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Identifying the key drivers of Bitcoin's emissions

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This study examines the environmental impact of blockchain technology operating under the Proof-of-Work (PoW) algorithm, with a focus on Bitcoin's (BTC) carbon footprint. Utilizing a comprehensive dataset comprising 2895 daily observations from 2014 to 2021, we analyze key mining-related variables—miner efficiency, miner revenues, total BTC mined, mining difficulty, and hash rate—through the application of a Bayesian Vector Autoregression (BVAR) model to evaluate their effects on CO_2 emissions over time. The primary objective is to identify the main determinants influencing BTC's carbon footprint within the current mining landscape. Our results indicate that BTC CO_2 emissions and mining difficulty are the most significant factors affecting carbon emissions. As mining difficulty increases—typically due to the entry of more miners and the deployment of more powerful hardware—profit margins decrease. High-cost, energy-intensive rigs may temporarily cease operations, leading to a reduction in output and a shift towards more efficient equipment. These findings reinforce and expand upon previous research by elucidating both the causal and time-varying dynamics of mining in relation to environmental outcomes. The results underscore the necessity for policies and industry practices that promote the adoption of more energy-efficient mining hardware and encourage the use of renewable energy sources in cryptocurrency mining. Supporting technological innovation and sustainable energy integration is essential for mitigating the environmental footprint associated with PoW-based blockchain systems such as BTC.

Environmental significance

BTC mining, operating under the PoW algorithm, significantly contributes to the increasing global CO_2 emissions due to its substantial energy demands. This study offers a comprehensive quantitative assessment of the primary factors influencing BTC's carbon footprint, particularly focusing on mining difficulty and energy consumption. Utilizing a Bayesian VAR model applied to an extensive dataset, the research identifies the correlation between rising computational demand and increased reliance on fossil fuel-based energy sources. The findings underscore the urgent need for a transition to more efficient mining technologies and renewable energy alternatives. As BTC continues to gain economic prominence, addressing its environmental impact is essential to align with global climate objectives and sustainable development pathways.

Introduction

Following the introduction of BTC, blockchain technology has been adopted across various domains, including international trade financing, supply chain and logistics, and energy. However, it is essential to consider consensus mechanisms to ensure the security and integrity of the blockchain across these platforms. It is well-documented that platforms utilizing the PoW consensus mechanism exhibit significant energy consumption.[1,2] The PoW mechanism is fundamentally dependent on mining activities, which entail substantial energy expenditure in the generation of BTC. Consequently, the high energy consumption associated with BTC raises critical environmental concerns due to its carbon footprint. Previous studies have underscored the extent of energy consumption and the associated carbon footprint issues related to BTC. This excessive energy usage and carbon footprint, particularly stemming from fossil fuel reliance in generation, contribute to pressing global challenges such as the climate crisis and the sustainability of energy sources. In light of these concerns, this study seeks to address the following research question: What are the key determinants of BTC's carbon footprint in PoW-based blockchain technologies, and how can the environmental impacts arising from the PoW algorithm be assessed in the context of existing literature? To guide the empirical analysis and provide a testable framework for answering this research question, we propose the following hypotheses:

H1: it is expected that increases in mining difficulty reduce miners' profit margins and thereby influence energy consumption, which may affect overall CO_2 emissions.

H2: a higher hash rate is expected to increase CO_2 emissions due to the greater computational power required.

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H3: improvements in miner efficiency (generating more output per unit of energy) are expected to decrease CO_2 emissions.

H4: increases in miner revenues are expected to encourage greater mining activity, leading to higher CO_2 emissions.

H5: higher levels of BTC mined and greater activity intensity are expected to raise energy demand and, in turn, CO_2 emissions.

BTC and PoW algorithm

The first sector to adopt blockchain technology was BTC. Following the introduction of BTC, blockchain technology has been applied across various domains, including international trade financing, supply chain and logistics, and energy. In these areas, consensus mechanisms play a crucial role in ensuring the security and integrity of the blockchain. Platforms that employ the PoW consensus mechanism are noted for their high energy consumption. This mechanism relies on mining activities, and the significant energy demands associated with mining contribute to an increase in carbon footprint.

The PoW consensus algorithm is a prominent and widely recognized mechanism, particularly in conjunction with BTC. For a transaction to be considered valid within the BTC blockchain, a supermajority consensus must be achieved through votes cast by the system's participants, facilitated by this mechanism. PoW provides a framework that rewards individuals, or miners, who solve complex cryptographic puzzles, thereby verifying transactions and creating new blocks. Two critical factors influence this system: processing power and the number of miners. The algorithm is theoretically more secure as both processing power and the number of miners increase. PoW is specifically designed to mitigate denial-of-service attacks, spam, and Sybil attacks.[3] The underlying hash algorithms of PoW cryptocurrencies are essential in determining the efficiency of mining operations. However, the current PoW mechanism poses significant environmental sustainability challenges due to its substantial energy consumption. While alternative consensus mechanisms, such as Proof of Stake (PoS), offer reduced environmental impacts, PoW continues to be widely utilized and is associated with considerably higher carbon emissions than PoS,[4] making its environmental implications a critical concern.

The environmental impacts of BTC have sparked discussions regarding blockchain mining technologies, particularly those employing PoW consensus. To identify the factors contributing to BTC's carbon dioxide (CO_2) emissions, this study examined the effects of predetermined variables associated with BTC mining on its carbon footprint. Accordingly, we evaluated BTC mining and its environmental implications. We analyzed selected variables related to BTC mining, comprising 2895 daily frequency data points collected between January 1, 2014, and December 11, 2021, using a Bayesian Vector Autoregression (VAR) model.

Based on a cryptographic framework, BTC can be understood as a system operating within blockchain technology. In essence, it is a decentralized cryptocurrency designed for efficient, low-cost, and secure cash transfer transactions. Key features of the BTC system are outlined below:[5]

- Facilitates decentralized transactions, eliminating the need for a trusted third party.
- Does not permit reversible or alterable transactions.
- Significantly lowers transaction fees due to inherent cost advantages.
- Effectively prevents double-spending.
- Ensures user anonymity.

BTC guarantees the security of transactions through blockchain technology. Furthermore, it serves as a payment tool that minimizes transaction costs, facilitates swift payments, and ensures confidentiality in the international market.[6]

BTC mining

BTC is a peer-to-peer (P2P) digital exchange platform that facilitates decentralized transactions through a distributed system.[5] BTC miners, responsible for verifying the processing of BTC transfers to the global ledger on the blockchain, are rewarded with cryptocurrency.[7]

BTC is generated not from a centralized source, but through the processing power of volunteer computers within a decentralized global network. Its open-source nature enables anyone who joins the BTC network to participate in the generation of Bitcoin. BTC mining occurs when miners solve complex encrypted mathematical problems, with the miner who successfully solves the problem receiving a reward of BTC.[8] There are two primary sources of mining rewards for BTC. The first is the transaction fee component. The total transaction fee is always greater than the fee transferred to the recipient's account, and the difference is awarded to miners as a transfer reward fee. On average, miners on the BTC network discover a new solution approximately every 10 minutes, which verifies the validity of the preceding 10 minutes' transactions, resulting in rewards of new BTC. Additionally, each new block includes an inherent coin reward—brand new BTC—until the total supply reaches 21 million coins. This reward is halved every 210 000 blocks,[9] meaning that the total number of BTC is programmed to asymptotically approach a maximum of 21 000

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000.[10] The halving process will continue until the final block is mined. Given that the average time to mine and save each block is 10 minutes, it is estimated that the last block will be mined by the year 2140.

The following outlines key information essential to mining:

PoW: in the BTC system, a new block is generated approximately every 10 minutes through the calculation of its difficulty value using the PoW protocol and the SHA-256 encryption algorithm. The creation of these blocks necessitates that computers perform complex mathematical calculations and execute transfer operations associated with the proposed blocks. Consequently, individuals who successfully validate these transactions are rewarded with BTC and receive a transfer fee for each block.[5] BTC employs the PoW consensus mechanism to mitigate the risk of double spending and to prevent manipulation within the blockchain.[11]

Hash rate: the hash rate, defined as the total computational power dedicated to mining, serves as a critical indicator of the significance of BTC mining. Specifically, a rate of 1 terahash per second (1 Th s^{-1}) equates to 1 trillion calculations per second.[12] The escalating difficulty of the BTC algorithm necessitates greater mining power, which in turn contributes to rising operational costs.[51] Fig. 1 illustrates the progression of the hash rate from 2019 to 2022. Consequently, the upward trend in the hash rate over these years suggests that the energy requirements for BTC mining are likely to continue increasing.

Difficulty: difficulty is defined as the effort required validating a block within the blockchain. More specifically, it represents the probability of solving the hash function.[12] Additionally, difficulty serves as a measure of the time required to compute the hash value of a specific node in relation to the target value. However, the rapid influx of new miners into the system is significantly increasing the difficulty level across the network.[13] Currently, an average of one block is mined approximately every 10 minutes, based on the existing difficulty value.

Mining return: this is the value derived from multiplying the daily amount of BTC mined, inclusive of transaction fees, by the current market value.[14] Factors influencing mining returns primarily include the price of BTC, halving events, elevated transaction fees, and mining difficulty.[15]

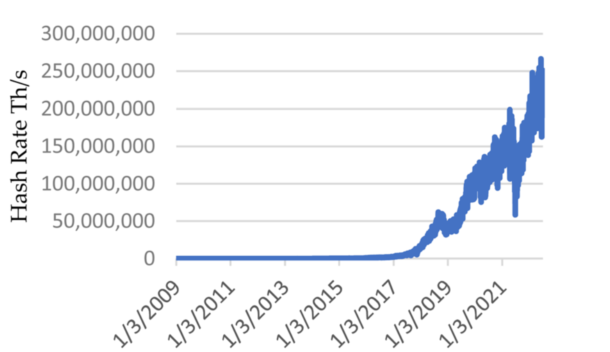

Fig. 1 Hash rates between 2019 and 2022. *Source: Nasdaq Hash (2023).

Efficiency is defined as the hash power—the total operational speed of the mining rigs used to generate BTC—divided by the energy consumed.[14] Sustainable mining operations depend on affordable energy sources and efficient practices.[15] As the number of processors contributing to the network continues to grow, computing power is expanding significantly. Initially, Bitcoin mining was conducted using CPU mining, which was profitable in the early years when rewards could reach 50 BTC. However, the reward has since decreased to 6.25 BTC, and CPU mining has become inefficient, as the energy consumed in relation to the BTC earned is now greater. Consequently, GPU mining utilizing advanced graphics cards has emerged as a more advantageous and efficient method.[16,17] Nonetheless, the continually increasing difficulty level necessitates the use of specialized devices, such as next-generation ASIC miners designed specifically for mining, indicating that technology will need to evolve consistently to enhance the efficiency and sustainability of mining operations.[17]

BTC and environment

BTC should be regarded as more than merely a digital currency. It is produced through blockchain technology, which entails significant electricity consumption, cooling expenses, and a complex algorithm.[18] Nakamoto (2008)[5] highlighted the ongoing improvements in mining hardware efficiency as a means to mitigate high electricity consumption. However, since 2013, the costs associated with energy, maintenance of cooling facilities and infrastructure, as well as the acquisition and upgrading of mining hardware, have continued to rise due to increasing computational challenges and the necessity for specialized mining equipment.[4]

Anticipating global actions against climate crises, the Paris Agreement highlights that the existing BTC system poses a significant threat to the implementation of international agreements.[19] Despite its potential as a transformative technology across various sectors, the excessive energy consumption and carbon footprint associated with cryptocurrencies appear to exacerbate global warming. It is estimated that BTC alone could contribute to a 2 °C increase in global temperatures over the next 30 years.[20] Additionally, numerous studies examining the impact of BTC's CO_2 emissions on climate change have emerged in recent years, identifying several factors that mediate BTC's environmental effects. Stoll *et al.* (2019)[11] calculated that BTC's annual electricity consumption was 45.8 TWh, with annual CO_2 emissions ranging between 22.0 and 22.9 million tons as of November 2018. These estimates suggest that emissions from BTC are roughly equivalent to those generated by countries such as Jordan, Sri Lanka, and even Canada. De Vries (2019)[16] asserted that BTC's energy consumption in 2018 resulted in a carbon footprint of between 19.0 and 29.6 million tons of CO_2 (475 g CO_2 per kWh). He further assessed that the average carbon footprint per transaction varied between 233.4 and 363.5 kg CO_2. In comparison, the average carbon footprint for a VISA transaction is approximately 0.4 g of CO_2, while a Google search generates a carbon footprint of about 0.8 g of CO_2.

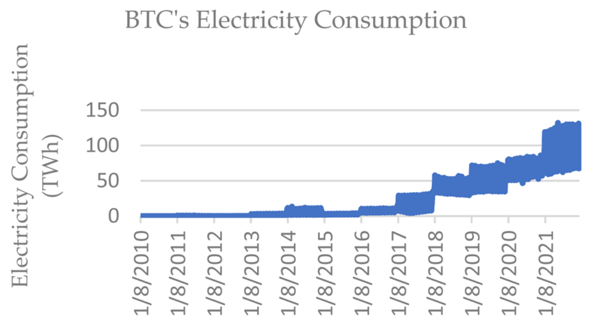

Fig. 2 BTC electricity consumption between 2010 and 2021.

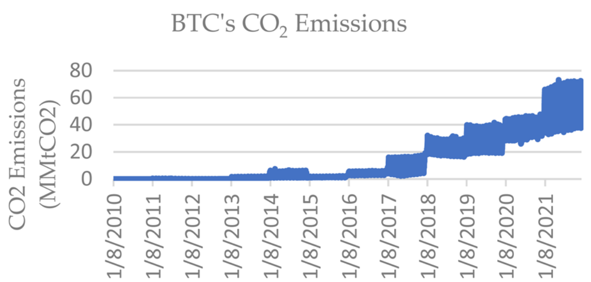

Fig. 3 BTC CO_2 emissions between 2010 and 2021.

Sarkodie *et al.* (2022)[25] observed that while an increase in BTC trade volume could elevate both BTC's carbon footprint and energy consumption by 24% in the long term, a dynamic shock in trade volume could contribute to these variables by 46.54%. In a separate study, Kohli *et al.* (2022)[23] stated that BTC consumes as much energy as Sweden. Furthermore, it was revealed that BTC's CO_2 emissions nearly align with those of Greece. Jungblut (2019)[48] concluded that cryptocurrencies are significant contributors to the global carbon footprint, noting that the energy consumed by a single BTC account is approximately equivalent to the energy consumption of a refrigerator over eight months. Gallersdörfer *et al.* (2020)[28] assessed the energy consumption of cryptocurrencies and BTC based on the algorithms specified in their study, current hash rates, and mining devices. They concluded that BTC accounts for two-thirds of the total energy consumption. As illustrated in Fig. 2 and 3, both electricity consumption and carbon footprint data for BTC have shown an upward trend over the years. Additionally, Das and Dutta (2019)[40] argue that BTC mining is not sustainable without the implementation of efficient mining practices and access to inexpensive electricity sources.

The reliance on fossil fuels for BTC mining, combined with significant energy consumption, raises concerns about the sustainability of this practice. A study[4] conducted by Cambridge University examined the environmental impacts of PoW mining to assess the extent of renewable energy utilization in mining operations and the proportion of total energy consumed from these sources. The 2020 report indicated that 76% of miners utilize renewable energy sources; however, only 39% of the energy consumed in mining activities is derived from renewables. The report highlighted that approximately 29% of BTC mining is powered by renewable energy sources. Table 1 illustrates the variety of energy sources employed in PoW mining across different geographical regions. Notably, hydroelectric energy is the predominant source, accounting for 60% of usage, while the adoption of low-cost renewable energy sources, such as solar and wind, remains limited. Nonetheless, as reported by the BTC Mining Council,[47] 58.4% of BTC mining activities utilized renewable energy sources in 2022, marking a 59% increase in the adoption of sustainable energy compared to the previous year. These findings suggest that the sector is experiencing a positive shift towards greater sustainability. Furthermore, the 59% increase in the utilization of sustainable energy in BTC mining compared to the prior year indicates progress in mitigating the environmental impact of mining activities.

The transition from conventional, non-renewable energy sources to sustainable and environmentally friendly alternatives in mining operations will result in reduced fossil fuel consumption and a subsequent decrease in the carbon footprint of BTC mining. These advancements can be viewed as a positive progression towards fulfilling the environmental responsibilities associated with BTC mining.

Literature review

The literature review analyzed studies on BTC's energy consumption and carbon footprint, as detailed in Table 2.

Table 1 Regional distribution of PoW energy sources[a]

Energy sources	Asia-Pacific	Europe	Latin America and the Caribbean	North America
Renewable energy sources				
Hydroelectric	65%	60%	67%	61%
Wind	23%	7%	0%	22%
Solar	12%	13%	17%	17%
Jeotermal	8%	0%	0%	6%
Nuclear	12%	7%	0%	22%
Fossil fuels				
Natural gas	38%	33%	17%	44%
Coal	65%	2%	0%	28%
Petrol	12%	7%	33%	22%

[a] Source: Blandin *et al.*, 2020.[21]

Table 2 Previous research on BTC energy consumption and carbon footprint

Author(s), year	Research objective(s)	Findings/conclusions
Bajra *et al.* (2024)[4]	This study investigates the environmental impact of cryptocurrency blockchains—focusing on Bitcoin (PoW) and Ethereum (PoS)—by examining how consensus mechanisms relate to carbon footprint; it also explores post-China relocation patterns, halving dynamics, and policy implications for future sustainability	The analysis finds a strong positive link between Proof-of-Work (PoW) adoption and carbon emissions, while Proof-of-Stake (PoS) is associated with much lower emissions per transaction The relocation of mining from China to the U.S./Europe is not sufficient on its own to reduce emissions; real reductions require a transition to verifiable low-carbon electricity. It also notes that halving events are expected to increase network difficulty and energy needs, underscoring the need for responsible innovation, transparent report Research method: instrumental variables regression
Stoll *et al.* (2023)[22]	This study provides empirical evidence on the extent and energy sources of Bitcoin mining in the U.S., measures the share that had shifted to the U.S. and Canada by end-2022, and assesses miners' carbon intensity and annual emissions using disclosures from publicly listed firms	This study shows that after 2021, a substantial share of Bitcoin mining shifted to North America—especially Texas—turning it into a new hub. Grid data and simultaneous changes in network activity confirm this relocation. However, moving operations to the U.S./Canada alone does not reduce emissions, because miners typically draw electricity with a carbon intensity close to the grid average. To mitigate the climate impact, the sector needs a verified transition to low-carbon electricity (*e.g.*, renewables) alongside clear, standardized reporting
Kohli *et al.* (2022)[23]	This study compared the energy consumption and carbon footprints of cryptocurrencies between countries and with centralized transaction methods (*e.g.*, Visa). Moreover, it attempted to identify cryptocurrency-related problems and identify solutions to help reduce the energy consumption and carbon footprints of these currencies	The results revealed that BTC and Ethereum consume as much energy as Sweden and Romania. Additionally, the CO_2 emissions of BTC and Ethereum almost overlap with those of Greece and Tunisia, respectively. In addition, Visa was found to be much more energy efficient and has a lower carbon footprint per transaction compared to the cryptocurrencies discussed in this review. The research concluded that wind and solar energy may be the best alternative energy sources for blockchain networks. Using such renewable energy sources would make the excessive energy consumption of PoW cryptocurrencies more environmentally friendly. The researchers also recommended that countries with high cryptocurrency mining invest in renewable energy Research method: conceptual
Sarkodie and Owusu (2022)[24]	The authors collected 4158 daily frequency data on the annual carbon footprint to assist prospective researchers in varying disciplines	The paper offers 4158 pieces of daily frequency data generated on BTC's annual carbon footprint between July 7, 2010 and December 4, 2021. The data consisted of annual carbon footprints of 12 variables (*e.g.*, coal, oil, and gas) and were collected from three sources. BTC's carbon footprint data are presented in kg/CO_2 based on emission factors for electricity generation from the IEA World Energy Outlook. The data are believed to contribute to multidisciplinary research on cryptocurrency in the fields of, for example, environment, energy, and economics

Table 2 (*Contd.*)

Author(s), year	Research objective(s)	Findings/conclusions
Sarkodie *et al.* (2022)[25]	This research adopted various empirical techniques to examine the relationships between financial indicators and BTC's energy consumption and carbon footprint	The findings showed that while an increase in BTC trade volume could increase both BTC's carbon footprint and energy consumption by 24% in the long run, a dynamic shock in trade volume could contribute to these variables by 46.54%. The authors suggested a significant relationship between the financial indicators addressed in the study (*e.g.*, market value, market price, and trading volume) and BTC's energy consumption and carbon footprint Research method: dynamic autoregressive distributed lag (ARDL) simulations and general-to-specific VAR estimation
Yılmaz & Kaplan (2022)[26]	These scholars scrutinized the multifaceted effects of cryptocurrency mining operations on environmental sustainability, global warming, and climate change	The findings demonstrated that the alarming amounts of energy consumed by cryptocurrency mining and the CO_2 emissions and resulting electronic waste have significant adverse environmental effects (*e.g.*, global warming, climate change, and air pollution) and that both cryptocurrency markets and environmental sustainability may be ruined unless these effects are attenuated. To reduce such effects and boost the efficiency of the hardware designed for crypto mining, relevant parties should take innovative steps to introduce new legal regulations, utilize different proof protocols, and encourage the use of renewable energy sources in mining Research method: conceptual
Koch (2021)[27]	A critical requirement for sustainability is not to strain natural resources to a great extent for the sake of blockchain technology but to maintain ecological balance. It is also claimed that blockchain technology has led to increased CO_2 emissions and, therefore, environmental problems. In this study, the authors addressed the ecological effects of blockchain technology and pinpointed how it can be evolved to help the environment and sustainable development with supplementary measures	The energy required to perform blockchain transactions from coal and thermal power plants results in increased CO_2 emissions, contributing to global warming, air pollution, and even mortality. Considering the measures against global warming and climate change specified in the Paris Agreement, this study proposes the impact of blockchain technology on recycling, energy functionality, environmental agreements, collaborations with non-profit organizations, CO_2 emission tax, and changing incentive mechanisms Research method: conceptual
Polemis *et al.* (2021)[14]	This research aimed to reveal the driving forces behind BTC's carbon footprint	The findings confirm a causal relationship between BTC use and CO_2 emissions in terms of increased energy load. The researchers also concluded a negative significant correlation between BTC miner revenues and CO_2 emissions. Overall, this study recommends that a strategy focusing on the use of renewable energy sources as well as energy-efficient mining hardware would reduce BTC's carbon footprint Research method: Bayesian cointegration analysis
Gallersdörfer *et al.* (2020)[28]	This study investigated the energy consumption of 19 mineable cryptocurrencies as well as BTC	Based on the algorithms set used in the study, current hash rates, and suitable mining devices, the authors concluded that while BTC accounts for 2/3, the remaining cryptocurrencies addressed represent 1/3 of the total energy consumption Research method: conceptual

Table 2 (*Contd.*)

Author(s), year	Research objective(s)	Findings/conclusions
Köhler & Pizzol (2019)[29]	This study aimed to measure the environmental impacts of mining BTC, the most widely known blockchain-based cryptocurrency, and contribute to debates on the excessive energy consumption and carbon footprint that blockchain technology is thought to create	Given the methods to calculate carbon footprint: • Stoll *et al.*[11] calculated carbon footprint by multiplying average emission factors in each country by their electricity consumption • Digiconomist asserted that 70% of miners are located in China, and about 30% are powered by renewable energy with a zero-carbon footprint. It reached this conclusion by multiplying the average emission factor in China by 0.7 • McCook identified emission factors using different global and specific energy sources to calculate the carbon footprint Research method: life cycle analysis and comparison of previous research
Stoll *et al.* (2019)[11]	This study offered empirical data on BTC's carbon footprint. The results are thought to help policymakers set relevant rules for the reasonable adoption of blockchain technology	The verification process of BTC is known to require large amounts of electricity consumption. The analysis showed that BTC's annual electricity consumption was 45.8 TWh and that its annual CO_2 emissions varied between 22.0–22.9 MT CO_2 as of November 2018. In this sense, these estimated figures imply that BTC-led emissions are almost equivalent to the amount generated in Jordan, Sri Lanka, and even Canada Research method: BTC's carbon footprint was calculated by multiplying the average emission factors in each country by their electricity consumption

These studies evaluated the environmental impacts of cryptocurrencies, addressing significant issues such as global warming, climate change, and air pollution. The research underscores the necessity for innovative solutions to mitigate these impacts.

There are two significant gaps in the existing literature. Firstly, while the majority of studies focus on quantifying the electricity consumption associated with BTC mining, they often overlook the examination of causal relationships and time-varying effects. Secondly, there are relatively few studies that concurrently address the primary determinants of BTC's carbon footprint—such as mining difficulty, hash rate, and miner revenue—within a multivariate framework. In this study, we utilize a comprehensive time-series dataset comprising 2895 days from 2014 to 2021 and employ a Bayesian VAR model to analyze not only the contemporaneous effects of individual variables but also the influence of their past and present values on each other and on carbon emissions over time.

Data and methodology

In this quantitative research, we incorporated secondary data obtained from the sources outlined in Table 4. We identified the following variables to analyze the driving forces behind BTC's CO_2 emissions: miner efficiency (eff), miner revenues (rev), the total number of Bitcoin mined daily in circulation (transactions; tran), difficulty as a measure of the effort required to verify a block in blockchain technology (difficulty), and the estimated computational power per second utilized in mining within the Bitcoin network (hash rate; Table 3).

Model selection

We utilized a Bayesian VAR (BVAR) model to examine the factors influencing CO_2 emissions from BTC mining. BVAR models facilitate flexible modeling of dynamic relationships among variables and help alleviate issues related to over-parameterization, particularly when dealing with limited datasets. Model selection was conducted using the Schwarz criterion, a widely recognized method known for its effectiveness with larger samples. Additional technical details regarding prior selection and estimation procedures can be found in Appendix A.

Bayesian VAR model and methodology

VAR models were popularized by Sims (1980)[52] and are now extensively utilized for multivariate time series analysis[30] and forecasting studies[31] in macroeconomics, finance, and other pertinent fields.[32]

In classical statistics, unknown parameters are treated as constant values. In contrast, Bayesian statistics regard these parameters as random variables, each characterized by its own distribution. The posterior distribution of the parameters is derived using this prior distribution alongside sample information.[33]

Table 3 Variable descriptions

	Variables	Description	Formula	Source
Dependent variable	CO_2 (BTC CO_2 emissions)	Estimated CO_2 emissions for BTC mining in kg CO_2eq. per kWh per day: electrical load (ELE) × average emission factor (AVEF)	CO_2 = ELE × AVEF	Stoll *et al.* (2019);[11] Polemis *et al.* (2021)[14]
		Energy consumption (EC) [kWh] × coal/gas/oil CO_2 emissions (EF) [kg CO_2 per kWh]	CF = EC × EF	Stoll *et al.* (2019);[11] Sarkodie and Owusu (2022)[24]
Independent variables	Eff (miner efficiency)	Calculated by the ratio of hash generated per second to electricity consumption (Hash: total operating speed of mining devices used to generate BTC)	EFF = HASH/ELE Efficiency/Watt	Li *et al.* (2019);[49] Polemis *et al.* (2021)[14]
	Rev (miner revenues)	Daily miner revenue in USD and equal to the multiplication of (the number of BTC mined per day + transaction fees) by the market price	REV = (TRAN + FEES) × RET	Stoll *et al.* (2019);[11] Polemis *et al.* (2021)[14]
	Tran (transactions)	The total number of BTC mined daily in circulation		Stoll *et al.* (2019);[11] Polemis *et al.* (2021)[14]
	Hash rate (computational power per second used when mining)	Estimated computational power per second used when mining in the BTC network (trillions of hashes per second)		Expert Opinion
	Difficulty	The measure of the effort exerted to verify a block in blockchain technology. Its main objective is to maintain the 10-minute mining interval between two blocks		Expert Opinion

The prior distribution, likelihood function, and posterior distribution are fundamental components of Bayesian statistics and econometrics. The prior distribution is informed by relevant parameter information, whereas the likelihood function is derived from sample data. By applying Bayesian theory, one can derive the posterior distribution of the parameters by integrating the prior distribution with the sample information.[34]

The detailed mathematical derivations of the BVAR model are provided in Appendix D.

Unit root test

The primary requirement for time series data is that the series must exhibit stationarity. Specifically, stationarity implies that the means and variances of the variables remain constant over time. However, many time series are often identified as non-stationary; therefore, it is essential to conduct tests to assess the stationarity of the data.[7] Stationarity in time series can be evaluated using unit root tests.

In the relevant literature, the Dickey–Fuller (DF) test for unit roots is often the most widely utilized method for assessing

Table 4 Data sources

	Variables	Source
Dependent variable	CO_2 (BTC CO_2 emissions)	Sarkodie and Owusu (2022)[24]
Independent variables	Eff (miner efficiency)	EFF: HASH/ELEELE: Sarkodie and Owusu (2022)[24] HASH: Nasdaq Hash (2023)[53]
	Rev (miner revenues)	Nasdaq Rev (2023)[54]
	Tran (transactions)	Nasdaq Tran (2023)[55]
	Hash rate	Nasdaq Hash (2023)[53]
	Difficulty	Nasdaq Difficulty (2023)[56]

stationarity. As previously noted, the condition of stationarity is characterized by the constancy of the mean and variance of a time series over time.[50] However, it is important to recognize that the DF test may be insufficient in certain circumstances. For instance, in the presence of autocorrelation in the error terms, the DF test may not provide an accurate assessment in the context of Vector Autoregressive (VAR) models.[44] Conversely, this issue can be addressed by incorporating lagged values. To this end, the Augmented Dickey–Fuller (ADF) test was developed, which includes the lagged values of the dependent variable as independent variables within the DF test framework.

Basic equations and hypotheses of the ADF test:

$$\Delta Y = \alpha_0 \Delta Y = \alpha_0 + \alpha_1\, t + \gamma\, Y_{t-1} + \beta_i \sum_{i=1}^{m} \Delta Y_{t-i} + \mu_t$$

Δ represents the difference that specifies the operator, while m indicates the lag length. The variable t is utilized to capture the time trend, and Y_{t-1} denotes the lagged dependent variable, $\sum_{i=1}^{m} \Delta Y_{t-i}$ representing the sum of the lagged differences. The parameter α_0 is the model's intercept, α_1 is the coefficient associated with the time trend, and γ is the coefficient for the lagged dependent variable. The notation β_i refers to the coefficients of the lagged differences, and μ_t represents the error term.

H0: a unit root exists; the series is not stationary $\gamma = 0$.

H1: a unit root does not exist; the series is stationary $\gamma < 1$.

The relevant test indicated that the series was non-stationary at I(0) and exhibited an autocorrelation issue. Consequently, we applied logarithmic transformations to the CO_2, rev, difficulty, tran, eff, and hash rate series, and subsequently took differences at I(1). The distribution graphs of the series after the logarithmic transformations are presented in Fig. 4. We then assessed the stationarity of the series by examining the distribution graphs depicted in Fig. 5 and the results from the ADF test. The findings from the unit root tests demonstrated that the series were stationary at I(1). The degrees of stationarity are summarized in Table 5.

In addition to the ADF unit root test, we conducted the KPSS stationarity test to further assess the robustness of our results. While the ADF test's null hypothesis posits the presence of a unit root (indicating non-stationarity), the KPSS test operates under the null hypothesis of stationarity. The KPSS test results for the first-differenced, log-transformed series corroborated

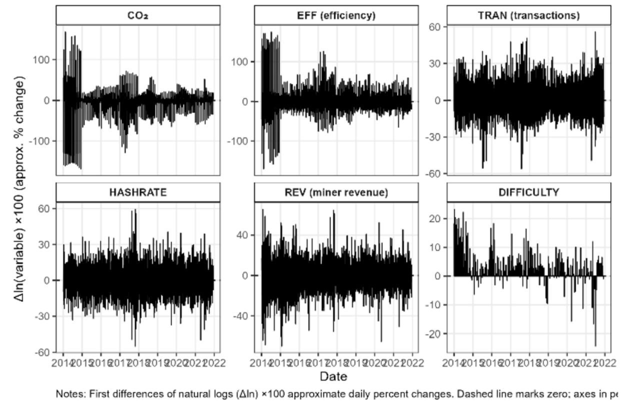

Fig. 5 Distribution of variables with logarithmic transformations after taking first differences.

Table 5 ADF test results

	Critical values of test statistics (tau)			
	1pct	5pct	10pct	Test statistics
CO_2[a]	−3.96	−3.41	−3.12	−23.564
EFF[a]	−3.96	−3.41	−3.12	−22.123
DIFFICULTY[a]	−3.96	−3.41	−3.12	−12.686
HASH RATE[a]	−3.96	−3.41	−3.12	−28.745
REV[a]	−3.96	−3.41	−3.12	−37.338
TRAN[a]	−3.96	−3.41	−3.12	−28.744
KPSS test statistics				
	Level	p-Value	Trend	p-Value
CO_2[b]	0.0057	−>0.1	0.0057	−>0.1
EFF[b]	0.0277	−>0.1	0.0048	−>0.1
DIFFICULTY[b]	0.011	>0.1	0.0092	>0.1
HASH RATE[b]	0.008	>0.1	0.004	>0.1
REV[b]	0.014	>0.1	0.0148	>0.1
TRAN[b]	0.039	>0.1	0.0131	>0.1
	Phillips–Perron (PP) unit root test (Z-tau)			
	1pct	5pct	10pct	Test statistics
CO_2[c]	−3.436	−2.863	−2.568	−70.565
EFF[c]	−3.436	−2.863	−2.568	−77.393
DIFFICULTY[c]	−3.436	−2.863	−2.568	−49.129
HASH RATE[c]	−3.436	−2.863	−2.568	−133.761
REV[c]	−3.436	−2.863	−2.568	−103.722
TRAN[c]	−3.436	−2.863	−2.568	−85.184

[a] For the ADF test, we chose the trend model, adopted the Schwarz information criterion, and considered the maximum lag length to be 12. [b] For the KPSS test, both level (with intercept) and trend (with intercept and trend) models were applied. [c] For the PP test, the Z-tau statistic is reported for the first-differenced series using the intercept (μ) specification.

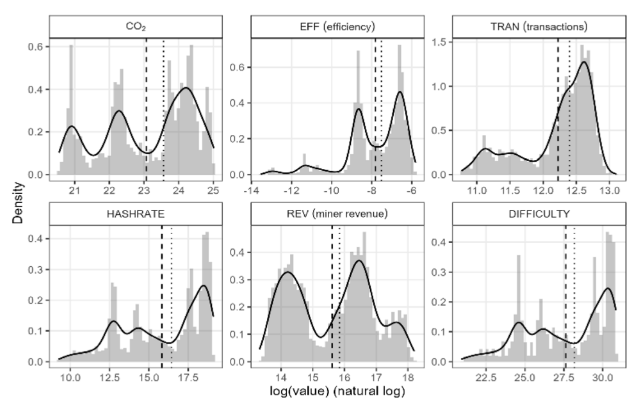

Fig. 4 Distribution of the series following logarithmic transformations.

Table 6 Optimal lag length

Lag	AIC(n)/10	HQ(n)/10	SC(n)/9	FPE(n)/10
1	26.502	26.533	26.589	3.232562×10^{11}
2	26.036	26.094	26.197	2.029256×10^{11}
3	25.748	25.833	25.984	1.521059×10^{11}
4	25.596	25.708	25.906	1.306399×10^{11}
5	24.506	24.645	24.891	4.394150×10^{10}
6	17.828	17.994	18.288	5.529535×10^{7}
7	17.516	17.709	18.050	4.047357×10^{7}
8	17.333	17.552	17.941	3.369597×10^{7}
9	17.253	17.499	17.936[a]	3.111693×10^{7}
10	17.188[a]	17.461[a]	17.945	2.915504×10^{7}[a]

[a] FPE: final prediction error; AIC: the Akaike information criterion; SC: the Schwartz information criterion; HQ: the Hannan–Quinn information criterion.

the findings of the ADF test, revealing that all variables were stationary under both level and trend specifications (all KPSS p-values > 0.1). Consistently, Phillips–Perron (PP) tests (Z-tau, intercept) applied to the first-differenced series also rejected the unit-root null for all variables, further reinforcing this result. A summary of the KPSS and Phillips–Perron statistics is presented in Table 5 alongside the ADF test results. These findings provide compelling evidence for the stationarity of the differenced series utilized in our empirical analysis.

Calculation of lag length

Criteria such as the Akaike Information Criterion (AIC), the Schwarz Information Criterion (SC), and the Hannan–Quinn Information Criterion (HQ) can be employed to determine the appropriate lag length. Previous studies in the literature frequently adopt the smallest lag length and/or the SC criterion[35–39] as the basis for lag selection. Consequently, we identified the SC criterion, with the smallest lag length, as 9, based on the data presented in Table 6.

Descriptive statistics and correlation matrix

Table 7 presents the descriptive statistics and correlation matrix for the variables included in the analysis. Notably, the variable "difficulty" exhibits the lowest standard deviation (SD; 2.14) among the sample variables. The variable "Rev" shows a negative skewness (−0.186), while its high kurtosis indicates a leptokurtic distribution (4.55 > 3). Consistent with previous research, the analysis confirms the rejection of normality for all variables.[14,40–42] Furthermore, the correlation matrix in Section B of Table 7 indicates that none of the independent variables are highly correlated, suggesting an absence of potential multicollinearity.

Johansen cointegration test

After assessing the stationarity of the time series and determining the appropriate level at which the series is stationary, we proceeded to analyze the potential existence of any cointegration relationships among the series. Series that are stationary at the same level can be incorporated into the Johansen integration analysis. Conversely, any series that does not meet this criterion cannot be included in the analysis. Furthermore, if the series is found to be non-stationary at level I(0) based on unit root tests (*i.e.*, the p-value is not significant at the specified level), the series will be re-evaluated by applying logarithmic transformations or differencing to achieve stationarity at I(d).[43]

The Johansen cointegration test is fundamentally based on VAR. When the dataset comprises two or more time series, this test offers distinct advantages over the Engle–Granger and Phillips–Ouliaris tests, as it can estimate multiple cointegration

Table 7 Descriptive statistics and correlation matrix of the variables

A:

Variables	Mean	Median	Min	Max	SD	Skewness	Kurtosis
Dependent variable							
CO_2	0.11	0.77	−168.59	168.35	22.17	−1.90	24.96
Independent variables							
REV	0.09	0.00	−69.73	65.53	14.71	−0.118	4.55
TRAN	0.06	−0.62	−56.06	55.85	12.23	0.33	4.18
HASH RATE	0.34	0.00	−54.85	59.43	11.63	0.07	4.20
DIFFICULTY	0.34	0.00	−24.28	23.24	2.14	3.88	47.4
EFF	0.22	−0.88	−170.46	175.53	24.97	1.28	16.85

B: Correlation matrix

Variables	CO_2	DIFFICULTY	EFF	HASH RATE	REV	TRAN
CO_2	1					
DIFFICULTY	0.023	1				
EFF	−0.884	−0.013	1			
HASH RATE	−0.03	−0.03	0.02	1		
REV	−0.04	−0.09	−0.01	−0.29	1	
TRAN	−0.01	−0.04	−0.02	−0.14	0.31	1

Table 8 Johansen cointegration test results

Null hypothesis	Alternative hypothesis	Test statistics	10%	5%	1%	Result
J_{trace} test						
$r \leq 5$	$r > 5$	348.52	7.52	9.24	12.97	H0 rejected
$r \leq 4$	$r > 4$	869.10	17.85	19.96	24.60	H0 rejected
$r \leq 3$	$r > 3$	1512.49	32.00	34.91	41.07	H0 rejected
$r \leq 2$	$r > 2$	2172.37	49.65	53.12	60.16	H0 rejected
$r \leq 1$	$r > 1$	4257.86	71.86	76.07	84.45	H0 rejected
$r \leq 0$	$r > 0$	18 272.37	97.18	102.14	111.01	H0 rejected
J_{max} test						
$r = 5$	$r = 6$	348.51	6.50	8.18	11.65	H0 rejected
$r = 4$	$r = 5$	520.58	12.91	14.90	19.19	H0 rejected
$r = 3$	$r = 4$	643.39	18.90	21.07	25.75	H0 rejected
$r = 2$	$r = 3$	659.88	24.78	27.14	32.14	H0 rejected
$r = 1$	$r = 2$	2085.49	30.84	33.32	38.78	H0 rejected
$r = 0$	$r = 1$	14 014.49	36.25	39.43	44.59	H0 rejected

relationships.[44] The Johansen cointegration test advocates for the application of trace and maximum eigenvalue analyses through sequential cointegration testing.

As presented in Table 8, we concluded that cointegrated equations exist between the variables at both the 0.05 and 0.01 significance levels, based on their trace and eigenvalues. In practical terms, the presence of cointegration implies that any short-term deviations among the series are corrected over time, restoring their long-run equilibrium relationship. Therefore, incorporating the cointegration structure into the VAR framework ensures that our modeling strategy captures not only short-term dynamics but also stable long-term relationships among the variables included in the study and CO_2 emissions. We formulated hypotheses regarding the existence of cointegrating vectors between the series.

H0 = there are no cointegrations between the series ($r = 0$).

H1 = there are cointegrations between the series ($r + 1$).

Estimated BVAR model

We identified the priors for the model and conducted model estimation using the Hierarchical BVAR model developed by Kuschnig and Vashold (2021)[32] within the R programming environment. The analysis included a dataset comprising 2885 observations, 6 variables, and 9 lags spanning the years 2014 to 2021. The identified Bayesian VAR model was executed for 20 000 iterations, with a thinning period of 5 and a burn-in period of 5000.

Simulations utilizing Bayesian methods are significantly dependent on the convergence of models, particularly in the context of hierarchical models. The convergence of a BVAR model is assessed through the Markov Chain Monte Carlo (MCMC) Geweke identification test.[45] Additionally, convergence

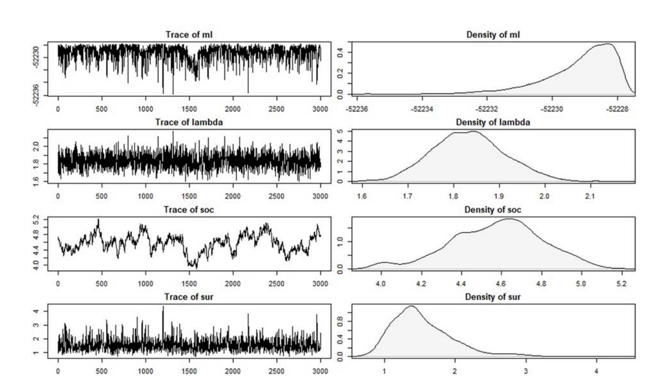

Fig. 6 Maximum likelihood (ML) trace and density plots of the hierarchically treated hyperparameters.

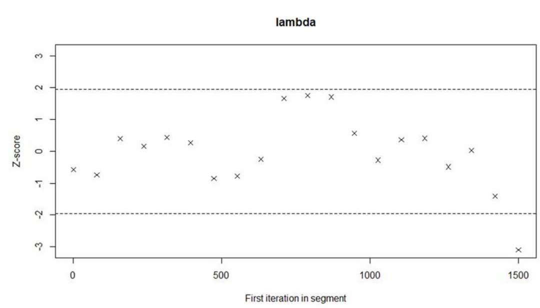

Fig. 7 Lambda plot.

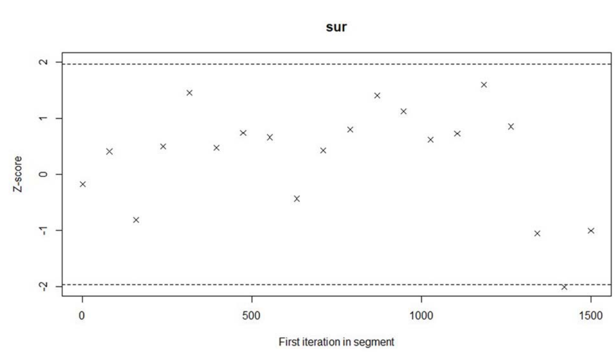

Fig. 8 Geweke plot of single-unit-root (SUR) prior.

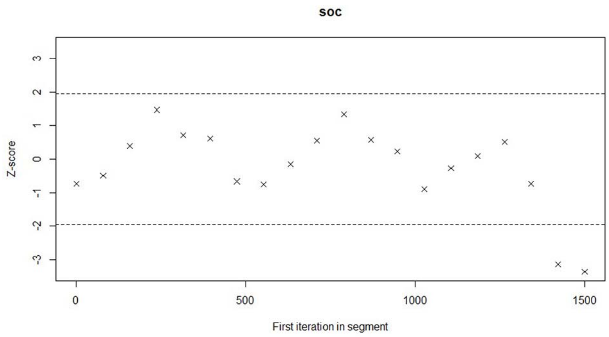

Fig. 9 Geweke plot of sum of coefficient (SOC) prior.

can be evaluated using trace and density graphs. The results of the model tests are illustrated in Fig. 6–10.

The coefficients presented in Table 9 appear to indicate an economic trend. Furthermore, all variables in this table were identified as having significant effects on BTC's CO_2 emissions. The coefficients for difficulty in periods two and three (difficulty (−2)–(−3)) were negative, indicating that difficulty contributed to an increase in BTC's CO_2 emissions after these periods. Additionally, it can be asserted that the hash rate did not have a significant short-term impact on BTC's CO_2 emissions, but it exhibited a reducing effect on emissions values in the medium term, with an increasing effect observed in the long term. While the coefficients for miner efficiency in periods one and three (eff (−1)–(−3)) were negative, they were positive for periods four and five (eff (4)–(5)). Thus, miner efficiency had an increasing effect on BTC's CO_2 emissions in the short term, but a reducing effect in the medium term. Moreover, miner revenues exhibited a fluctuating impact on BTC's CO_2 emissions over different periods. Lastly, transactions had a negative effect on BTC's CO_2 emissions in the short term.

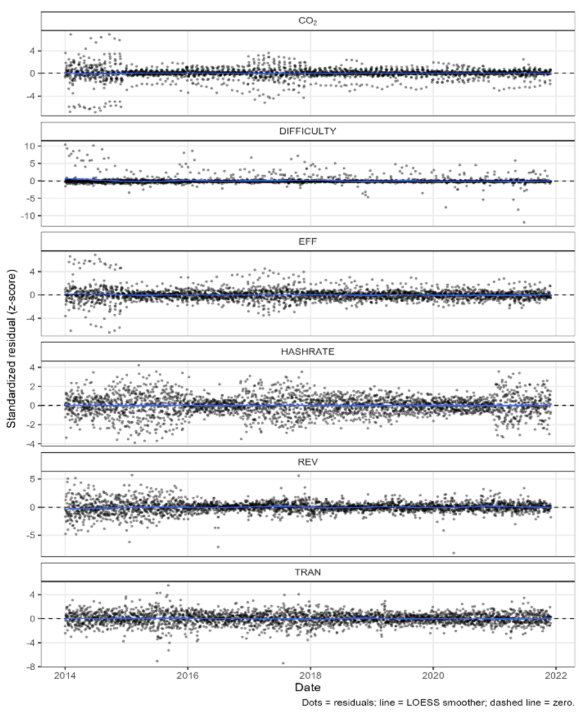

Fig. 10 Residual plot of the adjusted BVAR model data.

Descriptive tests of the BVAR model

The convergence of a Markov chain can be assessed using trace and density plots. In this context, the absence of trends or significant fluctuations in the trace plot suggests a lack of convergence, indicating that the target distribution has been reached. Another method for evaluating the chain's convergence is the Geweke identification test.[45] This test primarily relies on a comparative score between the initial and final segments of the chain, with default values typically set at 10% and 50%, respectively. Ultimately, the chain is deemed convergent if the averages of these segments are closely aligned.

Fig. 6 illustrates the trace and density plots of the hierarchical BVAR model. The sample exhibits oscillations across a broad range, centering around the mean. The bell-shaped appearance of the posterior probability density distributions of the parameters indicates convergence. Additionally, convergence can be assessed using the Geweke identification test. Fig. 7–9 present the Geweke plots for MCMC comparisons of hyperparameters, utilizing the "CODA" package in R. The *z*-scores fall predominantly within the acceptable range; however, one *z*-score for the Lambda parameter and two *z*-scores for the SOC parameter exceed the range with a *p*-value of 0.01. Therefore, we can assert that the MCMC draws from the hierarchical BVAR model demonstrate satisfactory convergence. Furthermore, the residual plot reveals a few outliers in the model (Fig. 10).

Impulse response analysis and variance decomposition table

In both Bayesian and standard VAR models, the analysis that illustrates how the dependent variable responds to a sudden shock applied to an independent variable is referred to as impulse response analysis. Fig. 11 presents plots depicting the responses of BTC CO_2 emissions to a "one standard error" shock of the variables presumed to influence mining, as indicated in the impulse response functions. Utilizing the Monte Carlo simulation technique to derive the standard errors, confidence intervals were computed for the point estimates in the impulse response functions over 20 000 iterations. In this context, the dark gray areas in the plots represent the "one" standard error confidence intervals, while the solid lines indicate the point estimates. As a general guideline, results may be considered unreliable when one confidence interval lies within the positive range while the other remains within the negative range.[46]

Upon examining BTC's CO_2 responses to one-standard-deviation shocks in the selected variables, we observe that a shock to mining DIFFICULTY reduces emissions up to a horizon of four (*e.g.*, horizon 2: median = −0.086, 95% CI [−0.110, −0.048]; horizon 3: median = −0.115, 95% CI [−0.140, −0.078]; see Appendix B). Following the removal of outliers and winsorization (refer to Appendix C), this short-term effect diminishes, and at longer horizons, the credible bands

Table 9 Estimated BVAR model for BTC's CO_2 emissions

Bayesian VAR

Prior type: Litterman/Minnesota

Diagonal Var

Hyper-parameters: μ_1: 1, L_1: 0.1, L_2: 0.99, L_3: 1

(Standard error)

[t stat.] [a]

	CO_2	DIFFICULTY	HASH RATE	EFF	REV	TRAN
$CO_2(-1)$	0.260331	0.004343	0.155293	−0.179156	−0.033549	0.072531
	(0.02337)	(0.00139)	(0.01172)	(0.03408)	(0.01505)	(0.02072)
	[11.1384]	[3.13470]	[13.2506]	[−5.25650]	[−2.22909]	[3.50124]
$CO_2(-2)$	0.064837	−0.016004	0.009189	−0.026262	−0.017123	−0.037708
	(0.02442)	(0.00145)	(0.01224)	(0.03561)	(0.01572)	(0.02164)
	[2.65527]	[−11.0577]	[0.75052]	[−0.73754]	[−1.08895]	[−1.74228]
$CO_2(-3)$	0.353873	−0.004531	−0.019261	−0.468320	0.030512	−0.075591
	(0.02484)	(0.00147)	(0.01246)	(0.03623)	(0.01600)	(0.02202)
	[14.2440]	[−3.07680]	[−1.54610]	[−12.9269]	[1.90723]	[−3.43287]
$CO_2(-4)$	−0.183605	−0.001068	−0.263746	0.175153	0.072016	−0.041167
	(0.02508)	(0.00149)	(0.01257)	(0.03657)	(0.01615)	(0.02223)
	[−7.32210]	[−0.71874]	[−20.9759]	[4.79002]	[4.45992]	[−1.85227]
$CO_2(-5)$	−0.332210	0.005272	−1.027.879	0.303445	0.006946	0.058102
	(0.02435)	(0.00144)	(0.01221)	(0.03550)	(0.01568)	(0.02158)
	[−13.6449]	[3.65307]	[−84.1946]	[8.54685]	[0.44304]	[2.69245]
$CO_2(-6)$	0.027656	0.003908	0.265152	−0.266951	0.142256	0.117969
	(0.04383)	(0.00260)	(0.02198)	(0.06392)	(0.02822)	(0.03885)
	[0.63097]	[1.50414]	[12.0643]	[−4.17660]	[5.04010]	[3.03662]
$CO_2(-7)$	0.041007	−0.011136	0.181441	−0.013546	−0.136086	0.099970
	(0.04383)	(0.00260)	(0.02198)	(0.06392)	(0.02823)	(0.03885)
	[0.93557]	[−4.28658]	[8.25543]	[−0.21193]	[−4.82147]	[2.57331]
$CO_2(-8)$	0.379758	−0.006719	−0.368810	−0.651830	0.182989	−0.018713
	(0.04183)	(0.00248)	(0.02097)	(0.06099)	(0.02693)	(0.03707)
	[9.07923]	[−2.71033]	[−17.5845]	[−10.6867]	[6.79379]	[−0.50477]
$CO_2(-9)$	−0.048292	−0.017962	−0.347853	0.317110	−0.045127	−0.002027
	(0.04299)	(0.00255)	(0.02156)	(0.06269)	(0.02768)	(0.03810)
	[−1.12336]	[−7.04936]	[−16.1369]	[5.05846]	[−1.63013]	[−0.05320]

[a] t statistics greater than 1.8 are interpreted as the significant impact of the specified variable on the dependent variable.

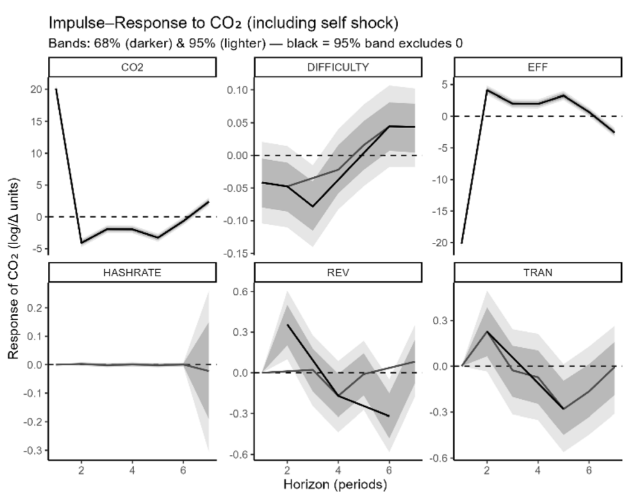

Fig. 11 Impulse response functions.

frequently encompass zero, indicating an uncertain and non-robust long-term effect (*e.g.*, horizon 6: median = 0.007, 95% CI [−0.018, +0.044]). In contrast, the other shocks do not demonstrate clear or robust effects. HASH RATE: regarding hash rate, the credible bands generally include zero (*e.g.*, horizon 3: median = −0.006, 95% CI [−0.009, −0.002]). TRAN: for transactions, the effect is negative in the baseline (horizon 3: median = −0.201, 95% CI [−0.315, −0.027]) but disappears after outlier removal and winsorization. REV: miner revenue shows a positive effect only at horizon 2 (median = 0.202, 95% CI [0.100, 0.357]), which is not significant elsewhere. EFF: efficiency presents some mid-horizon increases (horizon 4: median = 1.530, 95% CI [1.243, 1.958]); however, these are sensitive to specification and not robust in further checks. Therefore, we conclude that only the difficulty variable and the independent variable itself significantly influenced BTC CO_2 emissions.

The detailed median and 95% credible intervals for the impulse-response estimates of CO_2 emissions in response to

Table 10 Variance decomposition analysis for BTC's CO_2 emissions[a]

Period	1	2	3	4	5	6	7
CO_2	100.00	95.19	93.12	90.81	86.73	87.01	86.54
DIFFICULTY	0.00	2.51	2.54	3.37	6.63	6.19	6.15
EFF	0.00	2.24	2.96	3.09	2.96	2.91	3.36
HASH RATE	0.00	0.02	0.18	1.31	1.64	1.78	1.83
TRAN	0.00	0.05	0.38	0.64	0.70	0.66	0.67
REV	0.00	0.002	0.83	0.79	1.33	1.45	1.45
S. E.	5.73	6.37	6.46	6.73	6.90	7.14	7.16

[a] Cholesky ordering: CO_2, DIFFICULTY, EFF, HASH RATE, TRAN, REV.

a one-standard-deviation shock to each explanatory variable over a seven-period horizon are provided in Appendix B. To evaluate the robustness of these findings, Appendix C presents the corresponding estimates after excluding outliers and applying winsorization, along with graphical illustrations of the impulse responses. As shown in Appendix C, when outliers are excluded and winsorization is applied, the short-term negative effect of difficulty on CO_2 emissions decreases in magnitude (for example, at horizon 2 the median declines from -0.086 to -0.048). This indicates that the effect becomes weaker and more uncertain. Therefore, while the finding that difficulty shocks may reduce emissions in the short run is preserved, the effect does not appear to be persistent in the long run.

The variance decomposition analysis indicated that 100% of the responses of the independent variable (BTC's CO_2 emissions) to a unit standard error shock attributed to itself are accounted for by the variable in the first period. By the conclusion of the seventh period, 86% of the response remains attributable to itself, with contributions of 6.15% from difficulty, 3.36% from eff, 1.83% from hash rate, 0.67% from tran, and 1.45% from rev (see Table 10). This high share suggests that BTC's CO_2 emissions are largely self-driven and path-dependent, meaning past emission levels are the dominant predictor of future emissions, while other mining-related factors play only a secondary role.

Results

Our research examined the key factors influencing the carbon footprint of BTC generated through mining using the PoW algorithm. The variables selected for this analysis included miner efficiency, miner revenues, transactions (the total number of BTC mined daily), mining difficulty, and hash rate. We conducted relevant estimations using a BVAR model in R. The impulse response analysis indicated that our dependent variable, BTC's CO_2 emissions, was significantly influenced by both its own past values and mining difficulty. Specifically, the difficulty variable exhibited a decreasing effect on BTC's carbon footprint up to the fourth period, beyond which the long-term impact remained uncertain, with credible intervals frequently encompassing zero. Additionally, we observed that a one standard deviation shock to the BTC CO_2 emissions variable had a negative effect on itself. However, the other variables did not demonstrate a significant impact on BTC's CO_2 emissions.[20,27]

The variance decomposition analysis revealed that 100% of the responses of the dependent variable (BTC's CO_2 emissions) to a unit standard error shock from itself were accounted for in the first period. It is expected that BTC's CO_2 emissions would respond immediately to a unit shock from their own values. Nonetheless, BTC's CO_2 emissions are projected to have cumulative effects over the long term, potentially contributing to rising global carbon levels. Consequently, it is reasonable to conclude that ongoing mining activities and increased BTC utilization could lead to a progressive rise in emissions, aligning with evidence suggesting that mining operations may exacerbate global warming. By the end of the seventh period, 86% of the variance in BTC's CO_2 emissions was attributed to its own past values, with 6.15% explained by mining difficulty, 3.36% by miner efficiency, and 1.83% by hash rate. Thus, mining difficulty and hash rate emerged as significant factors influencing miners' energy consumption, beyond electricity usage, during the analyzed periods. The mining devices utilized and the number of miners within the system are critical contributors to the increasing difficulty level. Difficulty is recognized as one of the determinants of mining revenues, alongside BTC price, halving events, and elevated transaction fees.

Our findings are consistent with those of Polemis *et al.* (2021),[14] who investigated the carbon footprint of BTC utilizing Bayes and CQVAR models. They established a causative relationship between BTC energy consumption and CO_2 emissions, based on data from 50 countries spanning from July 2, 2016, to November 30, 2018. Their research also revealed a negative correlation between miner revenues and BTC's carbon footprint. However, our study builds upon their work by incorporating additional mining-related variables and analyzing a more comprehensive dataset, encompassing 2895 days of time-series data from 2014 to 2021. In contrast to Polemis *et al.* (2021),[14] we identified BTC's own value and difficulty level as the primary determinants of its carbon footprint, while other variables did not exhibit a significant impact.

Furthermore, while Stoll *et al.* (2019)[11] presented annual aggregate estimates of Bitcoin's carbon footprint using hardware data and regional energy assumptions, their study did not examine the causal relationships among variables or their interactions over time. In contrast, our Bayesian VAR approach enables a comprehensive modeling of the interdependencies among multiple mining variables—such as difficulty, hash rate, miner revenue, and total Bitcoin mined—alongside their effects on carbon emissions, both in the present and with time lags.

In this context, increases in difficulty exert pressure on miners' profit margins. In the short term, high-cost, energy-intensive rigs may cease operations, prompting operators to transition to more efficient hardware, which may temporarily reduce electricity consumption and CO_2 emissions. Consistent with this mechanism, our BVAR impulse-response functions indicate a short-term decline in CO_2 following a one-standard-deviation difficulty shock (horizons 1–4; see Appendix B). Subsequently, after outlier removal and winsorization (Appendix C), the effect diminishes, and the credible bands for the longer term frequently include zero, suggesting an uncertain long-term impact.

Discussion

The primary factors contributing to difficulty in mining are the number of miners and the computational power of the devices integrated into the network. While increased difficulty inherently elevates the computational demands, our findings suggest a short-term decrease in CO_2 emissions following a difficulty shock. This reduction is likely attributable to the temporary cessation of high-cost rigs and the accelerated replacement of inefficient hardware. However, the long-term effects are less consistent. Energy sourcing is a critical element; enhanced reliance on renewable energy and the adoption of more efficient equipment can significantly diminish the carbon footprint of mining activities.[13,23,26] Consequently, policies that promote the use of energy-efficient hardware and facilitate the integration of renewable energy sources are expected to alleviate the environmental impacts associated with PoW systems. Additionally, empirical research indicates that difficulty is a key determinant of CO_2 emissions on PoW platforms. Variations in difficulty levels directly influence the long-term sustainability of BTC mining operations. As difficulty increases, miners are required to provide greater computational power; however, the overall emissions response is not consistently upward. In the short term, high-cost, energy-intensive rigs may temporarily shut down, prompting operators to transition to more efficient hardware, which can lead to reductions in total electricity consumption and CO_2 emissions. Over extended periods, the impact remains uncertain and is influenced by energy prices, the dynamics of miner entry and exit, and advancements in hardware efficiency. By employing appropriate mining hardware and implementing a more efficient validation and block generation mechanism, the environmental impact of PoW consensus-based blockchain platforms can be effectively minimized.

The utilization of renewable energy in mining is demonstrating a consistent upward trend annually. Kohli *et al.* (2022)[23] concluded that wind and solar power represent the most viable alternative energy sources for blockchain networks. The adoption of these renewable sources has the potential to render PoW algorithm-based blockchain networks, which are typically characterized by high energy consumption, more environmentally sustainable. Looking ahead, the shift towards lower-cost, renewable, and clean energy sources, as opposed to fossil fuels, is expected to play a significant role in reducing environmentally harmful emissions. The majority of mining activities currently occur in China, and the nation's future energy transformation strategy aims to decrease fossil fuel reliance to 35% by 2050. This shift suggests that hydroelectric, solar, and wind power will increasingly contribute to energy supply for mining operations. Furthermore, it is essential to implement cleaner, sustainable systems—such as energy-efficient equipment, materials with a reduced carbon footprint, and low-carbon waste management—to optimize energy generation from renewable sources and further mitigate the mining industry's carbon footprint. Policymakers should also prioritize straightforward, measurable incentives that reward miners for utilizing verifiable low-carbon electricity and promote investment in additional low-carbon capacity to achieve enduring emissions reductions. Additionally, targeted tax measures, such as carbon pricing, may be considered, tailored to specific countries and timeframes where the carbon cost of mining is elevated.

Conclusion

We investigate the environmental impact of BTC mining, with a particular emphasis on the carbon footprint associated with the PoW algorithm. Our findings indicate that an increase in mining difficulty correlates with a short-term decline in BTC's CO_2 emissions. Mining difficulty is influenced by the number of miners and the performance of mining hardware. Although higher difficulty inherently increases the computational burden, it can prompt the shutdown of high-cost, energy-intensive rigs in the short term, thereby facilitating the replacement of less efficient hardware. This phenomenon helps to explain the observed temporary reduction in emissions. In the long term, however, the net effect remains uncertain and is likely influenced by factors such as energy prices, miner dynamics in terms of entry and exit, and advancements in hardware efficiency. To address environmental concerns, it is essential to adopt more efficient mining devices and transition towards renewable energy sources. Renewable energy options, such as wind and solar, provide a sustainable alternative to fossil fuels, while enhancements in validation and block production processes can further improve energy efficiency and mitigate the environmental footprint of PoW-based systems.

Our findings are directly relevant to PoW platforms that exhibit similar consensus mechanisms and operational dynamics to BTC, including difficulty adjustment, hardware-driven efficiency gains, and miner entry and exit behavior. Given these conditions, the qualitative patterns we have identified are likely to generalize to other PoW chains; however, the magnitudes may differ based on factors such as algorithm, hardware, market structure, and, notably, the underlying energy mix. In particular, the heterogeneity of regional energy mixes plays a crucial role. For instance, mining activities concentrated in regions dominated by hydropower (*e.g.*, Sichuan, Yunnan) are associated with substantially lower CO_2 emissions compared to coal-heavy grids (*e.g.*, Xinjiang, Inner Mongolia). This implies that while the overall patterns we identify are generalizable, their environmental magnitude depends strongly on the local electricity mix, as also highlighted in the 3rd Global Cryptoasset Benchmarking Study.[21]

Recent studies provide supporting evidence for our findings. For instance, Bajra *et al.* (2024)[4] demonstrate that PoS systems reduce energy consumption substantially compared to PoW, which confirms our result that increasing mining difficulty and hash rate drive higher emissions under PoW. Similarly, the evidence presented by Stoll *et al.* (2023)[22] on the migration of mining to the United States shows that geographic relocation alone does not reduce emissions, as miners largely remain dependent on carbon-intensive grids. Taken together, these studies indicate that while technological transitions such as PoS offer an effective pathway to emission reduction, BTC's continued reliance on PoW and the limited effectiveness of geographic shifts in mining to reduce emissions highlight the urgency of stricter regulatory frameworks and policies promoting renewable energy integration. Among such regulatory measures, the introduction of targeted electricity taxes on mining operations could serve as a form of carbon pricing, discouraging fossil-fuel-based mining activities. At the same time, tax incentives and subsidies could be designed to encourage miners to relocate to regions with abundant renewable energy resources. In this way, mining operations could shift away from carbon-intensive regions while simultaneously adopting more efficient technologies and integrating renewables, as illustrated by pilot projects directly linked to solar or wind power plants. Furthermore, regulatory frameworks could promote grid-balancing services and foster investment in clean energy infrastructure, thereby enhancing the sustainability of the sector.

While this study represents a significant advancement in understanding the environmental impacts of BTC mining, it does possess certain limitations. The analysis focuses on a limited number of variables and does not consider other potential influencing factors. Future research should aim to broaden this analysis by incorporating a wider array of variables that may affect energy consumption and carbon emissions. Furthermore, given that the VAR framework treats all variables as endogenous, subsequent studies could benefit from employing structural identification methods, such as SVAR, to derive clearer causal inferences. Additionally, the BVAR model utilized in this study fails to account for structural breaks, such as the 2021 China mining ban, when Bitcoin's global hash rate dropped by more than 50% within weeks.[21] This sharp decline was accompanied by a temporary reduction in electricity use and emissions, before mining activity relocated mainly to the U.S. and Kazakhstan, where the hash rate and emissions gradually recovered. A more comprehensive investigation into the impact of renewable energy sources in mining operations is also warranted. Future studies should focus on developing policies and strategies to promote the adoption of renewable energy within mining activities.

Author contributions

The research was designed and performed by G. A. and H. O. The data were collected and analyzed by G. A. This paper was written by G. A. and finally checked and revised by H. O. All authors read and approved the final manuscript.

Conflicts of interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Data availability

The dataset supporting the findings of this study ("Daily Bitcoin mining and carbon emissions data", covering 2014–2021) is openly available in Zenodo[57] at**https://doi.org/10.5281/zenodo.17085697**. The R scripts used for the analysis can be shared upon reasonable request with appropriate justification.

The supplementary information (SI) contains Appendix A, Appendix B, Appendix C, and Appendix D, which include additional methodological details, extended tables, and supplementary figures related to the Bayesian VAR estimations and robustness analyses. See DOI: **https://doi.org/10.1039/d5va00143a**.

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