model is a standard least squares regression that uses the lags of both the independent and dependent variables as regressors. ARDL has grown in prominence as a technique for evaluating the cointegration of proposed economic variables as per Pesaran and Shin (1999) and has been extended by Pesaran *et al.* (2001). The ARDL test has three significant advantages. The first is that, regardless of whether the regressors are stationary at their level, integrated of order one, or a combination of the two, they can be adapted for performing cointegration analysis to empirically establish the relationship among the economic variables. The ARDL test is significantly more effective in small and finite sample data sizes (50 monthly observations in our case), which is the second benefit (Belloumi, 2014). The ARDL technique allows us to obtain estimates of the long-run model that are free of bias, which brings us to our third and last advantage (Harris and Sollis, 2003).

The ARDL model should meet the assumption of Linearity, Homoscedasticity, No Multicollinearity, No Autocorrelation and Normality, just as in the case of the Ordinary Least Square method. The ARDL model is made up of two components, one being the lags of the dependent variables (Autoregressive) and the other being the lags of the regressors or independent variables (Distributed Lags). It can be expressed in equation (1) as follows for our case:

$$(\ln(\mathrm{CBECI_t})) = \alpha_1 + \sum_{i=1}^{p} a_{1i}(\ln(CBECI_{t-i})) + \sum_{i=0}^{q} a_{2i}(\ln(Avg.\,Block\,Size_{t-i})) + \sum_{i=0}^{q} a_{3i}(\ln(Hash\,Rate_{t-i})) + \sum_{i=0}^{q} a_{4i}(\ln(No\ of\ Transactions_{t-i})) + \sum_{i=0}^{q} a_{5i}(\ln(CIX200_{t-i})) + \sum_{i=0}^{q} a_{6i}(\ln(Ethereum\,price_{t-i})) + \varepsilon_{1t} \quad (1)$$

where p and q represent the number of lags of CBECI and Other independent variables, respectively.

5. Empirical findings

In this section, we discuss the short-run relationship using the Ordinary least Square method followed by the ARDL model discussed in the methodology section. With variables of different integration of order and different lag of dependent and independent variables, the reporting results in higher R^2 or better explanation of the dependent variables, i.e. CBECI in our case.

5.1 Short-run relationship using ordinary least square (OLS) method

The short-run results indicate all the variables as significant at 5% or 1% (see Table 4). The model is relatively stable, with the Adjusted R^2 being 38.8%, significant F-statistics at 1%, and the Durbin–Watson test is well within the range of 1.5–2.5. However, we perform the short-run model diagnostics test reported in Table 5 to ensure the reliability of the results.

The results of Table 5 confirm there is no serial correlation (Breusch, 1978; Godfrey, 1978) and heteroskedasticity (Breusch and Pagan, 1979) as far as residuals are concerned. Also, the residuals are normally distributed (Jarque and Bera, 1987), making the model apt to draw inferences.

Table 4.
OLS-based results for short-run relationship

Variable used	Coefficient	Standard error	*T*-statistic
C	−3.2138	1.3223	−2.3950**
BT Avg. Block Size	0.3343	0.0901	2.8136***
D (BT Hash Rate)	0.3231	0.1196	3.0233***
BT No of Transactions	0.2526	0.1046	2.3584**
D (CIX200)	0.2381	0.0942	2.1526**
D (Ethereum Price)	−0.2816	0.0918	−2.9006***
F-Statistic = 7.10***	R^2 = 0.452	Adj. R^2 = 0.388	D–W = 2.18
	AIC = −1.61	SC = −1.38	HQC = −1.52

Note(s): *** significant at 0.01, ** significant at 0.05, and * significant at 0.10
Source(s): Author's calculation

Table 5.
Short-run model diagnostics tests

Residual tested for	Test	Chi-square	*p*-value
Serial Correlation	Breusch–Godfrey LM	2.9986	0.2233
Homoskedasticity	Breusch–Pagan–Godfrey	4.9332	0.4241
Normality	Jarque–Bera	0.5770	0.7493

Source(s): Author's calculation

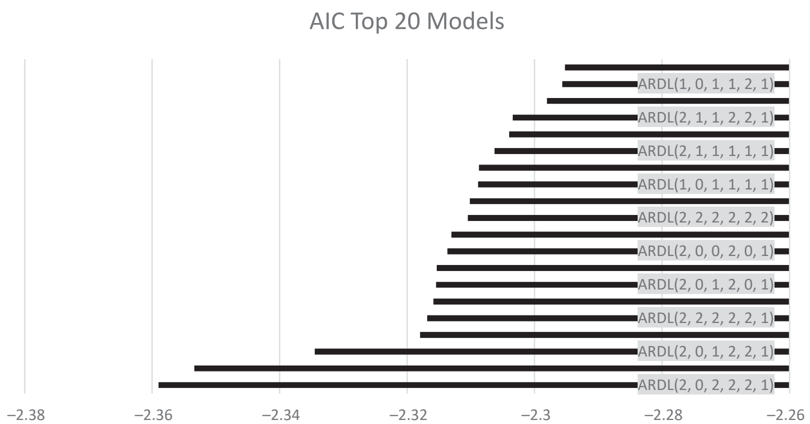
5.2 Long-run relationship using ARDL model

The long-run ARDL model using the automatic lag selection and Akaike Information Criteria is ARDL (2, 0, 2, 2, 2, 1). Since both level and stationary transformed variables can be chosen in ARDL, we used log-transformed level variables for the analysis. The EViews V12 was used for the analysis with a maximum of two lags, as a greater number of lags were not significantly adding to the adjusted R^2. The probable reason for this could be the monthly frequency of the data. More lags would have made sense if the data had been in daily frequency.

The final model was an outcome of 486 model evaluations by the software (refer to Figure 2). We preferred AIC over other criteria because it outperforms the other criteria for small samples (60 observations or less). AIC decreases the chance of underestimation while maximizing the chance of discovering the correct lag length (Liew, 2004). Therefore, the model with the least AIC value was the final one.

The results in Table 6 were obtained using the Autoregressive Distributed Lag (ARDL) model that evaluates the relationships between multiple variables. A maximum of two lags were chosen manually before running the automatic lag selection feature in Eviews v12. In order to avoid long-term biases, we restricted ourselves to just two lags. In addition, the bitcoin market is highly volatile, with market participants being updated on a real-time basis. It, therefore, made sense to restrict our analysis to two lags which means two months for our analysis. The model incorporates both lagged and current variable values, and the coefficients and *t*-statistics for each variable are reported. The *F*-statistic measures the model's overall significance, which is highly statistically significant (at 0.01). The *R*-squared value indicates that the model accounts for a significant percentage of the variation in the dependent variable. The adjusted *R*-squared value is slightly lower than the *R*-squared value since it accounts for the number of independent variables in the model. The Durbin–Watson statistic assesses the degree of autocorrelation in the model, and a result of 1.85 indicates that the residuals have some positive autocorrelation. However, it falls well within the acceptable limit. Finally, the AIC, SC and HQC are goodness-of-fit measures, with lower values indicating a better fit of the model. The chosen AIC model is reported in Figure 2.

In the current period, the lag 1 of CBECI (a measure of bitcoin-based electricity consumption) has a significant positive effect on its current period. This effect is consistent throughout lags, as indicated by the positive and significant coefficient even at lag 2. The average size of Bitcoin blocks positively affects the CBECI in the current period, as indicated



Source(s): Authors own creation

Figure 2.
The model selection summary graph

Table 6.
Results of long-run ARDL (2,1,1,0,1,2) model

Variables used	Coefficient	Standard error	T-statistic
CBECI (−1)	0.43838	0.13174	3.32767***
CBECI (−2)	0.25328	0.12353	2.05030**
BT Avg. Block Size	0.24526	0.10166	2.41264**
BT Avg. Block Size (−1)	−0.12094	0.10680	−1.13236
BT Avg. Block Size (−2)	−0.16429	0.07976	−2.05987**
BT Hash Rate	0.38481	0.07933	4.85081***
BT Hash Rate (−1)	0.00177	0.09822	0.01800
BT Hash Rate (−2)	−0.22420	0.08725	−2.56961**
BT No of Transactions	0.15328	0.12358	1.24039
BT No of Transactions (−1)	0.07093	0.08714	0.81398
BT No of Transactions (−2)	0.24200	0.10818	2.23708**
CIX200	0.38053	0.05032	7.56246***
Ethereum Price	−0.36906	0.04768	−7.74051***
Ethereum Price (−1)	0.18205	0.03961	4.59600***
C	−9.33619	2.79996	−3.33440
F-Statistic = 81.27***	R^2 = 0.971	Adj. R^2 = 0.959	D–W = 1.85
	AIC = −2.35	SC = −1.77	HQC = −2.13

Note(s): *** significant at 0.01, ** significant at 0.05, and * significant at 0.10
Source(s): Reported and calculated by authors

by the positive and significant coefficient in the case of BT Avg. Block Size. This effect, however, is not substantial at lags 1 or 2.

Furthermore, as indicated by the positive and highly significant coefficient, BT Hash Rate has a strong positive effect on Bitcoin-based electricity consumption in the current period. This effect is insignificant at lag 1, but the significance reappears at lag 2. In terms of Bitcoin transaction volume, it positively impacts the CBECI in the current period. This effect, however, is not significant at lag 1 but is significant at lag 2. In the context of trading variables, we examined the CIX200 and Ethereum prices. As indicated by the positive and highly significant coefficient, the CIX200 (Cryptocurrency market Index) has a substantial positive effect on Bitcoin-based electricity consumption (CBECI) in the current period. Finally, the current price of Ethereum has a significant adverse effect on the dependent variable. The lagged values of Ethereum, on the other hand, have a positive and statistically significant coefficient, indicating that a fall in Ethereum price will reduce Bitcoin-based electricity consumption or CBECI.

5.3 Cointegration and error correction model

The ARDL bounds test approach was employed in this study to check for evidence of cointegration between the variables. The results are shown in Table 7. At the 1% significance level, the findings imply that the null hypothesis of no cointegration is rejected. The F-test statistic value of 10.07 surpasses critical levels at 1% with a value of 3.674 (finite sample n = 45). As a result, the variables in the model have certain co-integrating relationships (Pesaran *et al.*, 2001).

Since cointegration is present in the model, we need to check the convergence and divergence pattern of the variable in the long term. The same is reflected through the coefficients and their corresponding values in Table 7.

A positive coefficient denotes divergence, whereas a negative value indicates convergence. If the Error Correction Term (ECT) estimate equals 1, then the correction is instantaneous and complete or happens at 100% during the period. If the estimate of ECT equals 0.5, then 50% of the adjustment occurs each period/year. ECT = 0 indicates that there

F-statistic	10.07***	Cointegration exists
Case 2- With No Trend and Restricted Constant		
Variable	Coefficient	*t*-Statistic
Δ CBECI (−1)	−0.25328	−2.83784***
Δ BT Avg. Block Size	0.245261	2.997631***
Δ BT Avg. Block Size (−1)	0.164289	1.904592*
Δ BT Hash Rate	0.384812	5.200864***
Δ BT Hash Rate (−1)	0.224196	2.572667**
Δ BT No of Transactions	0.153281	1.634934
Δ BT No of Transactions (−1)	−0.242	−2.88608***
D (Ethereum Price)	−0.36906	−7.73026***
Cointegration Equation (−1) *	−0.30834	−9.12726***
R^2 = 0.824	Adj. R^2 = 0.788	DW = 1.85

Source(s): Author's calculation

Table 7. Bound test results and error correction model

is no adjustment, and it makes no sense to assert that there is a long-term relationship. In our case, the ECT is negative and significant at a 1% level (highly significant), with convergence in the long term as indicated by the negative coefficient of −0.30, indicating a 30% correction as convergence every month. The convergence happens every 3.33 months or three months and ten days.

6. Discussion

We started by taking three mining-specific and two trading-specific variables to analyze the reasons behind Bitcoin's colossal energy consumption proxied by CBECI. We used then OLS regression for the short-run analysis, and for the long run, we considered ARDL. The ARDL model was chosen because of a smaller number of observations (50 monthly observations) and the variables being of different integration order −I (0) and I (1), except for I (2).

The model with a maximum of two lags revealed a significant association between the four independent variables (including mining and trading specific variables) and the CBECI proxy index for bitcoin-based electricity consumption as a dependent variable. The model indicated that the independent variables included in the study considerably affected the dependent variable. The model's *R*-squared score indicated that the independent variables explained 95% of the variation in the dependent variable. At the 5% significance level, the model's *F*-statistic value was significant, indicating that the model was a good fit for the data. In addition, at the 5% significance level, the individual coefficients of the independent variables were also significant, except for the monthly Bitcoin number of transactions.

In order to determine the model fit, we refer to two types of diagnostic checks – Stability and Residuals. While the stability check will determine the stability of parameters and model, the residual diagnostics check whether the model follows the assumptions of no serial correlation, presence of homoskedasticity and normality of residuals.

The short-run dynamics show how stable the long-run coefficient is. Once the ECM model has been estimated, we employ two recursive estimates: the cumulative sum of recursive residuals (CUSUM) and the CUSUM of square (CUSUMSQ) to verify the stability of the parameters (Pesaran and Pesaran, 1997). Figure 3 plots the results for both CUSUM and CUSUMSQ tests. Because the CUSUM and CUSUMSQ statistics plot lies inside the critical bands of the 5% confidence interval of parameter stability, the results indicate the absence of any instability of coefficients in the model. In other words, the model was found to be stable.

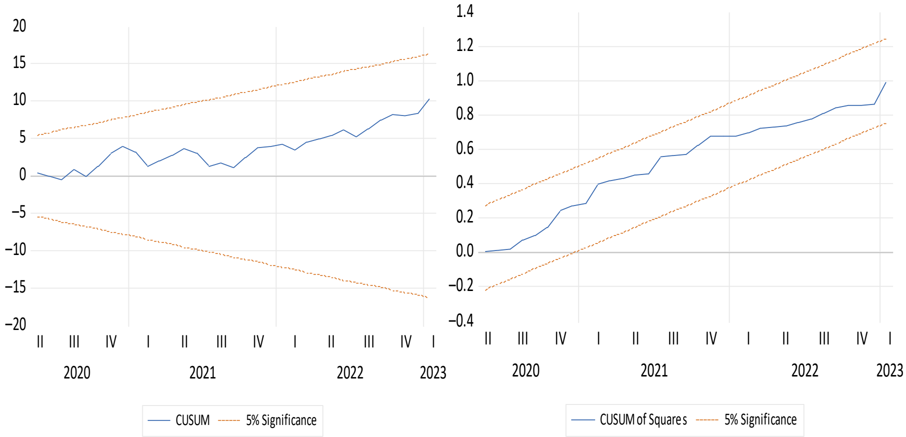


Figure 3.
Results of CUSUM and CUSUMSQ tests

Source(s): Authors own creation

After CUSUM and CUSUMSQ tests, we conducted an additional Ramsey RESET test to ensure the model was well specified (Ramsey, 1969). The results of the Ramsey test were also favorable, with a likelihood ratio of 0.0413 and a corresponding p-value of 0.8389 (Table 8).

After testing the model's residuals, we conclude that the underlying ARDL Eq. (1) regression fits quite well. The model (Table 6) is significant at the 1% level, with independent variables at the 1% or 5% levels except for the BT number of transactions. Table 9 shows that the model passes all residual diagnostic tests for serial correlation (Durbin and Watson, 1950; Breusch, 1978; Godfrey, 1978), heteroskedasticity (Breusch and Pagan, 1979) and normality (Jarque and Bera, 1987).

Since the p-value of all the tests mentioned above was more than 0.05, it was evident that the residuals in the final model were free from serial correlation and heteroskedasticity and normally distributed.

The significant positive influence of the lagged CBECI (−1) on the dependent variable CBECI indicates an auto-regressive long-term link inferring the self-explanatory power of previous electricity consumption on the current electricity consumption by Bitcoin. The study's findings

Table 8.
Ramsey RESET test

Statistics	Value	df	Probability
T-statistic	0.165993	32	0.8692
F-statistic	0.027554	(1, 32)	0.8692
Likelihood ratio	0.041313	1	0.8389

Source(s): Author's calculation

Table 9.
Residual diagnostics test

Residual tested for	Test	Chi-square	p-value
Serial Correlation	Breusch–Godfrey LM Test	0.0723	0.9645
Homoskedasticity	Breusch–Pagan–Godfrey	16.5176	0.2828
Normality	Jarque–Bera	2.3858	0.3033

Source(s): Author's calculation

suggest that the size of the Block, Hash rate, number of Bitcoin transactions and crypto may positively impact Bitcoin-based energy consumption (CBECI), while Ethereum has a negative relationship. For the long-run analysis, Ethereum turns out to be positively impacting the CBECI, indicating a behavior as a substitute for Bitcoin in the cryptocurrency market. The findings show that all the above hypotheses are accepted, confirming that the block size, network hash rate and the number of transactions on the Bitcoin network positively correlate with Bitcoin-based electricity consumption. On the trading side, the crypto market is positively associated with bitcoin-based electricity consumption. While Ethereum is negatively associated in the short run, at a lagged value of a month, the relationship between Ethereum and Bitcoin-based electricity consumption becomes positive, indicating Ethereum is an energy-efficient substitute for Bitcoin. Due to the high level of activities on a daily basis on the Bitcoin network, the authors believe that a lagged value of more than 1 (a month ago) does not provide a valid explanation for the phenomenon under consideration. Therefore, for the long-run results, we request the readers to confine their interpretations up to 1 lag only.

In the short run, the model explains 45% of Bitcoin's electricity consumption. With an increase in block size by 1 MB, there is a 33% change in the CBECI, and with a 1% change in hash rate, the network energy consumption increases by 32%. With the addition of 100 more transactions in the network, energy consumption increases by approximately 25%. On the trading-specific variables, a 1% growth in the crypto market increases the bitcoin energy consumption by approximately 24%, and a 1% fall in Ethereum prices increases the energy consumption by approximately 28%.

In the long run, the lags add up to 50% more explanation. Average block size, change in hash rate and prices of CIX200 have an immediate impact on the monthly Bitcoin electricity consumption. After considering the lags in the number of transactions, it becomes irrelevant as a current contributor to Bitcoin-based energy consumption. Regarding Ethereum prices, they indicate a substitute nature at a month lag with a positive coefficient of 18%.

In a nutshell, we suggest that investors and policymakers mitigate Bitcoin's colossal energy consumption after determining the relevant factors contributing to this enormous energy consumption.

7. Conclusion and implications

To meet RQ1 and RQ2, this study identifies five critical factors responsible for massive bitcoin-based energy consumption. These five factors are bifurcated into mining and trading-specific variables. The Bitcoin block size, Hash rate in the Bitcoin network and the number of Bitcoin transactions are three mining-specific variables that are positively related and significantly contribute to bitcoin-based energy consumption (CBECI). On the other hand, the Crypto market index (CIX200) and Ethereum prices have a significant impact on Bitcoin-based electricity consumption. While the crypto market index and CBECI are positively related, Ethereum negatively impacts energy consumption in the short run and has a positive role to play in the long run by reducing the bitcoin-based electricity consumption with the fall in its prices. This is in line with the Theory of Cross Elasticity of Demand for substitute goods (Atkinson and Miller, 2005). In our analysis, the cross-elasticity coefficient measures the relationship between the demand for two commodities. The degree of their substitutability can be reflected by the size of the coefficient, with close substitutes having a higher cross-elasticity of demand and poor substitutes having low cross-elasticities (Kuhlman and Thompson, 1965). While we have empirically tested the substitutability between Bitcoin and Ethereum as financial assets, the strength of the substitution effect can be explored or evaluated by future researchers.

Finally, meeting the RQ3, we make the following recommendations to green investors and policymakers by substantiating the results of this study with literature support. The positive association between Ethereum pricing and CBECI suggests that investors may reallocate their funds to Ethereum and other cryptocurrencies that are less energy intensive. With a recent shift of Ethereum from Proof of Work (PoW) to Proof of Stake (PoS), there has been an energy saving of more than 99% in mining and validation of transactions of the Ethereum network (Islam *et al.*, 2022). A similar move from PoW to PoS consensus is also proposed for Bitcoin. In addition, a decline in the price of Ethereum will effectively lower Bitcoin-based energy use by one day. The government can promote energy-efficient cryptocurrencies to interested investors and regulate mining by offering energy-efficient rules. The government can meet its net-zero commitments if it considers crucial variables that affect energy consumption.

As the globe continues to confront the issue of climate change, investors are becoming more conscious of the environmental impact of their investments. Green investors may switch to Ethereum or other less energy-intensive cryptocurrencies in the cryptocurrency market. This study also suggests that some investors may choose to diversify their portfolios away from the cryptocurrency market entirely. Surprisingly, a decline in Ethereum's price may have a favorable effect by reducing Bitcoin's energy consumption. This is because an eventual decline in the price of Ethereum could attract Bitcoin investors. The decline in Bitcoin's demand due to investors' shift to Ethereum leads to a reduction in Bitcoin mining activity, essentially reducing Bitcoin's energy consumption. According to the investigation findings, this effect of a shift in Ethereum remains for around one month.

By encouraging investors to prioritize energy-efficient cryptocurrencies, the government may promote energy efficiency in the cryptocurrency industry. In addition, regulating the Bitcoin mining process using energy-efficient guidelines may assist in lowering the Bitcoin industry's overall energy usage. The government can meet its net-zero objectives if it considers important factors discussed in this study that influence energy consumption within the industry. Adopting these measures can go a long way toward decreasing the industry's carbon footprint and assisting the government in achieving its sustainability goals. The government has a crucial role in accomplishing the enormous potential benefits of fostering energy-efficient cryptocurrencies. Regulating the cryptocurrency industry with potential regulatory mechanisms can help lower Bitcoin's energy consumption (Howson and de Vries, 2022) and, at the same time, can provide the liberty to investors to keep investing in a greener way. The miners may be encouraged to use energy from renewable sources; taxing the miners who use non-renewable energy or rebates for miners using renewable power to mine Bitcoins can be provided by the policymakers (Howson and de Vries, 2022).

We contribute to the literature on this topic by identifying significant factors affecting Bitcoin's energy consumption. We empirically validate the impact of average block size, hash rate and number of Bitcoin transactions on Bitcoin's energy consumption. In addition, the study finds that the crypto market (CIX200) and Ethereum prices impact Bitcoin's overall energy consumption. The findings suggest a positive relationship between Bitcoin's electricity consumption and the prices of Ethereum, suggesting Bitcoin and Ethereum are substitutes for investing. We use the findings and substantiate them with the literature to suggest certain energy mitigation measures to policymakers, including promoting energy-intensive cryptocurrencies and regulating the crypto industry by enforcing energy-efficient mining guidelines and higher taxes for energy-inefficient cryptocurrencies. Overall, a deeper grasp of the complex factors driving Bitcoin's energy usage is required to guide future policy choices and mitigate its environmental impact. Future researchers can further strengthen the research around this topic and may help advance the Green and sustainable investing agenda.

8. Limitations and future research

There are various limitations that must be considered in the aforementioned study. First, the study's data are limited regarding the number of observations, which may compromise the conclusions' precision. Second, the study depends on monthly data, omitting vital information that may have been gathered through daily observations. In addition, the study does not apply a multi-method strategy to test the model's robustness, which could result in potential biases or inaccuracies. While the study is of global significance from the trading point of view, the implementation of findings related to Bitcoin mining is limited to the United States, Russia and Kazakhstan, which are the major Bitcoin miners in the world (Statista, 2022). Moreover, the low R^2 value shows that significant variables that explain Bitcoin mining's enormous energy use may have been omitted. While interpreting the outcomes of this study, these restrictions must be considered.

As concerns about the environmental impact of Bitcoin mining continue to grow, experts may examine alternative methods for estimating the carbon footprint of Bitcoin mining. One method involves extending the research to daily observations, which might uncover patterns and trends that may not be apparent at larger time scales. In addition, a nonlinear analysis of the relationship between Bitcoin price and energy use can shed light on the market's dynamics. Additionally, it is important to understand the dynamics of the Bitcoin market, in which both primary and secondary markets are integrated. Future researchers may study additional factors to explain energy usage better. As regulators debate how to regulate this fast-expanding Bitcoin business, experts may evaluate the effects of crypto taxes on energy consumption.

Notes

1. Senator Ed Markey (D-Massachusetts) chaired a session of the Committee on Environment and Public Works on 7th March 2023, focusing on the energy usage of mining. He tweeted it right after this session. The post is publicly available on the twitter platform.
2. 44,400 metric tons = 66,600 metric tons/1.5 years [66,600 = 0.3 (Weight/hash rate) * 222 Exahash rates (hash rate of bitcoin per second)] Source-Table 1: "Renewable Energy will not solve bitcoin's sustainability problem".

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