

Unveiling the Environmental Cost of Bitcoin: A Quantile-Based Investigation of Energy Use and Carbon Emissions

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Abstract

This research employs quantile-on-quantile (QQ) connectedness, QQ regression, and quantile-based causality analysis to investigate the evolving and asymmetric relationships between Bitcoin price fluctuations, its energy consumption, and associated carbon emissions. Using daily data spanning from July 18, 2010, to December 15, 2024, we find that, particularly during extreme market conditions, Bitcoin's energy use and carbon emissions exhibit significant nonlinear dependencies on price movements. The results indicate that mining activity intensifies during Bitcoin bull markets, thereby amplifying the cryptocurrency's environmental footprint. These dynamics are further influenced by macroeconomic conditions and regulatory developments. Moreover, our analysis reveals that changes in Bitcoin's energy consumption can both influence market behavior and respond differently across price quantiles. Overall, the findings underscore the increasing relevance of sustainability concerns in determining the valuation and future trajectory of cryptocurrencies, with important implications for risk management, regulatory frameworks, and the adoption of environmentally friendly blockchain technologies. By illustrating how energy-intensive digital financial systems interact with market forces and policy interventions, the study offers valuable insights to advance SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action) through targeted regulations, the promotion of clean energy in mining, and the development of greener blockchain infrastructure.

1. Introduction

Financial technology has seen remarkable progress, attracting considerable attention, particularly with the growing presence of cryptocurrencies in investor portfolios. The cryptocurrency market's recent expansion has stimulated investment opportunities, financial innovation, and market interconnectedness, emphasizing its transformative role in finance and economic progress (Xiao et al. 2023; Jiang et al. 2024). However, while these technological advancements have unlocked new possibilities, they have also raised environmental concerns (Zhang et al. 2023). Consequently, tackling human-induced global warming—an essential pillar of sustainable development—has become increasingly urgent. Yet, the continued rise in global CO₂ emissions and the slow pace of progress toward the Paris Agreement's goal of limiting warming to a maximum of + 2°C indicate that current efforts remain inadequate (Kohli et al. 2023).

Building on these advancements, policymakers and market participants have placed greater emphasis on the environmental impact of crypto mining, particularly amid global efforts to reduce carbon footprints and mitigate climate change (Long et al. 2023). While cryptocurrencies offer investment opportunities as an alternative asset class, their significant environmental externalities discourage institutions with strict sustainability policies from investing in them (Yan et al. 2022). While some countries have imposed stricter regulations on crypto mining due to rising environmental concerns, others have sought to attract miners to regions rich in renewable energy, potentially reducing the crypto market's overall carbon footprint (Yousaf et al. 2025). Consequently, crypto miners began adopting renewable energy sources and integrating climate change policies into their mining processes to safeguard their profits and enhance environmental sustainability (Lorente et al. 2023). Additionally, the Crypto Climate Accord [CCA] was introduced in April 2021 as an industry-led effort to minimize the environmental impact of digital asset mining and encourage the transition to renewables [see <https://cryptoclimate.org/>]. Even with these efforts, supporters of digital currencies believe that using cryptocurrencies will automatically become greener through clean energy, but this hope is overly optimistic, as making this change quickly is very difficult (Corbet et al. 2021). This challenge is further compounded by regional disparities in the energy mix of crypto mining, with Europe and the United States (US) relying more on renewable energy, whereas coal continues to dominate in the Asia-Pacific region, supplying 65% of the industry's energy consumption (Yan et al. 2022). As a result, given the substantial carbon footprints of cryptocurrencies, they still depend heavily on fossil fuels, intensifying environmental concerns (Kohli et al. 2023).

Given the growing global environmental concerns and the rapid expansion of cryptocurrency markets, this study employs quantile-based econometric techniques to explore the evolving, nonlinear interconnections among Bitcoin price fluctuations, energy consumption, and carbon emissions. By utilizing Quantile-on-Quantile (QQ) connectedness, QQ regression, and a quantile-based causality test, the research provides a comprehensive perspective on how variations in the Bitcoin sector affect its carbon footprint and vice versa. Moreover, it examines the dynamic nature of these relationships over time, considering the effects of macroeconomic conditions, advancements in mining efficiency, and regulatory changes on Bitcoin's energy demand and emissions.

A key contribution of this study is the application of the novel QQ connectedness analysis developed by Gabauer & Stenfors (2024), which captures nonlinear and asymmetric relationships by assessing the interconnectedness of variables across different quantile levels. This approach offers deeper insights than traditional methods by revealing shifts in connectivity dynamics, particularly during periods of crisis or extreme volatility. Additionally, the study combines causality-in-quantiles with a rolling-window method, enabling a test that shows how causal relationships change over time and across different data ranges.

From a methodological standpoint, this research introduces a fresh quantile-based approach to understanding the interplay among Bitcoin price movements, energy consumption, and environmental impact. By capturing time-varying effects and nonlinear dependencies, it underscores the influence of market fluctuations on Bitcoin's sustainability. Furthermore, it points out the need for adaptive regulatory policies and sustainable mining strategies, offering important guidance to investors, policymakers, and industry stakeholders.

Following the subsection "Bitcoin: Its Energy Consumption and Carbon Footprint," the remainder of this research is systematically arranged as follows: Section 2 provides an extensive examination of the pertinent literature, while Section 3 delineates the Model, Data, and Theoretical Framework. Section 4 elaborates on the methodological framework in detail. Section 5 expounds upon the empirical outcomes alongside analytical discussions, and Section 6 encapsulates the principal conclusions and regulatory implications.

Bitcoin: Its Energy Consumption and Carbon Footprint

Bitcoin, introduced by Satoshi Nakamoto in 2008 and built on blockchain technology, was the first cryptocurrency to enable secure, anonymous, and decentralized value transfers online with unparalleled speed (Bejan et al. 2023). Since its creation, Bitcoin has attracted strong investor interest due to its

price volatility and profit potential (Baur and Oll 2022) and is recognized as the most valuable and widely known cryptocurrency (Küfeoğlu and Özkuran 2019). The increasing integration of Bitcoin into financial markets, commercial sectors, and political frameworks is progressively narrowing the divide between Bitcoin and traditional financial assets (Sarkodie et al. 2022). Its main goal is to serve as an alternative to conventional payment systems, enabling international transactions without relying on central banks, government authorities, or traditional financial intermediaries. By February 12, 2025, the aggregate count of digital currencies recorded in the CoinGecko Database was 17,116 [<https://www.coingecko.com/>]. Among them, Bitcoin remains the dominant cryptocurrency, with a market capitalization of nearly \$1.91 trillion, making up 58.02% of the entire market, which is currently valued at \$3.27 trillion.

In terms of environmental externalities, Bitcoin functions not only as a secure transaction tool but also requires substantial electricity for its mining process, contributing to a significant carbon footprint and raising concerns about environmental sustainability (Chen and Xu 2022). This impact is further exacerbated by the mining process's heavy reliance on fossil fuels, particularly its historical dependence on coal-powered operations in China, which has led to a high carbon footprint per transaction (Corbet et al. 2021; Sarker et al. 2023). As reported by Digiconomist [see <https://digiconomist.net/>], Bitcoin mining has a significant environmental externality, producing a yearly CO₂ emission impact of 98.10 megatons (Mt), comparable to Qatar's total emissions. Moreover, the network's electricity consumption reaches 175.87 terawatt-hours (TWh), equivalent to Poland's entire energy usage. Moreover, Bitcoin mining generates 43.64 kilotons (kt) of electronic waste, comparable to the IT equipment waste generated in the Netherlands, and consumes 2,772 gigalitres (GL) of freshwater, matching Switzerland's total water usage.

<Insert Fig. 1 Here>

Figure 1 illustrates Bitcoin's annual energy consumption relative to the electricity demands of various countries. The data reveal that Bitcoin's annual energy consumption exceeds the total electricity demand of some nations, such as the Czech Republic (251.60%) and the Netherlands (150.20%), and accounts for a significant share of others' energy use. For example, Bitcoin mining consumes electricity equivalent to 71% of Australia's total energy demand, 55.70% of Italy's, and 54% of the United Kingdom's. Additionally, Bitcoin mining's electricity consumption accounts for a significant share of the energy needs of France (36.60%), Germany (31%), Canada (30.70%), and Russia (17.59%). Meanwhile, in the US, Bitcoin mining accounts for only 4% of the country's vast energy usage. This data underscores the extraordinary energy demands of Bitcoin mining, which in some cases exceed national electricity usage, raising concerns about its sustainability and environmental impact.

Furthermore, Fig. 2 plots annualized Bitcoin electricity consumption and CO₂ emissions, as estimated by the Cambridge Center for Alternative Finance at the University of Cambridge.

<Insert Fig. 2 Here>

As illustrated in Fig. 2, a consistent upward trend is evident in the yearly energy usage and carbon output associated with Bitcoin, starting at minimal levels before 2016 and rising sharply from 2017 onward. After fluctuating between 2018 and 2020, energy consumption and CO₂ emissions surged significantly from 2020 to 2025, reaching nearly 200 TWh and 95 MtCO₂e, respectively. This overall trend emphasizes the expanding environmental externality of Bitcoin mining, as its energy-intensive operations continue to contribute to rising carbon emissions.

2. Overview of Relevant Literature

A growing body of research investigates the relationships among cryptocurrency prices, CO₂ emissions, and the energy consumption of crypto mining, employing various connectedness approaches, including quantile connectedness, dynamic connectedness, and wavelet analysis. Among these studies, Zhang et al. (2023), applying the quantile-based Granger causality examination, the cross-quantilogram technique, and dynamic dependency analysis, uncovered a significant predictive association linking Bitcoin's power consumption to its carbon footprint at the upper quantiles, indicating a nonlinear relationship between digital asset energy demand and the environmental footprint. In a similar study, Yousaf et al. (2025) found that changes in Bitcoin's value significantly affect both the power used and the CO₂ emissions from mining, particularly when Bitcoin prices are high. In a similar study, Dong et al. (2024) also used the MQQ regression to analyze the impact of financial volatility, energy price fluctuations, market uncertainties, and ecological considerations on Bitcoin's carbon emissions. Their findings revealed that while higher energy prices reduce emissions at lower quantiles, rising Bitcoin prices tend to increase carbon footprint—especially when both values are high—whereas climate policy uncertainty (CPU) is associated with lower emissions at extreme quantiles. Exploring the economic implications of energy consumption in mining, Das & Dutta (2020) utilized Quantile Regression (QR) and Markov Regime Switching (MRS) models to demonstrate that high energy costs act as a barrier to profitability, as Bitcoin's energy consumption negatively impacts miners' revenue, particularly during low and volatile periods. Using quantile connectedness analysis, Yuan et al. (2022) revealed that Bitcoin price transmits risk to Bitcoin's energy consumption by driving mining activity and electricity demand, while hash rate, mining difficulty, and energy costs are interlinked and collectively influence Bitcoin prices. Examining market dynamics, Sapra et al. (2024) utilized a vector autoregressive (VAR) framework, the Granger causality test, and Diebold-Yilmaz (DY) connectedness analysis, revealing that Bitcoin prices influence Bitcoin energy consumption in a Granger-causal manner, though the reverse effect was not observed. Moreover, their DY analysis determined that Bitcoin prices act as net transmitters of volatility spillovers, whereas Bitcoin energy consumption and market fluctuations function as net recipients. In the same way, Long et al. (2023) used a VAR framework with DY connectedness analysis to show that Bitcoin prices and their volatility have a big impact on carbon emissions. They also identified bidirectional spillover dynamics between Bitcoin prices and energy consumption. Similarly, Huynh et al. (2022) used a VAR model, the DY spillover method, and a Time-Varying Parameter VAR (TVP-VAR) setup to identify two-way relationships among Bitcoin returns, trading volumes, and energy consumption. Notably, trading volumes have a more pronounced impact on energy consumption, while energy consumption significantly predicts Bitcoin returns and volumes, raising concerns about an increasing carbon footprint. Shifting focus to long-term relationships, Polemis & Tsionas (2023) applied Bayesian quantile regression and a Cointegrated Vector Autoregression (CVAR) model to examine the effects of cryptocurrency mining on carbon footprints, finding

that most variables are positively correlated across quantiles, thereby reinforcing the strong link between Bitcoin mining and environmental degradation. However, their results also indicated that miners' revenues are negatively related to emissions at higher quantiles, suggesting that profitability pressures may curb emissions under extreme conditions.

Beyond the analyses mentioned earlier, many studies in this field have employed diverse empirical techniques to investigate the interplay among price dynamics, power consumption, and environmental impact associated with cryptocurrency mining. Notably, one such approach is cointegration analysis, a type of time series analysis. For instance, Sarkodie et al. (2022) applied dynamic ARDL modeling alongside a refined VAR approach, demonstrating that a 10% increase in Bitcoin's power usage and carbon emissions leads to a 0.25% increase in its long-term market value. Similarly, Tissaoui et al. (2024), employing the Quantile Nonlinear ARDL (QNARDL) model and machine learning techniques, demonstrated that positive shocks to Bitcoin prices increase mining's energy consumption over short horizons but lead to a decline over extended horizons, whereas negative shocks trigger the opposite response. In addition, Sapra & Shaikh (2023) employed the ARDL bounds cointegration test along with ordinary least squares (OLS) to examine how trading- and mining-specific factors influence Bitcoin's energy consumption. Their results reveal that all examined factors significantly influence energy consumption, with Ethereum prices causing a temporary decline but contributing to an increase over the long term. Broadening the application of cointegration analysis, Kristoufek (2020) implemented the Johansen methodology alongside a vector error correction (VEC) framework, uncovering a strong and sustained relationship between Bitcoin's market value and operational mining costs. The findings indicated that mining costs significantly respond to price changes, with an estimated elasticity of 1.30, whereas short-term effects remain minimal, underscoring the dominant role of long-run adjustments in the cryptocurrency mining sector.

Beyond cointegration analysis, various empirical methods have been applied in this field. For instance, Maiti et al. (2023) employed Shannon and Rényi transfer entropy, revealing a significant flow of information from Bitcoin prices to mining energy consumption, while the reverse flow remained weak and inconsistent. Their study further demonstrated that extreme events intensify the influence of Bitcoin prices on mining's electricity consumption, whereas chaotic effects predominate in the opposite direction. Complementing this perspective, Bejan et al. (2023) applied a sophisticated machine learning approach to identify a significant relationship between Bitcoin's monthly average values and its energy consumption by integrating trend analyses and predictive models. Broadening the analysis to environmental impacts, Bildirici & Ersin (2024) employed the Markov-Switching GARCH-Copula model to investigate the interplay among Bitcoin prices, mining energy consumption, and global CO₂ emissions. Their findings underlined a bidirectional relationship between Bitcoin price movements and energy consumption, as well as a one-way causal effect of energy usage on global carbon output. These results indicate that sharp increases in Bitcoin prices are linked to extreme surges in its energy usage and emissions, especially during volatile periods, thereby accentuating the environmental challenges posed by cryptocurrency mining. Adding to this discussion, Maiti (2022) examined the complex interactions linking Bitcoin price fluctuations to its overall energy consumption using a discrete threshold regression model, identifying six consumption thresholds that trigger regime transitions. The findings showed that Bitcoin's power usage has a notable impact on its market value, but only in elevated regimes, where rising energy costs drive price growth, further highlighting the complex relationship between cryptocurrency markets and energy demand. Finally, Sarkodie et al. (2023) utilized wavelet analysis, time-varying Granger causality, and a Kernel-driven regression method to assess how Bitcoin's technological factors influence the environment. All these studies reveal the complex, multidimensional interplay among Bitcoin prices, mining energy consumption, volatility, and environmental externalities, emphasizing the need for a comprehensive approach to understanding the sustainability impacts of cryptocurrency markets.

Another strand of research has examined the wider connections between cryptocurrency mining, particularly Bitcoin mining, and national or global energy, financial, and carbon markets. The literature review, which extensively covers studies that use the same variables as this research, provides only a concise overview of other related work. In this context, various analytical methods have been employed. For instance, Aye et al. (2023), Chen & Xu (2022), Di Febo et al. (2021), Jiang et al. (2024), Lorente et al. (2023), and Sharma et al. (2023) implemented different quantile-driven methodologies. Moreover, Othman & Ben Bob (2022) and Lorente et al. (2023) employed the wavelet coherence test, while Qin et al. (2023) adopted a VAR model with time-varying coefficients. Additionally, Dogan et al. (2022) conducted a dynamic Granger causality analysis, whereas Erdogan et al. (2022) performed both symmetric and asymmetric causality analyses. Moreover, Karmakar et al. (2021) and Corbet et al. (2021) implemented various GARCH models. Papp et al. (2023) used a regression technique, Sarker et al. (2023) applied a nonlinear ARDL model, Baur & Oll (2022) used mean–variance portfolio optimization, and Meiryani et al. (2022) performed multiple linear regression. These studies have generally found strong, statistically significant relationships between cryptocurrency mining—particularly Bitcoin mining—and national and global energy, carbon, and financial asset markets.

3. Model, Data, and Theoretical Framework

3.1 Theoretical Framework

Bitcoin's Proof-of-Work [PoW] design

The substantial power consumption of Bitcoin mining stems from its intricate consensus mechanism, which is designed to authenticate transactions and ensure network security (Podhorsky 2023; Long et al. 2023). Bitcoin mining, a distributed computing process, verifies transactions and records them in the blockchain, a publicly accessible ledger (Küfeoğlu and Özkuran 2019; Meiryani et al. 2022). This technology relies on decentralized protocols and extensive hash computations to facilitate peer-to-peer transactions without intermediaries, ensuring security (de Vries 2018; Stoll et al. 2019). In the mining process, participants solve complex hash puzzles to validate transactions and submit their solutions under the Proof-of-Work (PoW) algorithm (Stoll et al. 2019; Das and Dutta 2020; Kohli et al. 2023). The PoW system creates competition among miners for rewards, requiring them to use powerful, energy-hungry machines to solve math problems, which helps secure the network but also increases electricity consumption. In this system, all mining machines compete to append a new block to the blockchain, with the first participant discovering a valid solution receiving Bitcoin as a reward (Yuan et al. 2022; Kohli et al. 2023; Aye et al. 2023). Each new block is generated by processing data from the previous one, forming a continuous chain of computational work (Li et al. 2019). As Bitcoin mining progresses, the process becomes increasingly challenging and demands greater energy input (Zhang et al. 2023).

Theoretical linkages among Bitcoin value, its energy demand, and carbon footprint

The strong connection between Bitcoin prices, energy consumption, and mining costs raises significant concerns about the environmental effects of cryptocurrency mining, particularly its role in increasing global warming (Bejan et al. 2023). As Bitcoin's popularity continues to rise, its power-demanding nature and substantial carbon output have become pressing issues, prompting financial markets and regulators to integrate these factors into Bitcoin price modeling (Long et al. 2023). In this context, higher Bitcoin prices and the expectation of sustained profitability drive increased mining activity, leading to a sharp rise in the network's electricity consumption and overall carbon emissions (Das and Dutta 2020; Papp et al. 2023). Crucially, miners remain profitable as long as mining costs stay below Bitcoin's market value, making energy expenses a key determinant of mining viability (Maiti 2022). The production cost of a single Bitcoin consists of both fixed expenditures, such as mining hardware, and variable costs, primarily driven by electricity consumption (Kristoufek 2020). Given that energy expenses represent a significant share of total mining costs, variations in power costs exert a direct effect on Bitcoin's earning capacity and supply dynamics (Sarker et al. 2023; Maiti et al. 2023)

3.2 Data

This study examines the relationship between Bitcoin price fluctuations, environmental repercussions, and energy consumption patterns. The dataset includes: (i) Bitcoin prices, (ii) Bitcoin-related carbon emissions, and (iii) Bitcoin electricity consumption. To account for Bitcoin's volatility and market dynamics, log daily returns were utilized, covering a decade of market activity from September 17, 2014, to December 17, 2024. Given Bitcoin's growing influence in the realm of virtual assets and speculative trading, its price volatility is a key indicator of investor sentiment and market dynamics.

Bitcoin-related carbon emissions from July 18, 2010, to December 15, 2024, were utilized to assess its environmental impacts. This dataset provides daily estimates of carbon dioxide equivalent (MtCO₂e) emissions. The mining process, which is essential for securing the network and validating transactions, relies on processing power and often requires substantial electricity. As the computational complexity of the network increases, energy usage and associated emissions tend to rise, shaping the sustainability debate surrounding cryptocurrency. Besides, to assess the energy demand of Bitcoin mining, annualized electricity consumption estimates are incorporated. This dataset includes annualized energy usage (in terawatt-hours, TWh) from July 18, 2010, to December 15, 2024. Examining fluctuations in electricity demand helps explain how changes in mining difficulty, market conditions, and regulatory developments influence Bitcoin's energy consumption. Bitcoin energy consumption and carbon emission data were sourced from the University of Cambridge, Cambridge Center for Alternative Finance [<https://ccaf.io/cbnsi/cbeci/ghg/>], while Bitcoin price data (USD) were retrieved from Yahoo Finance [<https://finance.yahoo.com/quote/BTC-USD/history/>]

Table 1 provides an overview of the summary statistics for the log returns of electricity consumption, its carbon emissions, and Bitcoin returns, and Fig. 1 illustrates their trends.

Mean	$\sqrt{\text{varvec}B\text{varvec}T\text{varvec}C_{-}\text{varvec}P\text{varvec}r}$
	0.00144 ^b
Variance	0.001330
Skewness	-0.72558 ^a
Excess Kurtosis	11.37170 ^a
JB	20485.30580 ^a
ERS	-5.167950 ^a
$\sqrt{\text{varvec}Q(20)}$	15.002640
$\sqrt{\text{varvec}Q^2(20)}$	152.88801 ^a
Kendall correlation	$\sqrt{\text{varvec}B\text{varvec}T\text{varvec}C_{-}\text{varvec}P\text{varvec}r}$
$\sqrt{\text{varvec}B\text{varvec}T\text{varvec}C_{-}\text{varvec}P\text{varvec}r\text{varvec}i\text{varvec}c\text{varvec}e}$	1.000
$\sqrt{\text{varvec}B\text{varvec}T\text{varvec}C_{-}\text{varvec}E\text{varvec}l_{-}\text{varvec}C\text{varvec}o\text{varvec}n\text{varvec}s}$	0.014
$\sqrt{\text{varvec}B\text{varvec}T\text{varvec}C_{-}\text{varvec}C\text{varvec}O2_{-}\text{varvec}C\text{varvec}o\text{varvec}n\text{varvec}s}$	0.011
Notes: The symbols ^a , ^b , and ^c indicate significance levels of 1%, 5%, and 10%, respectively. Skewness is assessed using the D'Agostino (1970) test, while the Portmanteau test statistics proposed by Fisher & Gallagher (2012).	

As shown in Table 1, Bitcoin returns show a positive mean, underpinning an overall upward trend, but they also exhibit high volatility. The excess kurtosis indicates that the distribution has many extreme values, while the negative skewness suggests a greater likelihood of sharp price declines. The JB test statistic indicates rejection of the null hypothesis of normality, consistent with Bitcoin's well-known price fluctuations. Furthermore, the findings of the ERS test show stationarity, suggesting mean-reverting behavior. Time-varying volatility is tested by the $Q(20)$ and $Q^2(20)$ statistics, which validate substantial heteroscedasticity effects and persistent autocorrelations.

As for carbon emissions and electricity consumption, both series show positive means, reflecting the ongoing energy requirements of Bitcoin mining. The negative skewness of these series suggests sporadic, steep drops, potentially due to efficiency gains or regulatory actions. JB test findings and excess kurtosis scores point to non-normal distributions with heavy tails. The price of Bitcoin, power use, and emissions all show a weak but positive correlation, with the strongest correlation (0.112) observed between electricity use and emissions. This indicates that while Bitcoin's price influences the mining process, its electricity usage and carbon output are significantly shaped by external factors such as energy costs and policy regulations.

<Insert Fig. 3 Here>

As observed in Fig. 3, high volatility and frequent rapid variations are evident in Bitcoin price returns, especially during key market events such as the 2017 price spike and the 2020 pandemic-induced fall. Extreme negative returns indicate high downside risk, aligning with the negative skewness of the summary statistics. The clustering of volatility at certain times shows that ongoing market trends, often driven by speculative trading, regulatory news, and economic factors, are common. Furthermore, a prevalent characteristic of cryptocurrency markets is the leptokurtic nature of returns, implying that extreme price fluctuations occur more frequently than would be expected under a normal distribution.

Despite the distinct characteristics of the electricity consumption and carbon emissions series, they remain closely related. Frequent variations in electricity consumption changes (BTC_El_Cons) are indicative of the changing processing requirements of Bitcoin mining. Changes in mining difficulty, governmental actions, or movements in the global distribution of miners due to variations in electricity costs could all be responsible for the ups and downs in energy use. The carbon emissions series (BTC_CO2_Cons) exhibits similar variability, but the magnitude of these variations appears to stabilize over time. This consistency implies that emissions are still largely determined by long-term energy trends rather than transient price swings, even amid sporadic changes in mining activity. The notion that Bitcoin mining's ecological footprint is driven largely by energy-intensive computational requirements rather than by direct price swings is supported by the association between emissions and electricity use. These results highlight the ongoing debate over Bitcoin's sustainability and the need for regulatory oversight to mitigate its harmful environmental impacts.

4. Methodology

Figure 4 presents the sequence of the analyses used in the study.

<Insert Fig. 4 Here>

4.1 Quantile-on-quantile [QQ] connectedness

Gabauer & Stenfors (2024) proposed the QQ connectedness analysis, expanding upon the quantile connectedness method initially introduced by Chatziantoniou et al. (2021) A $QVAR(p)$ model is formulated as follows:

$$y_t = \mu(\tau) + \sum_{i=1}^p B_i(\tau) y_{t-i} + u_t(\tau) \quad [1]$$

The variables y_t , and y_{t-i} represent $N \times 1$ endogenous vectors spanning multiple dimensions, while τ denotes a vector of quantiles within the range $[0,1]$. The parameter p indicates the lag order in the QVAR model. The conditional mean vector $\mu(\tau)$ has dimensions $N \times 1$, while the QVAR coefficient matrix $B_i(\tau)$ is of size $N \times N$. The term $u_t(\tau)$ shows an error vector of size $N \times 1$, accompanied by a variance-covariance matrix $F[\tau]$ with dimensions $N \times N$. The QVAR model is transformed into its QVMA representation using the Wold decomposition theorem, as presented in Eq. [2].

$$y_t = \mu(\tau) + \sum_{i=1}^p B_i(\tau) y_{t-i} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} A_i(\tau) u_{t-i}(\tau) \quad [2]$$

The consequences of an external jolt in series i on series j over H steps are quantified by the forecast error variance decomposition:

$$\varnothing_{j \leftarrow i}^g(H) = \frac{\sum_{h=0}^{H-1} \left(\sum_{n=1}^N \left(\frac{g_{n,j}(\tau) F(\tau) A_{n,i}(\tau)}{\sum_{n=1}^N g_{n,j}(\tau) F(\tau) A_{n,i}(\tau)} \right)^2 \right)}{\sum_{n=1}^N \left(\sum_{h=0}^{H-1} \left(\frac{g_{n,j}(\tau) F(\tau) A_{n,i}(\tau)}{\sum_{n=1}^N g_{n,j}(\tau) F(\tau) A_{n,i}(\tau)} \right)^2 \right)} \quad [3]$$

in which e_j is a $N \times 1$ zero vector with j -th element set to one.

To calculate the rescaled GFEVD, $gSOT_{j \leftarrow i, \tau}^{gen}(H)$, we normalize $\varnothing_{j \leftarrow i}^{gen}(H)$ by calculating its proportion relative to the row sum in Eqs. [4] and [5]. The “TO” measure indicates the influence that series j exerts on the other series, whereas the “FROM” measure represents the impact of all other series on series j .

$$S_{j \rightarrow *, \tau}^{gen, to}(H) = \sum_{n=1, j \neq i}^N gSOT_{n \leftarrow j, \tau}^{gen, to}(H) \quad [4]$$

$$S_{j \leftarrow *, \tau}^{gen, from}(H) = \sum_{n=1, j \neq i}^N gSOT_{j \leftarrow n, \tau}^{gen, from}(H) \quad [5]$$

The NET total directional connectedness for series i is derived by deducing the total directional connectedness received (FROM) from the total directional connectedness given (TO).

$$S_{j, \tau}^{gen, net} = S_{j \rightarrow *, \tau}^{gen, to} - S_{j \leftarrow *, \tau}^{gen, from} \quad [6]$$

The adjusted Total Connectedness Index (TCI), as proposed by Chatziantoniou et al. (2021), is computed as follows:

$$TCI_{\tau}(H) = \frac{\sum_{n=1}^N S_{n \leftarrow *, \tau}^{gen, from}(H)}{\sum_{n=1}^N S_{n \leftarrow *, \tau}^{gen, to}(H)} \equiv \frac{\sum_{n=1}^N S_{n \leftarrow *, \tau}^{gen, from}(H)}{\sum_{n=1}^N S_{n \leftarrow *, \tau}^{gen, to}(H)} \quad [7]$$

4.2 Quantile-on-quantile (QQ) regression

Sim & Zhou (2015) expand the QQ regression approach, enhancing the quantile regression framework originally introduced by Koenker & Bassett (1978). This approach allows for the analysis of how particular percentiles of an explanatory variable influence the conditional quantiles of an outcome variable by combining nonparametric estimation with quantile regression methods.

Here, the superscript θ denotes the quantile of the y and x , allowing us to model the for the θ -quantile of y as a function of the x :

$$y_t = \beta_t^\theta x_t + \epsilon_t^\theta, \quad [8]$$

where ϵ_t^θ is a stochastic term that has a zero θ -quantile.

Due to our limited understanding of the relationship between the variations in y and x , we recognize that the association is yet to be established $\beta^\theta(x_t)$. To unclothe the association between the θ -quantile of y and τ -quantile of x , represented as x^τ , a first-order Taylor expansion was employed to linearize the function $\beta^\theta(x_t)$ around x^τ :

$$\beta^\theta(x_t) \approx \beta^\theta(x^\tau) + \beta^{\theta'}(x^\tau)(x_t - x^\tau) \quad [9]$$

Building upon the study of Sim & Zhou (2015), $\beta^\theta(x^\tau)$ and $\beta^{\theta'}(x^\tau)$ were defined respectively, as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$. Thereby, Eq. [9] can be reformulated as:

$$\beta^\theta(x_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(x_t - x^\tau) \quad [10]$$

Finally, Eq. [10] was inserted into Eq. [8] to yield the following:

$$y_t = \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(x_t - x^\tau) + \epsilon_t^\theta \quad [11]$$

The notation: $\beta_0(\theta, \tau) + \beta_1(\theta, \tau)(x_t - x^\tau)$ describes the association between the θ -quantile of the y and τ -quantile of x , with β_0 and β_1 are aligned with θ and τ .

To estimate Eq. [11], we solve for:

$$\min_{0,1} \sum_{i=1}^n \rho_\theta[y_t - \beta_0(\theta, \tau) - \beta_1(\theta, \tau)(x_t - x^\tau)] K\left(\frac{F_n[x_t] - \tau}{h}\right) \quad [12]$$

and derive the predictions $\hat{\beta}_0(\theta, \tau)$ and $\hat{\beta}_1(\theta, \tau)$. In this context, the function ρ_θ is the asymmetrical absolute value function that generates the θ -conditional quantile of y_t as the result. To consider the local effects by the τ -quantile of x , we apply a Gaussian kernel $K(\cdot)$ to assign weights to the observations in the near x^τ , based on bandwidth ($h=0.05$). The weights exhibit inverse relationship to the distance of x_t from x^τ , i.e., which is represented by the distance of the empirical distribution functions as follows:

$$F_n(x_t) = \frac{1}{n} \sum_{k=1}^n I(x_k < x_t) \quad [13]$$

from τ , where τ denote the value of the distribution function corresponding to x^τ .

4.3 Quantile causality methodology

This study employs the k -th order nonparametric causality-in-quantiles test methodology of Balcilar et al. (2017), which combines the higher-order nonparametric approach of Nishiyama et al. (2011) with the quantiles-based framework of Jeong et al. (2012).

Let y_t denote the dependent variable (i.e., Bitcoin returns, energy consumption, or carbon emissions) and x_t denote the independent variable (one of the remaining two series). Also, let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\bullet}(y_t|\bullet)$ denote the conditional distribution of y_t given $\bullet$. We define $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ to have $F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta$ with probability one. The θ -th quantile (non)causality hypotheses to be tested are as follows:

$$H_0 : P\{F_{y_t|Z}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \quad [14]$$

$$H_1 : P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \quad [15]$$

Jeong et al. (2012) show that the feasible kernel-based test statistics is given by:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^T \sum_{s=p+1, s \neq t}^T K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\epsilon}_t \hat{\epsilon}_s \quad [16]$$

where $K(\bullet)$ is the kernel function with bandwidth h , T is the sample size, p is the lag order, and $\hat{\epsilon}_t = 1\{y_t \leq \hat{Q}_\theta(Z_{t-1})\} - \theta$ is the regression error, with $\hat{Q}_\theta(Z_{t-1})$ being an estimate of the θ -th conditional quantile and $1\{\bullet\}$ is the indicator function. Note that, with $L(\bullet)$ denoting the kernel function, we use the *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$, which is given by:

$$\hat{Q}_\theta(Z_{t-1}) = \frac{\sum_{s=p+1, s \neq t}^T L\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) 1\{y_s \leq y_t\}}{\sum_{s=p+1, s \neq t}^T L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \quad [17]$$

5. Empirical Results and Discussions

The QQ connectedness analysis in Fig. 5 depicts the dynamic interlinkages among Bitcoin value, power consumption, and carbon output. The direct and reverse Total Connectedness Index (TCI) measures reveal how these variables influence each other across different market conditions. Interestingly, the reverse TCI (red) mainly outperforms the direct TCI (green), especially when the market is volatile. This situation indicates that variations in power usage and the subsequent release of carbon emissions from Bitcoin mining have a greater feedback effect on Bitcoin values rather than vice versa. This result suggests that mining activity is highly sensitive to external shocks, such as changes in electricity prices and government actions, which, in turn, influence Bitcoin's value. As emphasized by Maiti et al. (2023), the sharp increase in electricity consumption for Bitcoin mining significantly affects Bitcoin prices. In this context, energy expenses are a key determinant of Bitcoin mining viability, as rising energy prices increase operational expenses, reduce profitability, constrain production, and potentially create scarcity, driving up Bitcoin's value (Sarker et al. 2023). The ΔTCI (blue line) captures variations in the strength of these interlinkages over time. Notable increases are observed around major market events such as the 2017 bull run, the 2020 COVID-19 crisis, the 2021 crypto bull market, and the collapse of FTX in November 2022.

Furthermore, Bitcoin's high electricity consumption has faced significant criticism, sparking concerns about the sustainability of cryptocurrencies as both a monetary system and an investment asset (Corbet et al. 2021). In line with these concerns, stronger reverse connectedness during periods of high market volatility indicates that changes in mining technology, government regulations, and energy prices play a key role in shaping how the Bitcoin market behaves. This interconnection highlights that Bitcoin's energy demand not only responds to price movements but also actively drives market dynamics. Moreover, the observed asymmetry in connectedness suggests that Bitcoin's valuation is increasingly influenced by broader macroeconomic and environmental factors, underscoring the importance of energy-related risks in investment preferences. As a result, market participants must consider these sustainability challenges when assessing Bitcoin's long-term potential. Looking ahead, as mining technology advances and regulatory oversight strengthens, these interdependencies are expected to remain a key factor in Bitcoin's price stability and overall market sustainability.

<Insert Fig. 5 Here>

To provide robust statistical evidence, we now proceed with the QQ regression analysis on conditional quantiles. The slope estimates in the three-dimensional surface plots indicate that the sensitivity of Bitcoin electricity consumption (BTC_El_Cons) and carbon emissions (BTC_CO_2) to price fluctuations dissipate significantly across quantiles [see Figs. 6 and 7]. This indicates that the relationship between these variables is not consistent and varies with market conditions and the level of Bitcoin mining activity. It should be noted that the slopes in Fig. 6 are relatively stable across mid-range quantiles but exhibit more fluctuations at the extremes of Bitcoin price movements. Bitcoin mining's electricity consumption remains relatively stable during moderate price fluctuations. However, at the extreme upper and lower quantiles of Bitcoin price distribution, greater variability is observed, indicating that in highly volatile market conditions, Bitcoin's energy usage becomes more sensitive to price changes. In such scenarios, when prices are moderate, miners can maintain their operations, but sharp price declines reduce profitability, leading some miners to exit the market and lower overall energy consumption. Conversely, price surges attract more miners, increasing mining activity, energy demand, and carbon emissions (Papp et al. 2023). This dynamic is closely tied to Bitcoin's difficulty adjustment mechanism, which regulates energy consumption in response to price movements and miner participation. As prices rise, mining activity expands, driving up computational power requirements and energy use, while price drops force some miners, particularly those with higher costs, to exit, reducing overall energy demand (Corbet et al. 2021; Bildirici and Ersin 2024). Additionally, liquidity constraints and exit costs can further accelerate the departure of small-scale miners with high energy expenses, amplifying the influence of price fluctuations on mining activity. Beyond market-driven effects, regulatory actions are also a key factor influencing Bitcoin's energy consumption. During periods of extreme price volatility, governments and regulatory bodies may intervene by imposing restrictions on mining operations to mitigate environmental and financial risks. A notable example is China's 2021 crackdown on Bitcoin mining, motivated by concerns about excessive energy consumption, financial instability, and the government's desire to exert greater control over digital financial activities. This policy shift triggered significant price volatility and prompted a geographical redistribution of mining activity, altering regional energy consumption patterns (see <https://www.reuters.com/world/china/china-central-bank-vows-crackdown-cryptocurrency-trading-2021-09-24/>). In summary, Bitcoin mining's energy mixture is shaped by a complicated relationship among price dynamics, network adjustments, and regulatory interventions, making it highly responsive to both market forces and policy decisions.

A similar trend is observed in Fig. 7, where the correlation between Bitcoin's value and carbon footprint is more pronounced at the bottom and top quantiles. This suggests that Bitcoin's environmental impact increases during periods of significant price volatility or surges in mining activity. As Bitcoin prices rise, mining operations expand, leading to greater energy consumption and, consequently, increased carbon emissions. Conversely, during downturns, reduced mining demand lowers energy use and emissions (Yan et al. 2022). This asymmetric pattern highlights that while Bitcoin price fluctuations significantly shape energy consumption and emissions, external factors such as regulatory changes, improvements in mining efficiency, and electricity costs also have a significant influence. These factors can either amplify or mitigate Bitcoin's environmental footprint, underscoring the complex relationship between market dynamics, mining activity, and sustainability.

<Insert Fig. 6 Here>

<Insert Fig. 7 Here>

Also, the 200-day rolling-window causality-in-quantiles analysis in Figs. 8 and 9 provides a flexible view of how changes in power consumption, carbon footprint, and Bitcoin returns are connected. The findings reveal quantile dependence and considerable time variation, underscoring that the relationships among these variables are dynamic and adapt to evolving market conditions. Significant market and economic upheavals, such as the Bitcoin boom and bear cycles, regulatory changes, and broader macroeconomic shocks, coincide with periods of increased causality strength. This implies that during times of financial instability or extreme price fluctuations, the influence of Bitcoin price variations on power use and carbon output becomes more pronounced.

The variation among quantiles further highlights the asymmetrical character of these relationships. The causal effect of power usage and carbon footprint on Bitcoin price is more pronounced at higher quantiles, which relates to dramatic fluctuations in Bitcoin price. This illustrates how increased mining activity

during price booms produces a considerable effect on power consumption and carbon footprint. On the other hand, the causal relationship becomes less pronounced at lower quantiles, where there is less variation in Bitcoin prices. This indicates that, in a stable market, the environmental impact of Bitcoin is less susceptible to price swings. These results underscore the need for flexible regulatory and policy approaches that account for the non-linear and time-varying impacts of cryptocurrency market dynamics on sustainability and global energy consumption.

<Insert Fig. 8 Here>

<Insert Fig. 9 Here>

Our findings confirm the asymmetrical and complex relationships among Bitcoin price fluctuations, power use, and carbon footprint, as demonstrated in previous research. Consistent with the outcomes of Zhang et al. (2023) and Yousaf et al. (2025), we note that the effects of Bitcoin's price on mining operations and emissions are more pronounced at higher quantiles, particularly during price booms. This supports the argument that Bitcoin's mining operations expand rapidly when prices surge, leading to heightened electricity consumption and CO₂ emissions. Similarly, Dong et al. (2024) found that increases in Bitcoin prices exacerbate its carbon footprint, particularly under financial and geopolitical uncertainty, which aligns with our findings on asymmetric spillover effects. Additionally, Huynh et al. (2022), Long et al. (2023), and Bildirici & Ersin (2024) discovered that Bitcoin prices and energy use affect each other, which backs up our analysis showing that energy consumption plays an active role in shaping Bitcoin market behavior, rather than just reacting to price changes.

However, our results differ from those of Maiti et al. (2023) and Sapra et al. (2024), who proposed a unidirectional causal connection from Bitcoin price to energy consumption, with limited feedback effects. Our results challenge this assumption by demonstrating that electricity consumption and carbon emissions predict Bitcoin price changes, particularly under extreme market conditions. Furthermore, our research diverges from the conclusions of Polemis & Tsionas (2023), who found that Bitcoin mining revenues negatively correlate with emissions at higher quantiles, suggesting that high profitability may encourage cleaner mining practices. Conversely, our findings indicate that even under extreme conditions, mining activity remains predominantly fossil-fuel-dependent, reinforcing the environmental risks associated with Bitcoin's PoW mechanism. Additionally, our results contrast with Tissaoui et al. (2024), who argued that positive Bitcoin price shocks initially increase energy consumption but then decline over an extended period; instead, we observe persistent long-term growth in energy use and emissions, suggesting that structural market factors and regulatory actions are pivotal in shaping Bitcoin's carbon footprint.

Our findings emphasize the uneven dynamics between Bitcoin's return, electricity consumption, and carbon emissions, with a stronger effect observed at the upper quantiles. This suggests that during periods of price surges, mining activity intensifies, leading to a greater environmental footprint. Additionally, our analysis shows that Bitcoin's energy use is influenced not only by price changes but also by broader market trends, underscoring the need to consider sustainability when valuing cryptocurrencies. These insights demonstrate the value of adaptable regulatory structures that tackle the ecological challenges linked to Bitcoin mining, particularly through incentives for eco-friendly mining technologies and policy interventions that promote sustainable practices.

6. Conclusion and Policy Implications

Utilizing quantile-based econometric methods and daily data from July 18, 2010, to December 15, 2024, this study explores the dynamic and asymmetric relationships between Bitcoin price fluctuations, energy consumption, and carbon emissions. The findings underscore that these relationships are nonlinear and highly asymmetric, with more pronounced environmental effects at higher quantiles, particularly during Bitcoin bull markets. As mining activity surges in response to price increases, energy consumption rises sharply, leading to greater carbon emissions and intensifying environmental concerns (Sarkodie et al. 2023). Moreover, the results establish a feedback loop between Bitcoin price and energy consumption, demonstrating that energy costs and regulatory developments actively influence Bitcoin market behavior rather than simply reacting to it. This insight reinforces the growing importance of sustainability in cryptocurrency valuation, with crucial implications for regulatory policies and market stability.

Given these findings, addressing the environmental impacts of Bitcoin mining requires targeted policy interventions to reduce energy consumption, incentivize renewable energy adoption, and enhance mining efficiency. One of the most efficient strategies to achieve this is by motivating Bitcoin miners to switch from fossil fuels to clean energy through targeted incentives such as subsidies, tax benefits, and government-backed programs (Qin et al. 2023; Tissaoui et al. 2024). Countries like Iceland and Norway have successfully integrated hydropower and geothermal energy into their mining operations, setting a precedent for how clean energy can support cryptocurrency markets (Yousaf et al. 2025). If properly incentivized, miners could increasingly relocate to renewable-energy-rich regions, reducing the overall carbon footprint of cryptocurrency production.

In addition to diversifying energy sources, technological advancements play a key role in curbing Bitcoin's energy demand. Policies should support the adoption of energy-efficient mining hardware, such as next-generation ASIC machines, which significantly lower power consumption (Qin et al. 2023). Likewise, improving blockchain protocols through green mining algorithms and optimized cooling technologies could further enhance mining efficiency (Bildirici and Ersin 2024). The implementation of efficiency standards for mining equipment and blockchain hardware would help reduce excessive energy use per Bitcoin transaction, making mining operations more sustainable (Sarkodie et al. 2023). Alongside technological improvements, greater industry transparency is needed to hold mining operations accountable for their environmental impacts. Governments could require mandatory disclosures on mining-related electricity consumption and emissions, ensuring that both investors and regulators have access to accurate environmental data (Xiao et al. 2023).

Beyond direct energy reductions, financial instruments such as carbon taxes and emissions trading could help internalize the environmental costs of Bitcoin mining. Governments could implement cap-and-trade programs to regulate mining emissions, ensuring that high-carbon miners bear financial responsibility for their environmental footprint (Bildirici and Ersin 2024). Additionally, a tax structure aligned with Bitcoin's price elasticity could be introduced to adjust

mining incentives dynamically, discouraging excessive energy consumption while maintaining market stability (Podhorsky 2023). These fiscal measures would encourage miners to adopt low-carbon alternatives, further aligning cryptocurrency production with worldwide environmental objectives.

Additionally, the rising importance of ESG (environmental, social, and governance) factors in the financial area further highlights the importance of sustainable blockchain initiatives. Institutional investors are increasingly prioritizing green investment opportunities, leading to growing demand for environmentally conscious cryptocurrency projects (Zhang et al. 2023). Encouraging the development of ESG-certified blockchain initiatives, alongside sustainable mining certifications, could attract investment from environmentally aware financial institutions, reinforcing market-driven incentives for sustainability (Yousaf et al. 2025).

Overall, Bitcoin's environmental impact remains a critical issue requiring a multi-pronged policy approach that integrates technological innovation, financial regulation, and environmental responsibility. By implementing renewable energy mandates, carbon pricing mechanisms, and efficiency-driven regulatory frameworks, policymakers can mitigate Bitcoin's carbon footprint while preserving its role as a decentralized financial asset. The future sustainability of cryptocurrency markets hinges on coordinated global efforts that balance financial growth with responsible environmental stewardship. Developing energy-efficient blockchain technologies and fostering international cooperation will be pivotal to ensuring that cryptocurrency mining evolves toward a more eco-friendly and sustainable future.

Looking ahead, future research could extend this analysis by incorporating additional cryptocurrencies to analyze whether comparable energy-price patterns are present in other blockchain networks. We could learn more about the complex relationships between Bitcoin prices and environmental factors by exploring different modeling methods, like wavelet-based techniques or machine learning. Adding jurisdiction-specific regulatory modifications and energy policy interventions to the dataset could also provide insights into how national policies affect the sustainability of cryptocurrency mining. Future research could provide a more thorough understanding of the evolving relationship between cryptocurrency markets and environmental sustainability by examining additional aspects.

Declarations

Author Contribution

B. O. K: Conceptualization, Data curation, Writing – original draft, Writing – review & editing, Project administration. O. P: Formal analysis, Methodology, Software, Visualization, Writing – original draft. F. M: Conceptualization, Resources, Writing – original draft.

Data Availability

All data used in the analyses are provided as supplementary files.

References

1. Anscombe FJ, Glynn WJ (1983) Distribution of the kurtosis statistic b_2 for normal samples. *Biometrika* 70:227–234. <https://doi.org/10.1093/biomet/70.1.227>
2. Aye GC, Demirel R, Gupta R, Nel J (2023) The pricing implications of cryptocurrency mining on global electricity markets: Evidence from quantile causality tests. *J Clean Prod* 397. <https://doi.org/10.1016/j.jclepro.2023.136572>
3. Balcilar M, Bekiros S, Gupta R (2017) The role of news-based uncertainty indices in predicting oil markets: A hybrid nonparametric quantile causality method. *Empir Econ* 53(3):879–889. <https://doi.org/10.1007/s00181-016-1150-0>
4. Baur DG, Oll J (2022) Bitcoin investments and climate change: A financial and carbon intensity perspective. *Financ Res Lett* 47. <https://doi.org/10.1016/j.frl.2021.102575>
5. Bejan CA, Bucerzan D, Crăciun MD (2023) Bitcoin price evolution versus energy consumption; trend analysis. *Appl Econ* 55:1497–1511. <https://doi.org/10.1080/00036846.2022.2097194>
6. Bildirici ME, Ersin ÖÖ (2024) Bitcoin's Energy Consumption, Price Volatility, and Environmental Pollution: Contagion and Causality Dynamics Under Heteroskedasticity and Nonlinearity. *Int J Energy Res* 2024:. <https://doi.org/10.1155/er/8615220>
7. Chatziantoniou I, Gabauer D, Stenfors A (2021) Interest rate swaps and the transmission mechanism of monetary policy: A quantile connectedness approach. *Econ Lett* 204. <https://doi.org/10.1016/j.econlet.2021.109891>
8. Chen H, Xu C (2022) The impact of cryptocurrencies on China's carbon price variation during COVID-19: A quantile perspective. *Technol Forecast Soc Change* 183. <https://doi.org/10.1016/j.techfore.2022.121933>
9. Corbet S, Lucey B, Yarovaya L (2021) Bitcoin-energy markets interrelationships - New evidence. <https://doi.org/10.1016/j.resourpol.2020.101916>. *Resources Policy* 70:
10. D'Agostino RB (1970) Transformation to normality of the null distribution of g_1 . *Biometrika* 57:679–681. <https://doi.org/10.1093/biomet/57.3.679>
11. Das D, Dutta A (2020) Bitcoin's energy consumption: Is it the Achilles heel to miner's revenue? *Econ Lett* 186. <https://doi.org/10.1016/j.econlet.2019.108530>
12. de Vries A (2018) Bitcoin's Growing Energy Problem. *Joule* 2:801–805
13. de Vries A, Galleisdörfer U, Klaaßen L, Stoll C (2022) Revisiting Bitcoin's carbon footprint. *Joule* 6:498–502

14. Di Febo E, Ortolano A, Foglia M et al (2021) From Bitcoin to carbon allowances: An asymmetric extreme risk spillover. *J Environ Manage* 298. <https://doi.org/10.1016/j.jenvman.2021.113384>
15. Dogan E, Majeed MT, Luni T (2022) Are clean energy and carbon emission allowances caused by bitcoin? A novel time-varying method. *J Clean Prod* 347. <https://doi.org/10.1016/j.jclepro.2022.131089>
16. Dong X, Jiang Z, Yoon S-M (2024) Impact of global financial and energy markets, uncertainty, and climate change attention on Bitcoin carbon footprint. *Financ Res Lett* 70:106254. <https://doi.org/10.1016/j.frl.2024.106254>
17. Elliott G, Rothenberg TJ, Stock JH (1996) Efficient Tests for an Autoregressive Unit Root. *Econometrica* 64:813–836. <https://doi.org/10.2307/2171846>
18. Erdogan S, Ahmed MY, Sarkodie SA (2022) Analyzing asymmetric effects of cryptocurrency demand on environmental sustainability. *Environ Sci Pollut Res* 29:31723–31733. <https://doi.org/10.1007/s11356-021-17998-y>
19. Fisher TJ, Gallagher CM (2012) New Weighted Portmanteau Statistics for Time Series Goodness of Fit Testing. *J Am Stat Assoc* 107:777–787. <https://doi.org/10.1080/01621459.2012.688465>
20. Gabauer D, Stenfors A (2024) Quantile-on-quantile connectedness measures: Evidence from the US treasury yield curve. *Financ Res Lett* 60. <https://doi.org/10.1016/j.frl.2023.104852>
21. Huynh ANQ, Duong D, Burggraf T, Luong HTT, Bui NH (2022) Energy consumption and Bitcoin market. *Asia-Pac Financ Mark* 29:79–93. <https://doi.org/10.1007/s10690-021-09338-4>
22. Jarque CM, Bera AK (1980) Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Econ Lett* 6:255–259. [https://doi.org/https://doi.org/10.1016/0165-1765\(80\)90024-5](https://doi.org/https://doi.org/10.1016/0165-1765(80)90024-5)
23. Jeong K, Härdle WK, Song S (2012) A consistent nonparametric test for causality in quantile. *Econom Theory* 28(4):861–887. <https://doi.org/10.1017/S0266466611000685>
24. Jiang W, Zhu P, Korkmaz AG, Zhou H (2024) The asymmetric nexus between the cryptocurrency market and the carbon market: Evidence from the quantile-on-quantile method. *J Clim Finance* 7:100037. <https://doi.org/10.1016/j.jclimf.2024.100037>
25. Karmakar S, Demirel R, Gupta R (2021) Bitcoin mining activity and volatility dynamics in the power market. *Econ Lett* 209:110111. <https://doi.org/10.1016/j.econlet.2021.110111>
26. Koenker R, Bassett G (1978) Regression Quantiles. *Econometrica* 46:33–50. <https://doi.org/10.2307/1913643>
27. Kohli V, Chakravarty S, Chamola V et al (2023) An analysis of energy consumption and carbon footprints of cryptocurrencies and possible solutions. *Digit Commun Networks* 9:79–89. <https://doi.org/10.1016/j.dcan.2022.06.017>
28. Kristoufek L (2020) Bitcoin and its mining on the equilibrium path. *Energy Econ* 85. <https://doi.org/10.1016/j.eneco.2019.104588>
29. Küfeoğlu S, Özkuran M (2019) Bitcoin mining: A global review of energy and power demand. *Energy Res Soc Sci* 58
30. Li J, Li N, Peng J et al (2019) Energy consumption of cryptocurrency mining: A study of electricity consumption in mining cryptocurrencies. *Energy* 168:160–168. <https://doi.org/10.1016/j.energy.2018.11.046>
31. Long S, Lucey B, Zhang D, Zhang Z (2023) Negative elements of cryptocurrencies: Exploring the drivers of Bitcoin carbon footprints. *Financ Res Lett* 58. <https://doi.org/10.1016/j.frl.2023.104031>
32. Lorente DB, Mohammed KS, Cifuentes-Faura J, Shahzad U (2023) Dynamic connectedness among climate change index, green financial assets and renewable energy markets: Novel evidence from sustainable development perspective. *Renew Energy* 204:94–105. <https://doi.org/10.1016/j.renene.2022.12.085>
33. Maiti M (2022) Dynamics of bitcoin prices and energy consumption. <https://doi.org/10.1016/j.csfx.2022.10>
34. Maiti M, Vukovic DB, Frömmel M (2023) Quantifying the asymmetric information flow between Bitcoin prices and electricity consumption. *Financ Res Lett* 57. <https://doi.org/10.1016/j.frl.2023.104163>
35. Meiryani M, Delvin Tandyopranoto C, Emanuel J et al (2022) The effect of global price movements on the energy sector commodity on bitcoin price movement during the COVID-19 pandemic. <https://doi.org/10.1016/j.heliyon.2022.e10820>. *Heliyon* 8:
36. Nishiyama Y, Hitomi K, Kawasaki Y, Jeong K (2011) A consistent nonparametric test for nonlinear causality—Specification in time series regression. *J Econom* 165(1):112–127. <https://doi.org/10.1016/j.jeconom.2011.05.010>
37. Othman A, Ben Bob A (2022) Economic Studies Bitcoin Mining's Energy Consumption and Global Carbon Dioxide Emissions: Wavelet Coherence Analysis. *United Arab Emirates*
38. Papp A, Almond D, Zhang S (2023) Bitcoin and carbon dioxide emissions: Evidence from daily production decisions. *J Public Econ* 227. <https://doi.org/10.1016/j.jpubeco.2023.105003>
39. Podhorsky A (2023) Taxing bitcoin: Incentivizing the difficulty adjustment mechanism to reduce electricity usage. *Int Rev Financial Anal* 86. <https://doi.org/10.1016/j.irfa.2023.102493>
40. Polemis ML, Tsionas MG (2023) The environmental consequences of blockchain technology: A Bayesian quantile cointegration analysis for Bitcoin. *Int J Finance Econ* 28:1602–1621. <https://doi.org/10.1002/ijfe.2496>
41. Qin M, Wu T, Ma X et al (2023) Are energy consumption and carbon emission caused by Bitcoin? A novel time-varying technique. *Econ Anal Policy* 80:109–120. <https://doi.org/10.1016/j.eap.2023.08.004>
42. Sapra N, Shaikh I (2023) Impact of Bitcoin mining and crypto market determinants on Bitcoin-based energy consumption. *Managerial Finance* 49:1828–1846. <https://doi.org/10.1108/MF-03-2023-0179>

43. Sapra N, Shaikh I, Roubaud D et al (2024) Uncovering Bitcoin's electricity consumption relationships with volatility and price: Environmental Repercussions. *J Environ Manage* 356. <https://doi.org/10.1016/j.jenvman.2024.120528>
44. Sarker PK, Lau CKM, Pradhan AK (2023) Asymmetric effects of climate policy uncertainty and energy prices on bitcoin prices. *Innov Green Dev*. <https://doi.org/10.1016/j.igd.2023.100048>. 2:
45. Sarkodie SA, Ahmed MY, Leirvik T (2022) Trade volume affects bitcoin energy consumption and carbon footprint. *Financ Res Lett* 48. <https://doi.org/10.1016/j.frl.2022.102977>
46. Sarkodie SA, Amani MA, Ahmed MY, Owusu PA (2023) Assessment of Bitcoin carbon footprint. <https://doi.org/10.1016/j.horiz.2023.100060>. *Sustainable Horizons* 7:
47. Sharma GD, Shahbaz M, Singh S et al (2023) Investigating the nexus between green economy, sustainability, bitcoin and oil prices: Contextual evidence from the United States. <https://doi.org/10.1016/j.resourpol.2022.103168>. *Resources Policy* 80:
48. Sim N, Zhou H (2015) Oil prices, US stock return, and the dependence between their quantiles. *J Bank Financ* 55:1–8. <https://doi.org/10.1016/J.JBANKFIN.2015.01.013>
49. Stoll C, Klaaßen L, Gellersdörfer U (2019) The Carbon Footprint of Bitcoin. *Joule* 3:1647–1661. <https://doi.org/10.1016/j.joule.2019.05.012>
50. Tissaoui K, Zaghdoudi T, Boubaker S et al (2024) Testing the Nonlinear Long- and Short-Run Distributional Asymmetries Effects of Bitcoin Prices on Bitcoin Energy Consumption: New Insights through the QNARDL Model and XGBoost Machine-Learning Tool. <https://doi.org/10.3390/en17122810>. *Energies* 17:
51. Xiao Z, Cui S, Xiang L et al (2023) The environmental cost of cryptocurrency: Assessing carbon emissions from bitcoin mining in China. *J Digit Econ* 2:119–136. <https://doi.org/10.1016/j.jdec.2023.11.001>
52. Yan L, Mirza N, Umar M (2022) The cryptocurrency uncertainties and investment transitions: Evidence from high and low carbon energy funds in China. *Technol Forecast Soc Change* 175. <https://doi.org/10.1016/j.techfore.2021.121326>
53. Yousaf I, Mohammed KS, Yousaf U, Bin, Serret V (2025) The effect of crypto price fluctuations on crypto mining, and CO2 emissions amid geopolitical risk. *Financ Res Lett* 72. <https://doi.org/10.1016/j.frl.2024.106551>
54. Yuan X, Su CW, Peculea AD (2022) Dynamic linkage of the bitcoin market and energy consumption: An analysis across time. *Energy Strategy Reviews* 44. <https://doi.org/10.1016/j.esr.2022.100976>
55. Zhang D, Chen XH, Lau CKM, Xu B (2023) Implications of cryptocurrency energy usage on climate change. *Technol Forecast Soc Change* 187. <https://doi.org/10.1016/j.techfore.2022.122219>

Footnotes

1. For instance, after China imposed restrictions on blockchain-based mining in 2021, numerous mining enterprises moved to regions with more favorable regulations and access to cheaper or renewable energy sources (see (de Vries et al. 2022))
2. Log returns span the period September 17, 2014, to December 17, 2024.
3. <https://www.cnn.com/2022/11/11/crypto-peaked-in-nov-2021-investors-lost-more-than-2-trillion-since.html>

Figures

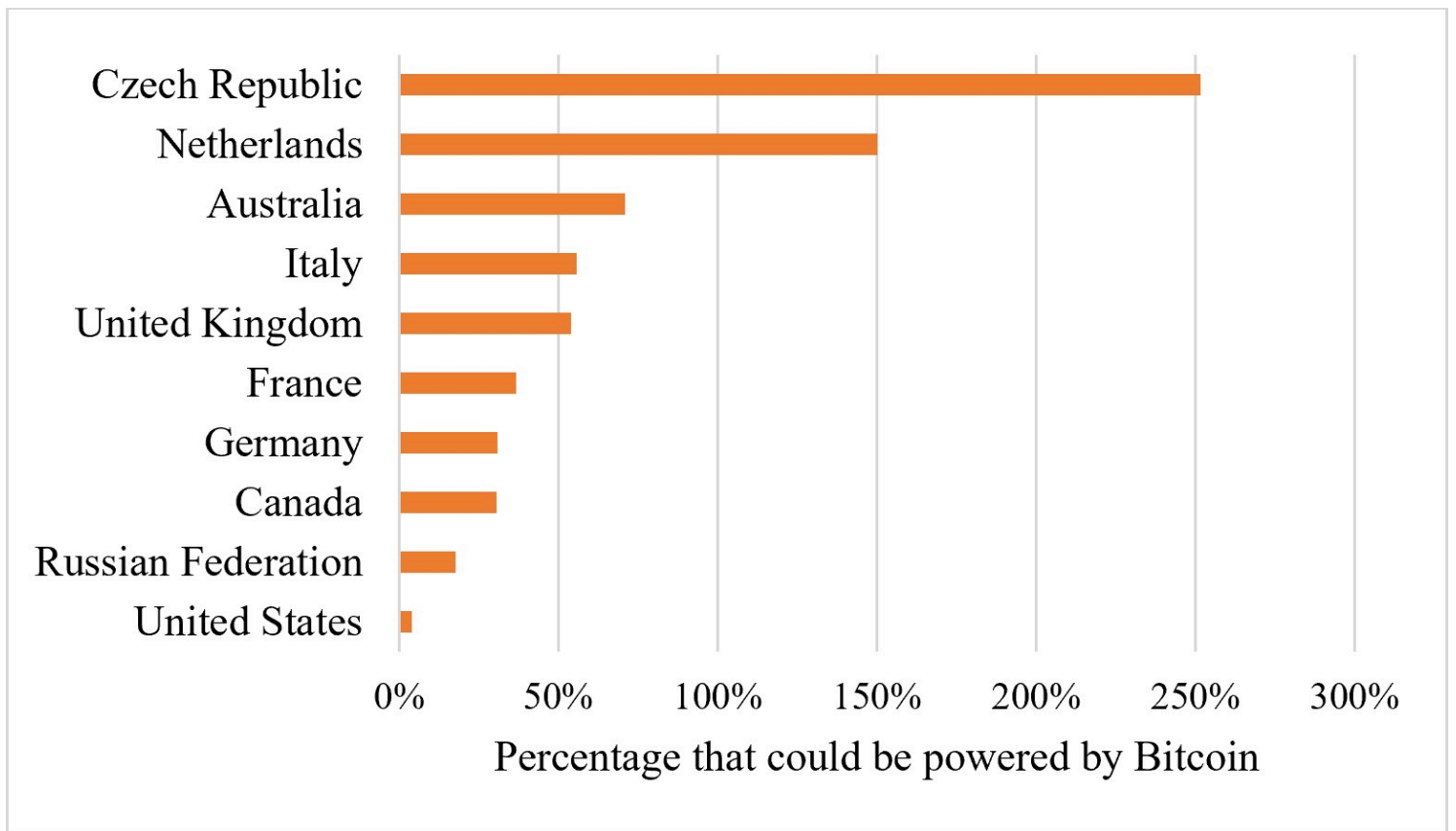


Figure 1

Bitcoin's Energy Consumption Relative to Several Countries

Source: Digiconomist. <https://digiconomist.net/bitcoin-energy-consumption> (Retrieved on February 11, 2025)

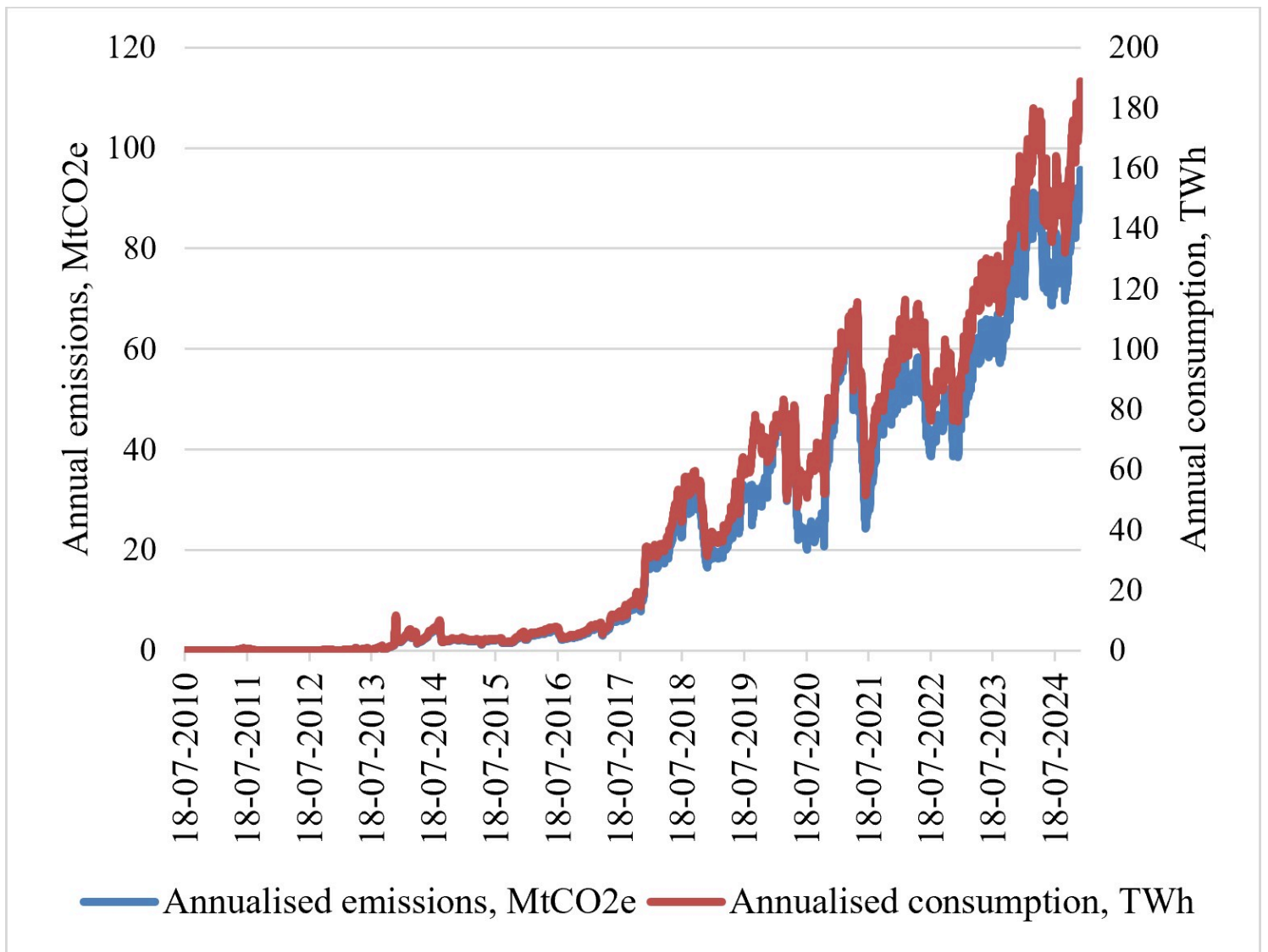


Figure 2

Estimated Annual Bitcoin Electricity Usage and CO₂ Emissions

Notes: TWh is terawatt-hour, and MtCO₂e is million tonnes of carbon dioxide equivalent

Source: The Cambridge Centre for Alternative Finance (CCAF). <https://ccaf.io/cbnsi/cbeci> (Retrieved on February 11, 2025)

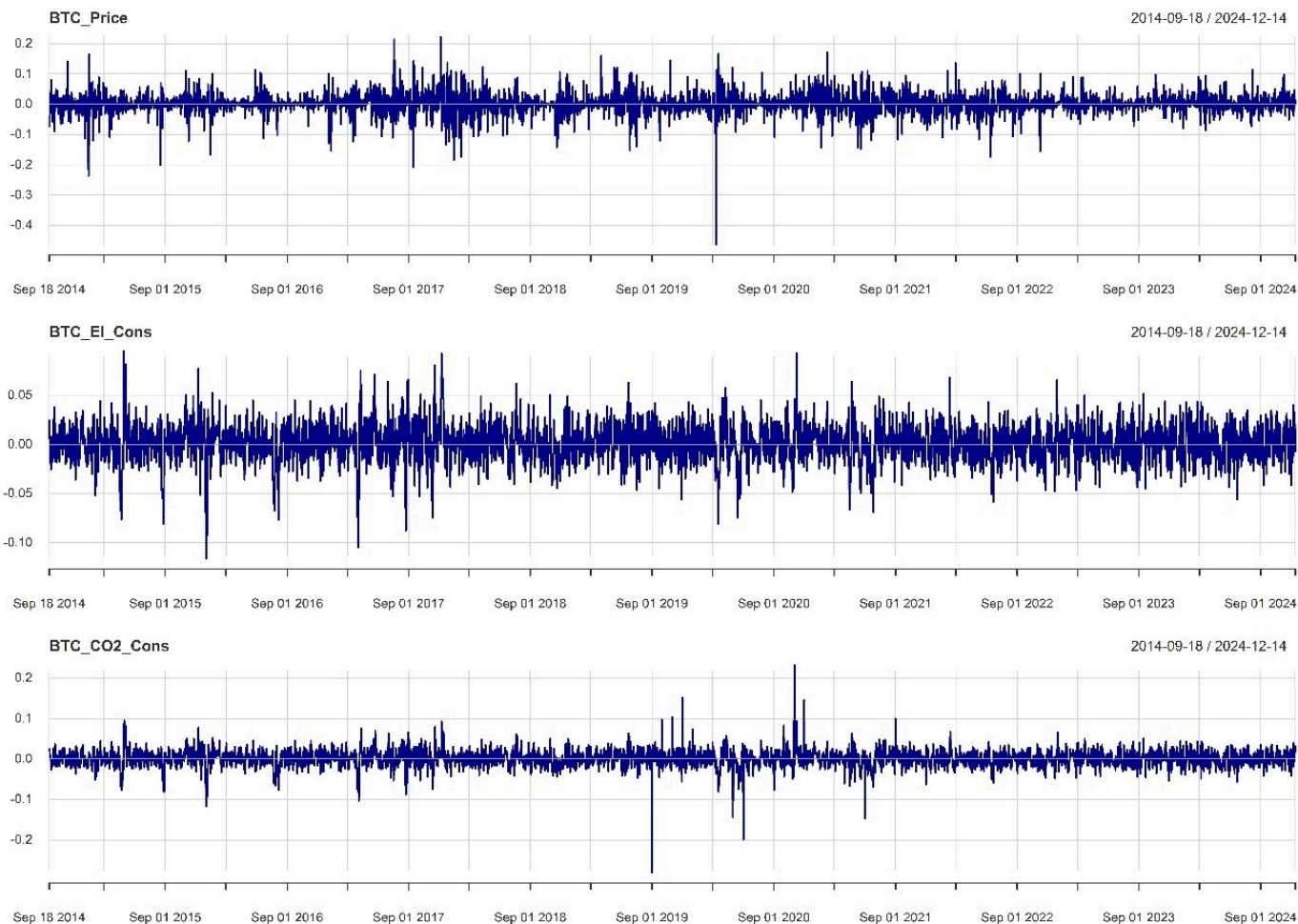


Figure 3

Trends in Returns

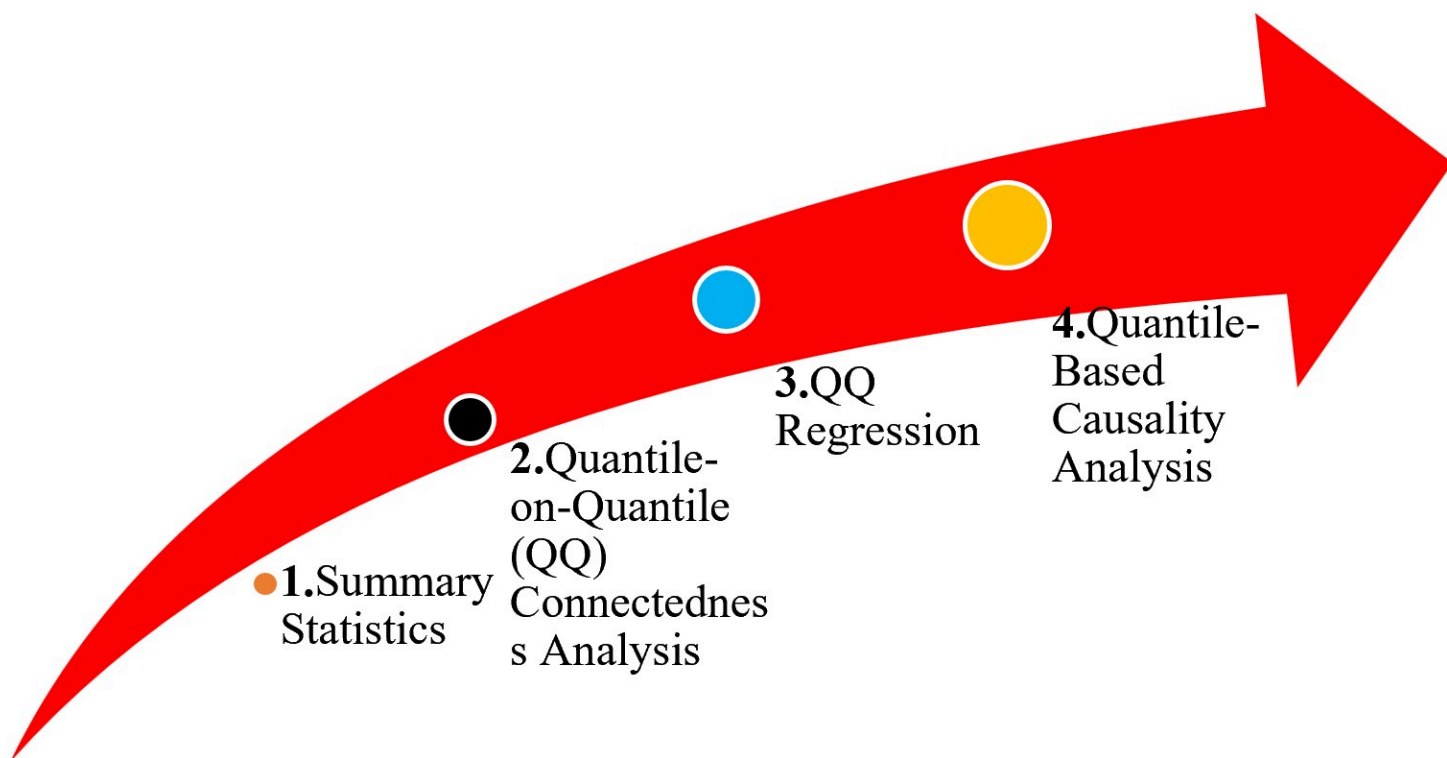


Figure 4



Figure 5

Dynamic directly- and reversely related quantiles overall connectedness

Notes: The results are obtained from a QVAR (τ_1, τ_2) model with a 200-day rolling window, employing a lag length of 1 as determined by the Bayesian Information Criterion (BIC) and producing a 20-step-ahead forecast.

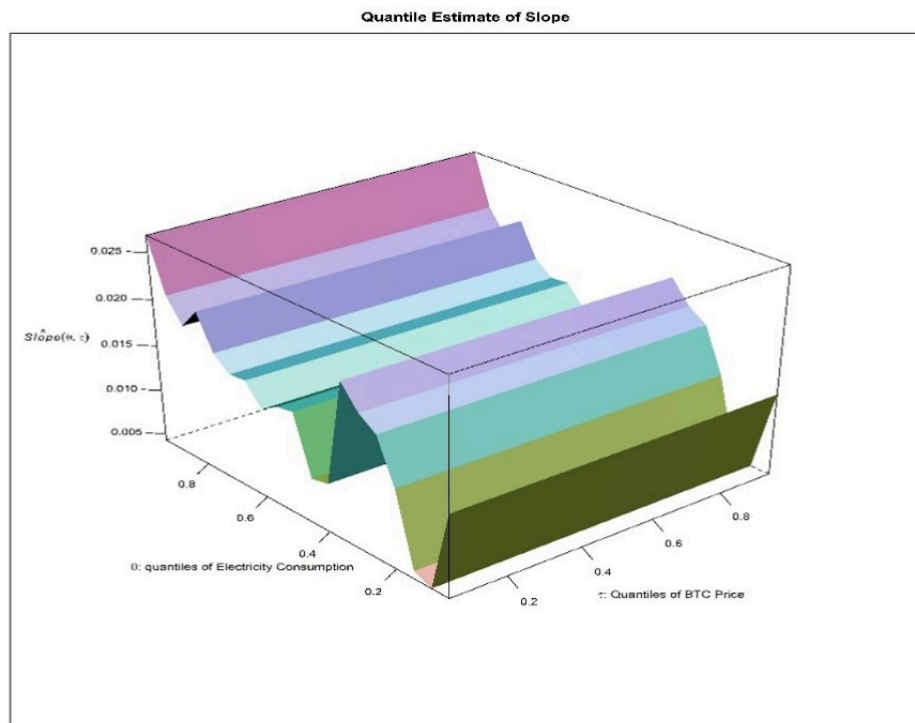


Figure 6

QQ regressions-based estimated impact of electricity consumption on Bitcoin price

Notes: x-axis: quantiles of electricity consumption, y-axis: quantiles of Bitcoin price, z-axis: slope

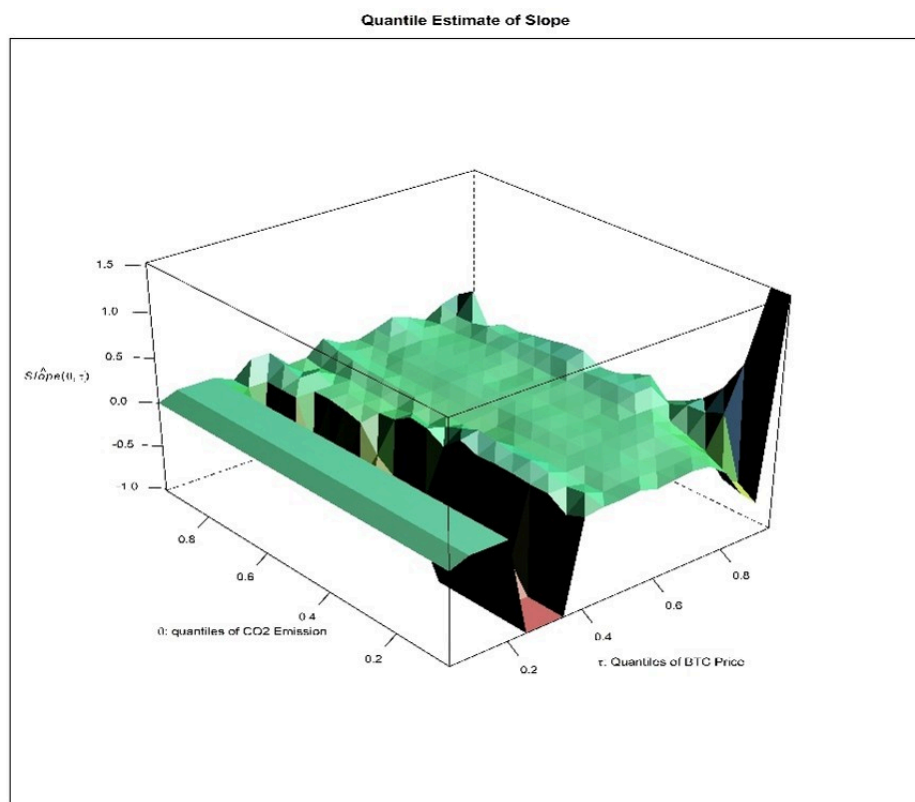


Figure 7

QQ regressions-based estimated impact of CO₂ emission on Bitcoin price

Notes: x-axis: quantiles of CO₂ emission, y-axis: quantiles of Bitcoin price, z-axis: slope

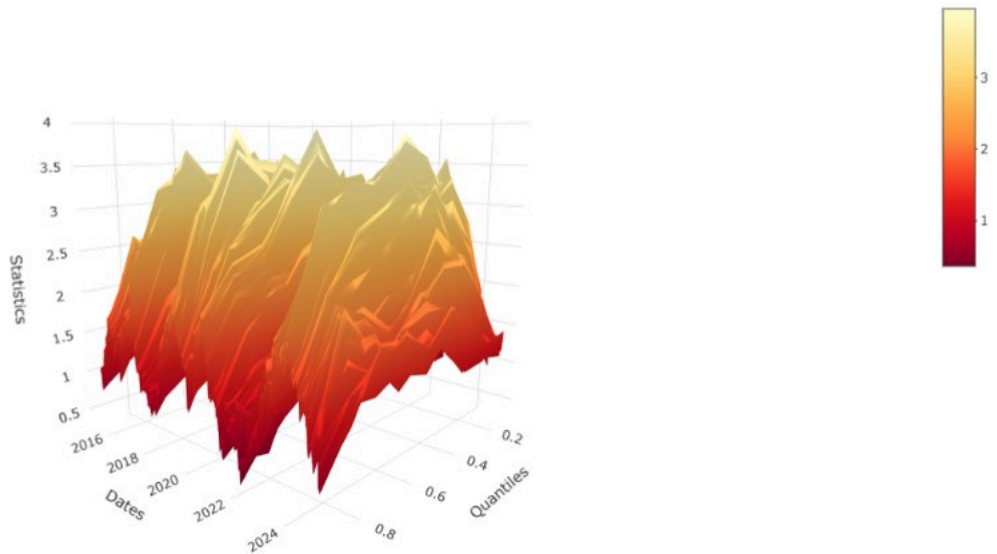


Figure 8
Causality-in Quantiles-based estimated impact of electricity consumption on Bitcoin price

Notes: x-axis: quantiles of electricity consumption, y-axis: dates, z-axis: statistics

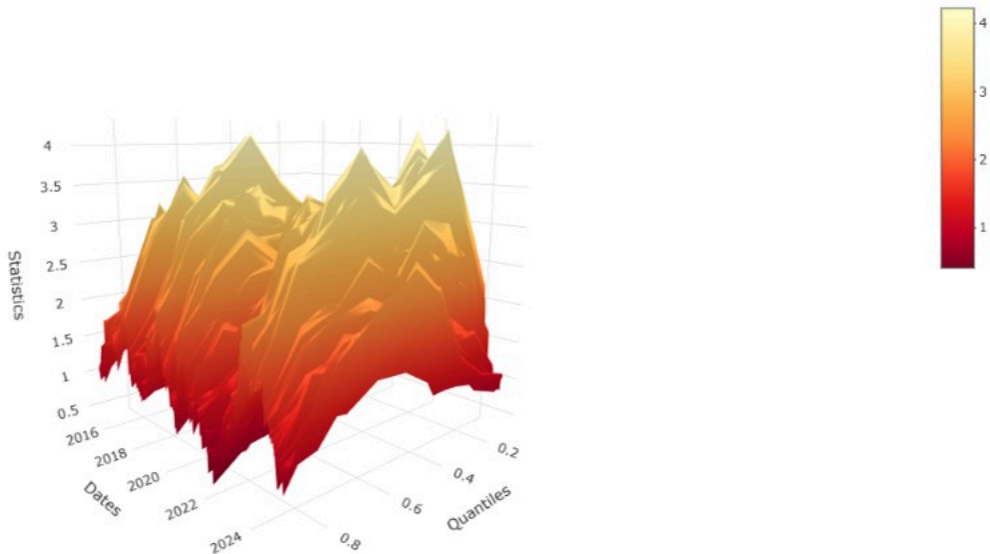


Figure 9
Causality-in Quantiles-based estimated impact of CO₂ emission on Bitcoin price

Notes: x-axis: quantiles of CO₂ emission, y-axis: dates, z-axis: statistics

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [ReplicationCode.r](#)

- [bitcoinpriceandlogreturns20140917to20241217.csv](#)
- [BitcoinsannualisedelectricityconsumptionTWh.xlsx](#)
- [BitcoinCO2Emissions.csv](#)