ISSN 2392-1641
e-ISSN 2450-0097

Economics and Business Review

Volume 12 (1) 2026

CONTENTS

Poznań University of Economics and Business Press

Economics and Business Review

Volume 12 (1) 2026

Paper based publication

https://doi.org/10.18559/ebr.2026.1

ISSN 2392-1641
e-ISSN 2450-0097

POZNAŃ UNIVERSITY OF ECONOMICS AND BUSINESS PRESS
ul. Powstańców Wielkopolskich 16, 61-895 Poznań, Poland
phone +48 61 854 31 54, +48 61 854 31 55
https://wydawnictwo.ue.poznan.pl, e-mail: wydawnictwo@ue.poznan.pl
postal address: Al. Niepodległości 10, 61-875 Poznań, Poland

Printed and bound in Poland by:
Perfekt – Gaul i wspólnicy sp. k.

Circulation: 80 copies

PUEB PRESS

Economics and Business Review
https://www.ebr.edu.pl

Vol. 12 (1), 2026: 159-182
https://doi.org/10.18559/ebr.2026.1.2793

From digital mining to market prices: An empirical analysis of the relationship between energy consumption and price dynamics of Bitcoin and Ether

Levent Sezal[1]

Abstract

This study compares the relationships between Bitcoin and Ethereum's energy consumption and price dynamics. Using daily frequency data, Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), ARDL cointegration tests, and Toda–Yamamoto causality analysis were applied to evaluate the effects of cryptocurrency markets on energy demand from both short-term and long-term perspectives. The results indicate that there is a long-term cointegration relationship between energy consumption and prices for Bitcoin, and also unidirectional causality from prices to energy consumption. In contrast, ARDL boundary test results for Ethereum revealed no long-term relationship, and causality analysis also failed to detect any directional causality between price and energy consumption. This indicates that with Ethereum's transition to a Proof-of-Stake mechanism, energy consumption has become independent of price movements. The findings reveal that the effects of cryptocurrency markets on the energy economy vary according to technology-specific structural characteristics.

Keywords

- Bitcoin
- Ethereum
- energy consumption
- cryptocurrency markets
- digital mining
- energy economy

JEL codes: C32, C58, Q55.

Article received 22 November 2025, accepted 15 January 2026.

Suggested citation: Sezal, L. (2026). From digital mining to market prices: An empirical analysis of the relationship between energy consumption and price dynamics of Bitcoin and Ether. *Economics and Business Review*, *12*(1), 159-182. https://doi.org/10.18559/ebr.2026.1.2793

[1] Vocational School of Social Sciences, Kahramanmaraş Sütçü Imam University, Kahramanmaraş, Türkiye, leventsezal@ksu.edu.tr, https://orcid.org/0000-0002-8873-7335.

Introduction

Cryptocurrencies, particularly since the emergence of Bitcoin (BTC) in 2009, have become a central topic in financial markets, the technology sector, and public policy debates. Although the distributed ledger technologies provided by cryptocurrencies are attractive due to their potential to reduce intermediary costs and enable decentralised payments, their energy and environmental costs have become a focus for both academic circles and policymakers in recent years. Due to the computationally intensive nature of Proof-of-Work (PoW) mining mechanisms, numerous studies have estimated the energy consumption of the Bitcoin network and the associated carbon emissions to be high. For example, De Vries (2018) demonstrated that the Bitcoin network has a significant electricity demand, and subsequent detailed calculations revealed that Bitcoin mining's annual electricity consumption could run to tens of thousands of GWh (De Vries, 2018; Stoll et al., 2019). Methodological studies on this subject emphasise that energy consumption estimates can vary significantly depending on the calculation method used and therefore highlight the need for both upper and lower band estimates and transparent data sources (CCAF, 2025; Gallersdörfer et al., 2020).

The price behaviour of cryptocurrency markets has also been studied extensively in academic literature. Early studies showed that cryptocurrencies are highly volatile assets exhibiting bubble tendencies and possessing price dynamics distinct from traditional assets (Cheah & Fry, 2015). Subsequent empirical analyses point to both short-term speculative movements and long-term structural changes in cryptocurrency prices; furthermore, it has been reported that volatility dependencies between cryptocurrency markets are increasing (Bouri et al., 2020; Koutmos, 2018).

The direct empirical link between energy consumption and crypto prices is more limited in the literature, but some studies have found co-movement and causality between the hashrate (the network's processing power) and prices at the time-frequency level. For example, studies examining the time-frequency relationships between hashrate, energy inputs, and prices have shown that energy costs and mining profitability can have both short- and long-term effects on prices (Das & Dutta, 2020; Fantazzini & Kolodin, 2020; Rehman & Kang, 2021). Although these findings are largely consistent, comprehensive comparisons of energy consumption indices with direct cryptocurrency price time series—particularly those using cointegration and causality frameworks—remain relatively scarce in the literature (Das & Dutta, 2020; Qin, 2023; Rehman & Kang, 2021).

Therefore, comprehensively testing the relationship between energy consumption indicators and the price dynamics of major crypto assets such as Bitcoin (BTC) and Ether (ETH) offers unique contributions to both financial economics and environmental policy discussions. Importantly, Ether refers to the crypto asset, while Ethereum denotes the underlying blockchain technology (EU Blockchain Observatory and Forum, 2023). Ether is included not to replicate Bitcoin's energy–price dynamics, but to serve as a benchmark case illustrating how transitioning the Ethereum network from Proof-of-Work to Proof-of-Stake (PoS) can fundamentally alter—and potentially eliminate—the link between market prices and energy consumption.

This study contributes to the growing literature on cryptocurrency energy economics in several important ways. Firstly, unlike most existing studies that focus primarily on Bitcoin, this paper provides a comparative analysis of Bitcoin and Ether within a unified econometric framework, allowing for a direct assessment of how different consensus mechanisms shape the price-energy relationship. Secondly, by jointly applying ARDL cointegration and Toda–Yamamoto causality tests, the study disentangles long-run equilibrium relationships from short-run causal dynamics. Thirdly, the findings offer post-Merge empirical evidence showing that Ethereum's transition to Proof-of-Stake has fundamentally altered the interaction between energy consumption and market prices. These results extend the literature by demonstrating that the energy–price nexus in cryptocurrencies is technology-specific rather than universal**,** with important implications for sustainability-oriented blockchain design.

Accordingly, this study empirically examines the long- and short-term relationships between cryptocurrency prices and energy consumption within a formal hypothesis-testing framework. In pursuit of this objective, the paper first defines the data set and variables, then applies unit root and cointegration tests (ADF, PP, and ARDL-bounds) as well as Granger (1969) Toda–Yamamoto causality analyses to identify potential long-term and directional linkages. The remainder of the paper is organised as follows: Section 1 reviews the relevant literature, Section 2 outlines the data and methodology, Section 3 presents the empirical results, and the final Section discusses the findings and draws conclusions, including the implications for policy and future research.

1. Literature review

Two main lines of research on cryptocurrencies stand out in the literature: (1) the energy consumption and environmental impacts of mining; (2) cryptocurrency price dynamics, volatility, and market linkages. This strand is discussed here in the context of crypto-energy interactions, as price dynamics and volatility directly affect mining incentives and energy demand.

In his study, de Vries (2018) focused on the energy consumption of Bitcoin mining and quantitatively assessed the contribution of the Proof-of-Work mechanism to the growing demand for electricity. He presented the concerns frequently voiced in public regarding the Bitcoin network's energy consumption with concrete data and computational approaches. He particularly emphasised the energy intensity of mining activities and its increase over time. This study is one of the first significant contributions that regularly brings the energy dimension of crypto mining into the academic research agenda.

Gallersdörfer et al. (2020) took a broader perspective, examining the energy consumption not only of Bitcoin but also of various other cryptocurrencies. This study demonstrated that other crypto assets besides Bitcoin are also significant in terms of energy consumption and that similar energy problems exist for many Proof-of-Work-based tokens. It also highlighted the limitations of the estimation methods used.

Kumar and Anandarao (2019) presented evidence on the time-frequency level regarding volatility spreads in cryptocurrency markets by combining GARCH and wavelet analyses. Their findings, particularly that volatility linkages change across different time scales (short, medium, long term), demonstrated the usefulness of wave-based methods in cryptocurrency research. On the other hand, Bouri et al. (2020), in their study on the volatility structure of cryptocurrency assets, separated the transient and persistent components of volatility and showed how the relationships between volatility components change during periods of market stress. Such studies are important for understanding the sources and persistence of volatility in cryptocurrency markets. In another study, Fantazzini and Kolodin (2020) focused on the relationship between Bitcoin's hashrate and its price, suggesting that changes in mining power could be linked to long-term price dynamics. Such analyses demonstrate that mining activities can indirectly influence market mechanisms.

Rehman and Kang (2021), meanwhile, identified time-frequency co-movement between Bitcoin's hashrate and energy commodity markets. This suggests that price changes in energy markets may be indirectly related to mining costs and, consequently, mining activities. The study is valuable in that it shows that energy-crypto interactions are influenced not only by local but also by global energy market conditions. In another study, Das and Dutta (2020) analysed the relationship between mining revenues and Bitcoin energy consumption, showing that energy consumption increases as mining profitability rises during periods of high prices. This finding directly supports the price-energy relationship, strengthening the hypothesis that price increases energy demand through mining incentives.

Marchewka-Bartkowiak and Wiśniewski (2022) examined energy-focused tokens as financial investment instruments and highlighted the intersection between energy markets and digital assets. This study emphasises that crypto assets should be examined not only for their financial returns but also for their energy market and sustainability dimensions, aligning with this study that addresses the energy consumption and price dynamics of Bitcoin and Ether together. In another study, Barbu et al. (2022) examined the safe-haven function of cryptocurrencies during the COVID-19 period using a threshold regression approach and found that cryptocurrencies exhibited different behavioural patterns depending on market conditions. These findings support the idea that crypto assets may be sensitive to regimes in terms of both financial stability and energy consumption, reinforcing the importance of the structures examined in our study using ARDL and causality analysis.

In Qin et al.'s (2023) study, the relationship between Bitcoin's energy consumption and carbon emissions in the US context was empirically examined. The study found that Bitcoin mining affected US energy consumption and carbon emissions during certain periods based on time-series analyses; however, the magnitude and direction of this impact were shown to vary depending on electricity generation sources, regional energy market conditions, regulatory interventions, and seasonal fluctuations in mining activity. This study contributes to the empirical literature by highlighting that the environmental effects of crypto mining are not uniform over time and depend on country-specific energy structures, thereby underlining the importance of contextual factors in price-energy interaction studies.

The study by Sapra et al. (2024) addressed the non-linear relationships and causality patterns between Bitcoin energy consumption, price, and the Crypto Volatility Index. Using time-frequency and causality methods, Sapra identified the asymmetric effects of price fluctuations on energy consumption, pointing to the necessity of using non-linear models in price-energy research.

Adewuyi et al. (2024) questioned whether Bitcoin's electricity consumption and carbon footprint time series conform to the random walk hypothesis. The research showed that energy consumption/CO_2 series exhibited surprising movements in some periods and that simple random walk assumptions are not always valid. In another study by Wang et al. (2024), dynamic volatility contagion between multiple cryptocurrencies and energy markets was examined. This study revealed that crypto-energy interactions may be related not only to direct energy consumption data but also to energy market prices and volatility indicators. The findings demonstrate the potential for macro-level linkages between crypto assets and energy markets and the need for flexible policies.

The study by Bilirer and Zeren (2024) is noteworthy as an empirical study centred on Turkey. In this study, Fourier Granger causality and Fourier-ADL cointegration tests were applied using weekly price, energy consumption, and CO_2 emission series for Bitcoin and Ethereum. The results indicated reciprocal effects between price and energy/CO_2 and highlighted how Fourier-based methods offer approaches beyond the median.

Although the existing literature on cryptocurrencies has expanded rapidly, it has largely evolved along two parallel strands. The first strand focuses on energy consumption and environmental impacts, examining electricity usage, carbon emissions, and sustainability concerns associated primarily with Proof-of-Work-based systems (e.g., De Vries, 2018; Krause & Tolaymat, 2018; Stoll et al., 2019). The second strand concentrates on price dynamics and market behaviour, analysing returns, volatility, and speculative characteristics of cryptocurrency prices (e.g., Cheah & Fry, 2015; Corbet et al., 2018; Koutmos, 2018). Despite the rich insights provided by both strands, studies that directly integrate energy consumption indicators with cryptocurrency price series using cointegration and causality frameworks remain relatively scarce (Das & Dutta, 2020; Qin et al., 2023; Rehman & Kang, 2021). By jointly examining energy consumption indices and price dynamics for Bitcoin and Ether within a unified empirical framework, the present study bridges this gap and contributes to a more integrated understanding of the economic and environmental dimensions of cryptocurrency markets.

Both the energy consumption and price dynamics of cryptocurrencies have attracted considerable attention in the literature; energy-focused studies quantify the environmental costs of mining, while financial studies provide in-depth empirical evidence on price volatility, volatility contagion, and market linkages. However, at the intersection of these two lines of research, comprehensive studies that systematically address the long-term cointegration and directional causality relationships between energy consumption indices and cryptocurrency prices are limited. The existing literature has mostly focused on the hashrate and price relationship or crypto-crypto volatility spillovers, and the assessment of the relationships between energy consumption indices and prices from a cointegration and causality perspective has rarely been conducted. This study contributes to the literature by testing long-term equilibrium relationships, short-term adjustment mechanisms, and directional causality between energy consumption indices and cryptocurrency prices, focusing specifically on Bitcoin (BTC) and the crypto asset Ether (ETH).

2. Dataset and variables

This study uses daily time series data covering the period from 20 May 2017 to 23 October 2025 to examine the long-term relationships and causality between energy consumption and price dynamics in the Bitcoin (BTC) and Ether (ETH) markets. The variables of the study are cryptocurrency prices and energy consumption indicators. Price data for Bitcoin and Ether are obtained from CoinMetrics, while energy consumption indicators are sourced from the Cambridge Bitcoin Electricity Consumption Index (CBECI) provided by the Cambridge Centre for Alternative Finance.

As cryptocurrency markets operate 24/7, the term “closing price” can be ambiguous. We therefore define the daily price as the data provider’s daily close (end-of-day) quotation recorded at 00:00 UTC for each calendar day, following the standard convention used by CoinMetrics. Accordingly, we use the term “daily close (end-of-day) price” to reflect the continuous trading structure of cryptocurrencies. The series have been transformed into natural logarithms, as is common practice in the financial literature. This approach, which aims to measure the impact of changes in energy consumption on price formation, has also been adopted in previous studies (Krause & Tolaymat, 2018; Sapra et al., 2024).

The key variables of the study are energy consumption indicators for Bitcoin and Ethereum. Bitcoin energy consumption data was obtained from the Cambridge Bitcoin Electricity Consumption Index (CBECI) platform, recognised as the most comprehensive data source on a global scale; Ethereum energy consumption data was obtained from the Digiconomist database, covering the Ethereum Proof-of-Work (PoW) period.

Energy consumption data shows estimated electricity consumption in terawatt-hours (TWh) or kilowatt-hours (kWh) per day. It is known that energy consumption indices are not officially reported and are largely modelled and calculated based on variables such as mining hashrate, hardware energy efficiency, and geographical distribution (CCAF, 2023). Therefore, although energy consumption series are based on estimates, the CBECI and Digiconomist platforms are widely referenced by academic circles (Rehman & Kang, 2021; Sapra et al., 2024). The variables used in the study are as shown in Table 1.

Table 1. Variable definitions

Variables	Definition	Period	Frequency	Source
BTC_P	Bitcoin daily close (end--of-day) price (USD)	2017–2025	daily	CoinMetrics
ETH_P	Ether daily close (end--of-day) price (USD)	2017–2025	daily	CoinMetrics
BTC_E	Bitcoin energy consumption index (TWh)	2017–2025	daily	CBECI
ETH_E	Ethereum energy consumption index (TWh)	2017–2025	daily	CBECI

Source: own work.

The “Estimated TWh per Year” series reported under the Cambridge Bitcoin Electricity Consumption Index (CBECI) was used as the energy consumption index. This series is widely used in the literature as the most probable energy consumption estimate, taking into account hardware efficiency and hashrate distribution (Sapra et al., 2024).

3. Method

This study examines the long-term relationship and causality between energy consumption and price dynamics in the Bitcoin and Ethereum markets. To this end, the following tests were applied: (1) Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests to determine the stationarity properties of the series; (2) the Autoregressive Distributed Lag (ARDL) cointegration test to investigate the long-term relationship between the series; (3) the Toda–Yamamoto (TY) Granger causality test to determine the direction of causality. The methodological framework is parallel to the econometric approaches frequently used in the literature for energy consumption-oriented analyses of crypto assets (Bilirer & Zeren, 2024; Mensi et al., 2022; Sapra et al., 2024).

3.1. Unit root tests

To avoid spurious regression in time series analyses, testing the stationarity of the series is a prerequisite (Enders, 2015). In this context, the stationarity levels of all series were first examined using the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. While the ADF test aims to eliminate autocorrelation by using additional lags in the model (Dickey & Fuller, 1981), the PP test has a more flexible structure against heteroscedasticity and serial correlation (Phillips & Perron, 1988). Applying both tests ensures the robustness of the stationarity results.

The stationarity of the series has been tested at the level and in the first difference. Determining the degree of stationarity is important for establishing the applicability of the ARDL model and for determining the necessary degree of integration for the Toda–Yamamoto test.

3.2. ARDL cointegration test

The Autoregressive Distributed Lag (ARDL) bounds test approach developed by Pesaran et al. (2001) was applied to examine the existence of a long-term relationship between the series. The ARDL model was preferred because it can work even when variables have different integration orders (I(0) or I(1)), it can provide reliable results in small samples, and it offers the possibility of estimating both short- and long-term coefficients simultaneously (Narayan, 2005).

In the ARDL bounds test approach, the appropriate lag lengths were first determined based on information criteria, and then the presence of cointegration was tested using the F-statistic. If the calculated F-statistic exceeds the upper critical values provided by Pesaran et al. (2001), it is concluded that there is a long-term relationship between the variables.

After estimating the long-term coefficients, short-term dynamics were analysed using an error correction model (ECM). The negative and statistically significant ECM parameter was interpreted as an indicator of the speed of return to long-term equilibrium (Banerjee et al., 1996). The ARDL Bound Test equation involving two variables to be performed in order to reveal the cointegration relationship is as follows:

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{m} \beta_{1i} Y_{t-i} + \sum_{i=1}^{m} \beta_{2i} X_{t-i} + \beta_{3i} Y_{t-1} + \beta_4 X_{t-1} + \varepsilon_t \quad (1)$$

where: ΔY_t represents the dependent variable, X_t represents the independent variable, ε_t represents the error term, and m represents the optimal lag length, which is the value where the information criteria are smallest. The hypotheses regarding the existence of cointegration in the ARDL bounds test model are as follows:

H0: $\beta_3 = \beta_4 = 0$ (There is no cointegration.)
H1: $\exists \beta_i < 0,\ i = 3{,}4$ (There is cointegration.)

"In the ARDL bounds test approach, after revealing the cointegration relationship for the variables, the long-term relationship coefficients of the variables are examined. Furthermore, the existence of short-term deviations from the long-term relationship can also be examined using an error correction model. Although the primary focus of the study is on long-term relationships, the error correction model is employed to capture short-run dynamics and the speed of adjustment toward long-run equilibrium. The equation for the long-term relationship is as follows:"

$$Y_t = \beta_0 + \sum_{i=1}^{m} \beta_{1i} Y_{t-i} + \sum_{i=0}^{n} \beta_{2i} X_{t-i} + \varepsilon_t \quad (2)$$

"In the equation, Y_t is the dependent variable, X_t is the independent variable, β_0 is the constant term, ε_t is the error term, is the error term, and m and n represent the optimal lag length."

3.3. Toda–Yamamoto causality test

The augmented Granger causality approach proposed by Toda and Yamamoto (1995) was used to determine the direction of causality between energy consumption and cryptocurrency prices. This test offers significant advantages over the traditional Granger causality test because it can be applied independently of the integration degrees of the variables and possible cointegration relationships (Dolado & Lütkepohl, 1996).

The study examined the bidirectional causal relationship between both the BTC price-BTC energy consumption and the ETH price-ETH energy consumption. The results obtained enable an assessment of whether energy consumption is a factor driving price formation in the market. The VAR ($m + d\max$) model estimated in the Toda–Yamamoto causality approach consists of (Toda & Yamamoto, 1995):

$$Y_t = \omega + \sum_{t-1}^{m} a_{1i} x_{t-i} + \sum_{i=1}^{m} \beta_{1i} Y_{t-i} + \sum_{j=m+1}^{d\max} \delta_{1i} X_{t-i} + \sum_{j=m+1}^{d\max} \theta_{1i} Y_{t-i} + \varepsilon_{1t} \tag{3}$$

$$X_t = \varphi + \sum_{i=1}^{m} a_{2i} X_{t-i} + \sum_{i=1}^{m} \beta_{2i} Y_{t-i} + \sum_{j=m+1}^{d\max} \delta_{2i} X_{t-i} + \sum_{j=m+1}^{d\max} \theta_{2i} Y_{t-i} + \varepsilon_{2t} \tag{4}$$

"The appropriate lag length (m) can be determined using information criteria, while the maximum integration order ($d\max$) can be determined using unit root tests. To determine the existence of a reciprocal causality relationship between the variables, the hypotheses $\mathrm{H}_0{:}\alpha_{1i} = 0$ and $\mathrm{H}_0{:}\alpha_{2i} = 0$ are tested using the adjusted Wald test statistic. If the calculated test statistic value is greater than the X^2 table value with k degrees of freedom, the above hypotheses are rejected (Toda & Yamamoto, 1995)."

3.4. Research hypotheses

This study aims to examine the relationships between price dynamics in the Bitcoin and Ether markets and the energy consumption indices of these networks from both long-term and short-term perspectives. While price–hashrate and price–volatility relationships have been extensively studied in the literature, only a limited number of studies have systematically examined cointegration and directional causality between energy consumption indices and cryptocurrency prices (Das & Dutta, 2020; Qin et al., 2023; Rehman & Kang, 2021). By extending this line of research, the present study provides a comparative analysis of Bitcoin and Ether within a unified econometric framework, thereby highlighting how consensus mechanisms shape the price-energy relationship. Four main hypotheses are presented below.

H1: There is a long-term cointegration relationship between the Bitcoin price and the Bitcoin energy consumption index.

Theoretically, persistent price increases may lead to increased mining profitability, thereby expanding mining capacity and, consequently, energy consumption. Conversely, persistent or long-lasting changes in energy costs may affect mining margins and thus long-term pricing expectations. Therefore, a long-term relationship (cointegration) may emerge between the BTC price and the BTC energy index. Empirically, this hypothesis is tested using the ARDL bounds test.

H2: There is a long-term cointegration relationship between Ether's price during its PoW period and the Ethereum energy consumption index; however, the transition to PoS (Merge) weakens or eliminates this relationship.

Under the PoW mechanism, sustained increases in the price of ETH are expected to affect energy consumption by increasing mining incentives; therefore, a long-term relationship similar to H1 is possible for the PoW period. However, due to the dramatic drop in energy consumption after 'The Merge' in September 2022, it is likely that the cointegration structure will change or disappear.

H3: Short-term shocks in cryptocurrency prices (especially positive price shocks) increase mining profitability, leading to short-term increases in energy consumption.

As a market mechanism, sudden increases in prices can raise mining revenues and, consequently, the intensity of mining activities; this results in an increase in energy demand in the short term. This directional effect will be tested using the Toda–Yamamoto method; finding positive causality provides empirical evidence that price fluctuations create physical effects through the

Table 2. Research hypotheses summary

Hypothesis Code	Hypothesis	Test method	Expected relationship / direction
H1	There is a long-term cointegration relationship between the Bitcoin price and the Bitcoin energy consumption index	ARDL Cointegration	Long-term positive relationship
H2	There is a long-term cointegration relationship between the price of Ethereum during its PoW period and the Ethereum energy consumption index; the transition to PoS weakens or eliminates this relationship	ARDL Cointegration + Sub-Period Analysis	PoW: positive long-term relationship; PoS: weak/no relationship
H3	Short-term changes in cryptocurrency prices Granger-cause energy consumption (Price → Energy)	Toda–Yamamoto Causality	Positive short-term effect
H4	Changes in energy consumption Granger-causally affect cryptocurrency prices (Energy → Price)	Toda–Yamamoto Causality	Weak/uncertain short-term effect

Source: own work.

energy demand channel and points to important policy implications for energy supply-demand management.

H4: Changes in energy consumption (e.g., rapid increases or cost shocks) may create short-term effects on cryptocurrency prices.

Sudden increases in energy consumption or rises in energy costs can affect mining profitability and perceptions of network security, thereby altering investor expectations and consequently prices. Identifying energy → price Granger causality will provide empirical evidence regarding the channel through which shocks in energy markets are transmitted to crypto asset prices.

According to Table 2, which summarises the research hypotheses, hypotheses H1 and H2 aim to test whether there is a long-term structural equilibrium relationship between market prices and energy consumption. Hypotheses H3 and H4, on the other hand, focus on the direction of the relationship and evaluate short-term dynamics.

4. Findings

First, the stationarity properties of the Bitcoin and Ether price series and the energy consumption indices related to these assets were examined using the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests. After determining the stationarity structure, the ARDL bounds test approach developed by Pesaran et al. (2001) was applied to test whether there was a long-term relationship between the variables. At this stage, optimal lag lengths were determined by considering information criteria, and appropriate ARDL models were constructed to estimate the long-term coefficients. In the subsequent stage, an extended VAR model based on the Toda–Yamamoto (1995) approach was used to reveal the short-term causality relationships between the variables.

4.1. Unit root test results

This subsection examines the stationarity properties of the Bitcoin and Ether price series used in the study and the energy consumption indices related to these assets. In this context, Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests were applied to assess whether the series are stationary at their levels or in their differences. While the ADF test addresses the autocorrelation issue with lagged difference terms, the PP test offers a more flexible structure by considering possible serial correlations and heteroskedasticity in the error terms using non-parametric methods. The combined use of both tests allows for a more robust determination of the degree of integration of the series. Table 3 presents the ADF and PP test results and provides a detailed interpretation of the findings regarding the degree of integration of the series.

Table 3. ADF and PP unit root test results

Variables	Test	Level t-statistic	Level p	1st difference t-statistic	1st difference p	Critical value (1%)	Result (I(d))
lnBTC_E	ADF	–4.0227	0.0013	–25.9362	0.0000	–3.435	I(0)
	PP	–4.1123	0.0009	–41.1083	0.0000	–3.435	I(0)
lnBTC_P	ADF	–1.6374	0.4632	–58.3172	0.0000	–3.435	I(1)
	PP	–1.6316	0.4662	–58.2538	0.0001	–3.435	I(1)
lnETH_E	ADF	–0.9510	0.7722	–18.8100	0.0000	–3.435	I(1)
	PP	–1.8902	0.3372	–107.9101	0.0001	–3.435	I(1)
lnETH_P	ADF	–2.1215	0.2363	–38.1731	0.0000	–3.435	I(1)
	PP	–2.1096	0.2410	–58.3352	0.0001	–3.435	I(1)

Note: The critical value threshold is 1%, in line with MacKinnon (1996).

Source: own work.

The ADF and PP unit root tests were applied to assess whether the series were stationary at their levels. The findings indicate that the Bitcoin energy consumption series (LNBTC_E) is stationary at its level, both according to the ADF and PP tests. In contrast, the Bitcoin price series (LNBTC_P), Ethereum energy consumption (LNETH_E), and Ether price series (LNETH_P) show the presence of a unit root at the level in both the ADF and PP tests.

ADF and PP unit root tests were applied to assess whether the series were stationary at their levels. The findings indicate that the Bitcoin energy consumption series (LNBTC_E) is stationary at its level, in both ADF and PP tests. In contrast, the Bitcoin price series (LNBTC_P), Ethereum energy consumption (LNETH_E) and Ether price series (LNETH_P) indicate the presence of a unit root at the level in both the ADF and PP tests, revealing that they are not stationary. These results validate the applicability of ARDL cointegration analysis and the methodological justification of setting the maximum degree of integration (d max) to 1 for the VAR model in the Toda–Yamamoto causality test.

4.2. ARDL bound test results

The unit root test results showed that the variables were integrated at the I(0) and I(1) levels, making the ARDL bounds test approach developed by Pesaran et al. (2001) applicable. The ARDL method allows series with different integration orders to be analysed in the same model and is widely preferred in the time-series literature due to its high estimation power in small samples. Descriptive statistics are evaluated in Table 4.

Table 4. Descriptive statistics

	LNBTC_E	LNBTC_P	LNETH_E	LNETH_P
Mean	1.740297	4.316554	–0.781668	2.931164
Median	1.731.895	4.363605	0.453821	3.130999
Maximum	2.195326	5.095823	1.287155	3.681995
Minimum	0.619043	3.281965	–5.723042	1.617629
Standard deviation	0.307732	0.454565	2.100261	0.522715
Skewness	–1.346475	–0.123947	–0.545067	–0.415975
Kurtosis	5.340976	1.915679	1.419403	1.798104
Jarque-Bera	1.632898	1.586713	4.726632	2.739421
Probability	0.000000	0.000000	0.000000	0.000000
Sum	5.356633	13286.35	–2.405191	9.019193
Sum of squared deviations	2.913880	6.357986	13568.53	8.404595
Observations	3078	3078	3078	3078

Source: own work.

The basic characteristics of the series differ in various aspects. The standard deviation values show that the volatility in Ethereum's energy consumption is relatively high compared to other series, indicating that seasonal changes in energy usage are more pronounced. The skewness and kurtosis values deviating significantly from normal distribution indicate that the series are not symmetrical and that the tail behaviour is heavier than in normal distribution.

Table 5. ARDL bound test for Bitcoin energy consumption

"Model	K	M	*F*-Statistic	Significance level	Lower bound	Upper bound
				1%	4.94	5.58
ARDL (10.9)	10	12	7.5573531	5%	3.62	4.16
				10%	3.02	3.51

Source: own work.

According to Table 5, the F-statistic value obtained from the ARDL(10,9) model, which examines the relationship between Bitcoin energy consumption and Bitcoin price, exceeds the upper limits of the critical values proposed by Pesaran et al. (2001) at 1% significance levels. Therefore, the null hypothesis of no cointegration is strongly rejected, and it is concluded that there is a long-term relationship between Bitcoin prices and energy consumption. This finding is consistent with the literature suggesting that Bitcoin mining is directly linked to economic incentives; as prices rise, mining becomes more profitable, leading to more miners joining the network and an increase in total energy consumption.

Table 6. ARDL Bitcoin energy consumption error correction model

Variable	Coefficient	Standard error	*t*-statistic	Probability
D(LNBTC_E(-1))	0.228412	0.018000	12.68948	0.0000
D(LNBTC_E(-2))	0.084282	0.018463	4.564906	0.0000
D(LNBTC_E(-3))	–0.038588	0.018327	–2.105546	0.0353
D(LNBTC_E(-4))	0.056194	0.018295	3.071488	0.0021
D(LNBTC_E(-5))	–0.046578	0.018253	–2.551816	0.0108
D(LNBTC_E(-6))	–0.068430	0.018230	–3.753721	0.0002
D(LNBTC_E(-7))	–0.149019	0.018275	–8.154469	0.0000
D(LNBTC_E(-8))	–0.014774	0.018422	–0.801944	0.4226
D(LNBTC_E(-9))	0.053736	0.017959	2.992183	0.0028
D(LNBTC_P)	–0.009857	0.010433	–0.944797	0.3448
D(LNBTC_P(-1))	–0.004102	0.010452	–0.392497	0.6947
D(LNBTC_P(-2))	–0.009433	0.010444	–0.903230	0.3665
D(LNBTC_P(-3))	–0.006628	0.010434	–0.635286	0.5253
D(LNBTC_P(-4))	0.029702	0.010426	2.848865	0.0044
D(LNBTC_P(-5))	–0.001947	0.010434	–0.186585	0.8520
D(LNBTC_P(-6))	0.000511	0.010427	0.048991	0.9609
D(LNBTC_P(-7))	–0.001867	0.010420	–0.179209	0.8578
D(LNBTC_P(-8))	0.034981	0.010407	3.361401	0.0008
CointEq(-1)*	–0.003092	0.000649	–4.763081	0.0000
R-squared	0.128387	Mean dependent variable		0.000465
Adjusted R-squared	0.123241	S.D. dependent variable		0.009810
S.E. of regression	0.009186	Akaike info criterion		–6.536199
Sum squared residuals	0.257257	Schwarz criterion		–6.498863
Log likelihood	10045.53	Hannan–Quinn criterion		–6.522785
Durbin–Watson statistic	1.999098			

Source: own work.

According to Table 6, the error correction term coefficient (–0.003092) in the model is statistically significant ($t = –4.763$; $p = 0.0000$). The negative and significant nature of the error correction term coefficient indicates that there is a long-term equilibrium relationship between the series and that short-term shocks gradually disappear in the long term. However, the coefficient's very small value indicates that the system's return to equilibrium is slow. The use of daily data, the lengthy adaptation process of mining equipment, and the difficulty adjustment occurring through block times are among the natural causes of these slow effects.

Looking at the short-term coefficients, it can be seen that a large proportion of the lags in the Bitcoin energy consumption series are significant. This indicates that energy consumption has a strong autoregressive structure and that short-term changes are largely influenced by its own internal dynamics. In contrast, the vast majority of Bitcoin price short-term coefficients are not significant; this indicates that short-term movements in the Bitcoin price do not have a rapid effect on energy consumption, and that energy consumption is shaped more by long-term price incentives.

Table 7. ARDL boundary test results for the Ethereum energy consumption model

"Model	K	M	F-Statistic	Significance level	Lower bound	Upper bound
				1%	6.84	7.84
ETH-ARDL (5.0)	10	12	1.2182841	5%	4.94	5.73
				10%	4.04	4.78

Source: own work.

According to Table 7, the F-statistic value in the ARDL (5.0) model established for Ethereum is well below even the lowest threshold of Pesaran critical values. Therefore, the null hypothesis, according to which there is no long--term relationship, cannot be rejected. In other words, there is no long-term cointegration relationship between the Ether price and Ethereum energy consumption. This finding is consistent with Ethereum's transition from the Proof-of-Work (PoW) mechanism to the Proof-of-Stake (PoS) mechanism in 2022. The PoS mechanism has dramatically reduced energy consumption and eliminated the structural relationship between price and energy consumption. The results support the notion that the energy consumption of the post-PoS Ethereum network has become independent of price changes.

According to Table 8, the long-term error correction term LNETH_E(-1) in the ARDL error correction model was not statistically significant, despite carrying the expected negative sign. This result indicates that there is no mechanism representing a return to long-term equilibrium in Ethereum's energy

Table 8. ARDL Ethereum energy consumption error correction model

Variable	Coefficient	Standard error	*t*-statistic	Probability
C	0.019212	0.018463	1.040528	0.2982
D(LNETH_E(-1))	–0.398638	0.018122	–21.99742	0.0000
D(LNETH_E(-2))	–0.377021	0.019447	–19.38731	0.0000
D(LNETH_E(-3))	–0.244722	0.020547	–11.91047	0.0000
D(LNETH_E(-4))	–0.168908	0.020970	–8.054624	0.0000
D(LNETH_E(-5))	–0.058415	0.021160	–2.760615	0.0058
D(LNETH_E(-6))	–0.082163	0.020954	–3.921122	0.0001
D(LNETH_E(-7))	–0.085698	0.020531	–4.174098	0.0000
D(LNETH_E(-8))	–0.079831	0.019380	–4.119135	0.0000
D(LNETH_E(-9))	–0.091660	0.018005	–5.090897	0.0000
CointEq(-1)*	–0.002530	0.002043	–1.238437	0.2156
R-squared	0.183425	Mean dependent variable		–0.001355
Adjusted R-squared	0.180744	S.D. dependent variable		0.233805
S.E. of regression	0.211623	Akaike info criterion		–0.264428
Sum squared residuals	136.4130	Schwarz criterion		–0.242748
Log likelihood	415.1787	Hannan–Quinn criterion		–0.256637
F-statistic	68.42150	Durbin–Watson statistic		1.997831
Prob(F-statistic)	0.000000			–6.522785

Source: own work.

consumption. In other words, it was observed that short-term shocks occurring in the series did not correct themselves based on a long-term relationship, and the system did not exhibit a tendency to return to equilibrium. This is consistent with the absence of cointegration and indicates that long-term dynamics are not affected by price changes. The fact that Ethereum's energy consumption began to follow a stable process after the transition to PoS provides an economically reasonable framework for the error correction coefficient being insignificant.

The fact that all lagged values of D(LNETH_E) in the model are highly significant indicates that Ethereum's energy consumption has a strong autoregressive structure in the short term. The sensitivity of energy consumption to past values reveals that the system is shaped by its own internal dynamics, with sudden changes being determined not by price but by previous levels of energy usage.

In contrast, the Ether price variable (LNETH_P) was found to be statistically insignificant in both level and difference equations. This indicates that Ether price fluctuations do not have any effect on energy consumption in the short term. Given the low and stable energy usage in the PoS system, it is a finding consistent with theory that price changes have no effect on energy consumption, even in the short term. The absence of a price-energy relationship for Ether should therefore be interpreted as evidence of a structural break induced by the Proof-of-Stake transition, rather than as a lack of economic relevance.

4.3. Toda–Yamamoto causality analysis results

The Toda–Yamamoto causality analysis was applied to reveal the directional relationship between energy consumption and price dynamics for Bitcoin and Ether. Previously conducted unit root and cointegration tests showed that there was no long-term relationship, particularly for Ethereum, while Bitcoin exhibited long-term dependence. However, the direction of these relationships had not yet been determined. Therefore, using the Toda–Yamamoto approach, which is unaffected by differences in the degrees of integration of the series, the analysis tested whether there was a causality flow from Bitcoin prices to energy consumption or from energy consumption to prices, and similarly, whether there were possible directional interactions between energy consumption and the price series for Ether. Below, the Wald test results obtained through the extended VAR model are presented, and the causality relationships for both cryptocurrencies are evaluated separately.

Table 9. Toda–Yamamoto causality test results-1

"Dependent variable	Independent variable	d max	k	Chi-Square test statistic	Chi-Square p-value	Relationship
LNBTC_E	LNBTC_P	8	8	2.303595	0.0033	there is a relationship
LNBTC_P	LNBTC_E	8	8	1.333014	0.1010	there is no relationship

Source: own work.

According to Table 9, the results obtained for the dependent variable LNBTC_E indicate that removing the LNBTC_P variable from the model leads to a statistically significant loss of information. This finding indicates a significant causal relationship from Bitcoin prices to energy consumption. Therefore, price changes are an important factor explaining the Bitcoin network's energy consumption. This result is fully consistent with the theoretical expectation that mining activities are sensitive to prices and that price rises increase the number of miners and energy consumption.

In contrast, no causality from energy consumption to prices was detected for the dependent variable LNBTC_P. A p-value above 10% indicates that energy consumption does not play a statistically significant role in explaining Bitcoin prices. This finding supports the view that price formation is largely determined by factors such as market expectations, liquidity, macroeconomic factors, and investor behaviour, and that energy consumption is not a variable that drives the price.

The Toda–Yamamoto causality test has revealed a unidirectional causal relationship for Bitcoin. According to the analysis results, significant causality was found from Bitcoin prices to Bitcoin energy consumption, while no causality was detected from energy consumption to prices. Due to Bitcoin's mining-based structure, price movements directly affect the profitability of mining activities, which in turn has a decisive impact on total energy consumption. The literature frequently emphasises that increases in Bitcoin prices raise energy demand by boosting investment in mining hardware and hash power (Hayes, 2016; Krause & Tolaymat, 2018). This theoretical expectation is consistent with the empirical findings of this study. The Toda–Yamamoto test identified a significant causal relationship from Bitcoin prices to energy consumption. This result indicates that price increases make mining more attractive, thus demonstrating that energy consumption is sensitive to price dynamics. Thus, hypothesis 3 has been empirically confirmed, revealing that Bitcoin prices are the fundamental factor driving the network's energy consumption.

Table 10. Toda–Yamamoto causality test results-2

"Dependent variable	Independent variable	d max	k	Chi-Square test statistic	Chi-Square p-value	Relationship
LNETH_E	LNETH_P	5	5	0.847907	0.9739	there is a relationship
LNETH_P	LNETH_E	5	5	2.387410	0.7933	there is no relationship

Source: own work.

According to Table 10, when LNETH_E (Ethereum energy consumption) is the dependent variable, the Wald test value measuring the contribution of the LNETH_P variable to the model indicates that Ether prices have no causal effect on energy consumption. This result is particularly important because Ethereum's transition from Proof-of-Work (PoW) to Proof-of-Stake (PoS) in 2022 ('The Merge') reduced energy usage by approximately 99.9% and eliminated the economically motivated relationship between price and energy consumption. Therefore, price increases in the post-PoS period do not increase mining activity or energy demand; validators' energy requirements are largely independent of price dynamics.

When LNETH_P (Ether price) is the dependent variable, the Wald statistic testing the contribution of the LNETH_E (Ethereum energy consumption) indicates that energy consumption does not have a statistically significant effect on explaining the Ether price. This result suggests that short-term Ether price movements are not directly linked to energy consumption associated with mining and validation processes, and are likely driven by factors other than energy-related dynamics. The fact that both test results have relatively high p-values clearly demonstrates that there is no bidirectional causality relationship in Ethereum. This result is consistent with Ethereum's current consensus mechanism, indicating that energy consumption is not driven by price and that changes in energy usage are not decisive for price. According to the Toda–Yamamoto causality test results, since no directional causality was detected between Ether price and energy consumption, hypothesis 4, according to which there is a causal relationship between Ether prices and Ethereum energy consumption, was rejected. This finding confirms that with Ethereum's transition to the PoS mechanism, energy consumption is largely determined by technological protocols and is no longer influenced by price-based economic incentives.

Conclusions

This study comprehensively examined the relationships between Bitcoin and Ethereum's energy consumption and price dynamics using cointegration and causality analyses. The findings obtained provide significant contributions when evaluated comparatively with the theoretical and empirical discussions that have emerged in the cryptocurrency energy economics literature, particularly in recent years, due to increased academic interest.

The results show that there is a long-term cointegration relationship between energy consumption and prices for Bitcoin. According to the ARDL bounds test results, the Bitcoin model produced an F-statistic above the critical values, and the long-term relationship was statistically confirmed. The negative and significant error correction term indicates that the short-term deviations experienced in both cryptocurrencies have returned to equilibrium. This finding is consistent with the literature on how prices affect mining profitability in Bitcoin's mining-based Proof-of-Work structure and how this determines energy consumption (Hayes, 2016; Krause & Tolaymat, 2018). Empirical results reinforce the view that prices drive energy demand in the long term.

The results obtained for Ethereum indicate a structure that is completely different from Bitcoin. The boundary test results for the ARDL model show that there is no long-term cointegration relationship between Ethereum's energy consumption and prices. The insignificance of the error correction term and the fact that the F-statistic remains below all threshold values confirm that Ethereum's energy consumption has evolved into a structure independent of price dynamics with the transition from PoW to PoS. Indeed, the dramatic drop in Ethereum's energy usage (approximately 99.9%) after 'The Merge' supports findings in the literature that the price-energy relationship has structurally weakened (de Vries, 2018).

Causality results reveal a clear divergence between the two cryptocurrencies. The Toda–Yamamoto test for Bitcoin shows a unidirectional causality relationship from Bitcoin prices to energy consumption. This result aligns with the economic incentive model, where mining activities increase during periods of rising Bitcoin prices, thereby driving up energy demand. Conversely, no causality was found in the opposite direction; that is, no effect of changes in energy consumption on Bitcoin prices was detected. In the causality analysis conducted for Ethereum, no unidirectional causality relationship was found. The absence of any causality detected from prices to energy consumption or from energy consumption to prices is consistent with the PoS mechanism making energy usage independent of network security.

When compared to previous studies in the literature, these findings offer significant parallels and new contributions. For example, the results are consistent with studies showing that Bitcoin energy consumption is affected by price movements (Corbet et al., 2022; Hayes, 2016). Similarly, the findings of this study are in line with recent research indicating that Ethereum lost its energy consumption–price relationship with its transition to PoS (de Vries, 2018). However, this study contributes to the literature by presenting a comparative analysis of both Bitcoin and Ethereum using the same dataset, the same methodological framework, and the same time frame.

The findings of this study carry various implications for policymakers and regulators. Bitcoin's price-sensitive, energy-intensive mining structure fuels sustainability debates and supports the idea that it should be directed towards more carbon-efficient technologies. Encouraging the use of renewable energy sources in Bitcoin mining, implementing carbon tax-like regulations, or establishing energy efficiency criteria can be considered among the policy objectives. For Ethereum, the reduction of energy consumption to very low levels demonstrates that the PoS mechanism is more advantageous in terms of environmental sustainability and strengthens the debate on transitioning to PoS-like mechanisms for other blockchain projects.

However, the study has some limitations. Firstly, the fact that energy consumption data is based on estimates and that different sources use different algorithms may limit the absolute accuracy of the results. Furthermore, the study only considers Bitcoin and Ethereum, and the exclusion of other PoW-based cryptocurrencies from the analysis creates a comparative diversity constraint.

There are many areas of research for future studies. Comparing different PoW and PoS-based coins with a broader sample could explain the energy consumption–price relationship more systematically. To assess potential structural changes in the long-term relationship between energy consumption and Ether prices more comprehensively, sub-period analyses surrounding the transition from PoW to PoS can be examined. Furthermore, directly incorporating carbon emission data into the model could reveal the environmental impacts of energy consumption in a more specific manner.

References

Adewuyi, O. A., Wahab, B. A., Tiwari, A. K., & Do, H. X. (2024). Do bitcoin electricity consumption and carbon footprint follow a random walk? *Journal of Environmental Management*, *367*, 121958. https://doi.org/10.1016/j.jenvman.2024.121958

Banerjee, A., Dolado, J., & Mestre, R. (2001). Error-correction mechanism tests for cointegration in a single-equation framework. *Journal of Time Series Analysis*, *19*(3), 267–283. https://doi.org/10.1111/1467-9892.00091

Barbu, T. C., Boitan, I.A. & Cepoi, C. O. (2022). Are cryptocurrencies safe havens during the COVID-19 pandemic? A threshold regression perspective with pandemic-related benchmarks. *Economics and Business Review*, *8*(2), 29–49. https://doi.org/10.18559/ebr.2022.2.3

Bilirer, M., & Zeren, F. (2024). The impact of energy consumption in crypto assets on crypto asset prices and carbon emissions: Case of Bitcoin and Ethereum. *Studii Financiare*, *28*(1), 6–25.

Bouri, E., Jawad, S., Shahzad, H., Roubaud, D., Kristoufek, L., & Lucey, B. (2020). Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. *The Quarterly Review of Economics and Finance*, *77*, 156–164. https://doi.org/10.1016/j.qref.2020.03.004

CCAF (Cambridge Centre for Alternative Finance). (2025). *Cambridge Bitcoin Electricity Consumption Index (CBECI).* https://ccaf.io/cbeci

Cheah, E. T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters*, *130*, 32–36. https://doi.org/10.1016/j.econlet.2015.02.029

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2018). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, 182–189. https://doi.org/10.1016/j.irfa.2018.09.003

Corbet, S., Hou, Y., Hu, Y., Larkin, C., Lucey, B., & Oxley, L. (2022). Cryptocurrency liquidity and volatility interrelationships during the COVID-19 pandemic. *Finance Research Letters*, *45*, 102137. https://doi.org/10.1016/j.frl.2021.102137

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

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

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, *49*(4), 1057–1072. https://doi.org/10.2307/1912517

Dolado, J. J., & Lütkepohl, H. (1996). Making Wald tests work for cointegrated VAR systems. *Econometric Reviews*, *15*(4), 369–386. https://doi.org/10.1080/07474939608800362

Enders, W. (2015). *Applied econometric time series* (4th ed.). Wiley.

EU Blockchain Observatory and Forum. (2023). *Ethereum merge trend report.* https://blockchain-observatory.ec.europa.eu/publications/trend-report-ethereum-merge_en

Fantazzini, D., & Kolodin, N. (2020). Does the hashrate affect the bitcoin price? *Journal of Risk and Financial Management*, *13*(12), 1–32. https://doi.org/10.3390/jrfm13110263

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

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

Hayes, A. (2016). *Cryptocurrency value formation: An empirical analysis leading to a cost of production model for valuing Bitcoin*. SSRN Working Paper. https://doi.org/10.2139/ssrn.2648366

Koutmos, D. (2018). Return and volatility spillovers among cryptocurrencies. *Economics Letters*, *173*, 122–127. https://doi.org/10.1016/j.econlet.2018.10.004

Krause, M. J., & Tolaymat, T. (2018). Quantification of energy and carbon costs for mining cryptocurrencies. *Nature Sustainability*, *1*(11), 711–718. https://doi.org/10.1038/s41893-018-0152-7

Kumar, A. S., & Anandarao, S. (2019). Volatility spillover in cryptocurrency markets: Evidence from GARCH and wavelet analysis. *Physica A: Statistical Mechanics and its Applications*, *524*, 448–458. https://doi.org/10.1016/j.physa.2019.04.154

MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics*, *11*(6), 601–618.

Marchewka-Bartkowiak, K., & Wiśniewski, M. (2022). Energy tokens as digital instruments of financial investment. *Economics and Business Review*, *8*(3), 109–125. https://doi.org/10.18559/ebr.2022.3.6

Mensi, W., Rehman, M. U., Al-Yahyaee, K. H., & Vo, X. V. (2023). Frequency dependence between oil futures and international stock markets and the role of gold, bonds, and uncertainty indices: Evidence from wavelet approaches. *Resources Policy*, *80*, 103161. https://doi.org/10.1016/j.resourpol.2022.103161

Narayan, P. K. (2005). The saving and investment nexus for China: Evidence from cointegration tests. *Applied Economics*, *37*(17), 1979–1990.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289–326. https://doi.org/10.1002/jae.616

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. , Wu, T., Ma. X., Albu, L. L., & Umar, M. (2023). Are energy consumption and carbon emission caused by Bitcoin? *Economic Analysis and Policy*, *80*, 109–120. https://doi.org/10.1016/j.eap.2023.08.004

Rehman, M. U., & Kang, S. H. (2021). A time–frequency comovement and causality relationship between Bitcoin hashrate and energy commodity markets. *Global Finance Journal*, *49*, 100576. https://doi.org/10.1016/j.gfj.2020.100576

Sapra, N., Shaikh, I., Roubaud, D., Asadi, M., & Grebinevych, O. (2024). Uncovering Bitcoin's electricity consumption relationships with volatility and price: Environmental repercussions. *Journal of Environmental Management*, *356*, 120528. https://doi.org/10.1016/j.jenvman.2024.120528

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

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, *66*(1–2), 225–250. https://doi.org/10.1016/0304-4076(94)01616-8

Wang, X., Fang, F., Ma, S., Xiang, L., & Xiao, Z. (2024). Dynamic volatility spillover among cryptocurrencies and energy markets: An empirical analysis based on a multilevel complex network. *North American Journal of Economics and Finance*, *69*, 102035. https://doi.org/10.1016/j.najef.2023.102035