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Implications of cryptocurrency energy usage on climate change

Dongna Zhang [a], Xihui Haviour Chen [b], Chi Keung Marco Lau [c,*], Bing Xu [b]

[a] Department of Accounting and Financial Management, Newcastle Business School, Northumbria University, Newcastle upon Tyne, UK
[b] Edinburgh Business School, Heriot-Watt University, Edinburgh, UK
[c] Department of Economics and Finance, The Hang Seng University of Hong Kong, Hong Kong, China

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ABSTRACT

This study investigates the environmental implications of cryptocurrency energy consumption on climate change. Using a spectrum of approaches, including Granger causality across quantiles, cross-quantilograms, and dynamic connectedness, we provide novel evidence on the nexus between Bitcoin mining and climate change. First, we find a significant Granger causality between carbon dioxide (CO_2) emissions and the energy usage of Bitcoin that concentrates on the right-tail quantiles. Second, we show that the directional predictability from hash rate, blockchain size, and Bitcoin returns to Bitcoin electricity consumption is heterogeneous. We also discover significant directional predictability between the energy usage of Bitcoin mining and CO_2 emissions. Third, the dynamic connectedness results show that hash rate transmits the most substantial net spillover effects to CO_2 emissions and Bitcoin electricity consumption. Accordingly, hash rate exerts a major influence on Bitcoin electricity consumption and climate change. This study highlights the necessity of stimulating technological advances in developing energy-efficient decentralized finance consensus algorithms to transform the cryptocurrency market into a climate-friendly market. The results provide policy implications by emphasizing the importance of cryptocurrency ecosystem decarbonization in addressing environmental concerns.

1. Introduction

The pace of climate change is accelerating at an unprecedented rate. The widespread harmful effects of climate change can result in more frequent extreme weather events and pose serious risks to public health. According to the Intergovernmental Panel on Climate Change (IPCC, 2018), global temperatures rising by 1.5 °C above pre-industrial levels could result in irreversible environmental effects, including the disappearance of Arctic ice and rising sea levels. The remarkable increase in global carbon dioxide (CO_2) emissions is the primary cause of global warming and exacerbates climate change, which threatens the health of the planet. Prompt collective action in achieving a carbon-neutral transition is strategically vital to mitigate the negative impacts of climate change and address sustainability challenges (IPCC, 2022).

Technological innovations bring new potential and environmental footprints. The cryptocurrency market capitalization has increased dramatically over the past decade. The growing energy consumption of Bitcoin, as the leading cryptocurrency, is not trivial (Corbet et al., 2021; Huynh et al., 2021). According to the estimation of Cambridge University's Bitcoin Electricity Consumption Index,[1] Bitcoin's energy use accounts for 0.38 % of global electricity consumption and surpasses the electricity usage of individual countries, such as Belgium and Finland. The reason behind the Intensive Bitcoin energy usage arises from the computationally demanding consensus mechanism adopted by the cryptocurrency ecosystem to verify the validity of transactions and ensure the security of the entire network. The rapid development of blockchain technology and the cryptocurrency market may undermine global efforts to curb climate change (Truby, 2018; Gaies et al., 2021; Jiang et al., 2021). Therefore, it is crucial to understand the environmental implications of cryptocurrency mining for climate change. In light of this background, empirical research has been conducted to investigate the sustainability of Bitcoin and blockchains (Vranken, 2017), electricity requirements of the Bitcoin network (De Vries, 2018), energy and carbon costs of cryptocurrency mining (Krause and Tolaymat, 2018), global warming consequences of Bitcoin emissions (Mora et al., 2018), and carbon footprint of Bitcoin (Stoll et al., 2019; De Vries et al., 2022).

Despite the growing body of literature on the energy consumption and environmental costs of cryptocurrency, little attention has been paid to the interactions between cryptocurrency mining, blockchain

* Corresponding author.
E-mail addresses: dongnazhang6688@gmail.com (D. Zhang), Xihui.chen@hw.ac.uk (X.H. Chen), marcolau@hsu.edu.hk (C.K.M. Lau), b.xu@hw.ac.uk (B. Xu).

[1] https://ccaf.io/cbeci/index/comparisons

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technology, and CO_2 emissions. To fill this empirical void, we analyze the causal effects, directional predictability, and dynamic connectedness between the Bitcoin network and CO_2 emissions by incorporating the electricity consumption of Bitcoin mining.

To promote an in-depth understanding and inform policy design on the nexus between cryptocurrency and climate change, this study addresses three key questions concerning the environmental implications of cryptocurrency energy usage: 1) Is there a causal link between the growing use of Bitcoin and CO_2 emissions? If so, is the causality distributed evenly across quantiles or asymmetrically? 2) Does directional predictability exist from the Bitcoin network to climate change? and 3) What are the features of the dynamic connectedness between Bitcoin electricity consumption, blockchain technology, and CO_2 emissions?

To conduct our empirical analysis, we employ two strands of variables associated with the Bitcoin network: the Bitcoin blockchain and Bitcoin trading. Note that the blockchain serves as a decentralized shared database that stores Bitcoin transaction data in cryptographically linked blocks. Bitcoin miners are responsible for increasing the chain of blocks and expect to obtain Bitcoin as a financial reward. The energy consumption of the Bitcoin network is inherently determined by the design elements of the blockchain system. Accordingly, we include three blockchain technology variables in this study: *network difficulty, hash rate, and blockchain size*. Meanwhile, the rise in the price of Bitcoin has attracted increasing interest in Bitcoin mining, thereby resulting in higher electricity consumption. Consequently, we incorporate two market condition variables related to Bitcoin trading, namely, *Bitcoin returns and volatility*, to address the motives driving up the energy usage of Bitcoin. In particular, Bitcoin electricity consumption serves as a medium in our framework to connect the Bitcoin network to the issue of climate change. In this regard, the intensive electricity consumption of Bitcoin mining contributes to higher CO_2 emissions, which in turn exacerbate the consequences of climate change, such as warming oceans and severe disasters. Our empirical framework is underpinned by the Environmental Kuznets Curve (EKC) theory (Grossman and Krueger, 1991, 1995) in the sense that economic growth (proxied by the development of the cryptocurrency ecosystem) tends to escalate environmental degradation (proxied by CO_2 emissions) before environmental quality can be improved by sustainable economic growth.

This study extends the empirical literature by providing new evidence of the environmental implications of Bitcoin mining. First, we demonstrate the existence of significant Granger causality at higher quantiles from the Bitcoin network to CO_2 emissions. This finding indicates that the causal dependence between cryptocurrency energy usage and climate change is asymmetric and intensifies in the right-hand tail. Second, we find that there is heterogeneous directional predictability from hash rate, blockchain size, and Bitcoin returns to the electricity consumption of Bitcoin. A significant directional predictability from the energy usage of Bitcoin mining to CO_2 emissions is also detected. Third, the dynamic connectedness results show a remarkable interdependence between the Bitcoin blockchain and CO_2 emissions. It is shown that hash rate transmits the largest net spillover effects to CO_2 emissions and Bitcoin electricity consumption. This suggests that hash rate, which is defined as the amount of computing power devoted to the mining and trading of cryptocurrency, plays a dominant role in influencing Bitcoin electricity consumption and climate change. Therefore, the key to mitigating CO_2 emissions and combating climate change is promoting technological advances in the blockchain consensus mechanism. In addition, the results imply that the implications of Bitcoin blockchain technology on climate change are more pronounced than those of the Bitcoin market conditions.

The contributions of this study are as follows. First, our analysis provides a comprehensive understanding of the implications of the cryptocurrency market on climate change. The findings shed light on the causal relationship, directional predictability, and dynamic interdependence between the Bitcoin network and climate change, thereby enhancing the empirical grounding of the environmental impact of Bitcoin mining. Second, the utilization of a spectrum of econometric methods in this study allows us to gain novel insights from different aspects to reveal the nexus between cryptocurrency energy usage, blockchain technology, and CO_2 emissions. To the best of our knowledge, this paper is the first empirical study to investigate cross-quantile causality, predictability, and dynamic connectedness to comprehensively analyze the implications of the cryptocurrency market on climate change. Finally, our results offer profound policy implications for governments and regulators that aim to achieve net-zero emissions and sustainable development. We argue that it is urgent to boost technological innovations in developing more energy-efficient decentralized finance consensus algorithms with comparable security characteristics and network features. The acceleration of the green energy transition in Bitcoin mining should also be considered a priority to decarbonize cryptocurrency.

The remainder of this paper is organized as follows. Section 2 presents a review of the related literature. Section 3 describes the data and methodology. Section 4 details the findings. Section 5 concludes the article with a discussion of the policy implications.

2. Literature review

2.1. Bitcoin mining and climate change

Both academia and practitioners have paid increasing attention to the impact of cryptocurrency mining on the energy system and environment (e.g., Howson, 2019; Rana et al., 2021; Farag and Johan, 2021). Note that Bitcoin's blockchain network is protected and verified by a process called proof of work (PoW), where miners use powerful computer processing capabilities to solve complex mathematical equations to prove the validity and creation of the blockchain network (Jiang et al., 2021; Namcios, 2021; Truby, 2018). To solve these mathematical equations, special computers that consume tremendous amounts of electricity must be built. According to Corbet et al. (2019), large-scale Bitcoin mining requires more specialized mining machines with relatively high power consumption. Each time a new block is generated for a certain number of Bitcoins, miners are rewarded for the time, energy, and expensive electricity they use. With the increase in the number of Bitcoins mined, the difficulty of mining and the energy supply required increase. The reward for mining Bitcoin is reduced by half at each Bitcoin halving event to reduce the number of Bitcoins in circulation and thereby increase the demand (Namcios, 2021). The total Bitcoin supply is capped at 21 million (M) by the consensus protocol that governs the currency, and about 90 % of the total number of Bitcoins (19M) was already in circulation in the market by 2021 (Namcios, 2021).

As the network of encrypted assets continues to grow, mining is becoming increasingly difficult, and the requirements for computing power to handle Bitcoin mining machines and the amount of energy required to generate digital tokens will continue to grow (Yan et al., 2022; Umar et al., 2021; Baur and Oll, 2022). Therefore, it is not surprising to see an increased concern about the environmental impact of Bitcoin mining (Huynh et al., 2020b). Browne (2021), for example, reports that Bitcoin mining might produce CO_2 emissions of up to 36.95 megatons per year, which is equal to or even higher than New Zealand's carbon footprint per capita. According to the Cambridge Bitcoin Electricity Consumption Index (CBECI), cryptocurrency consumes more energy than the total annualized energy consumption of the Netherlands (Browne, 2021). In addition, the CBECI estimates that the electricity used for Bitcoin mining is approximately 114.81 Terawatt hours (TWh) per year. This estimation is only 11.19 TWh less than the annual consumption of Norway, which has approximately 5.33 million residents. Despite cryptocurrency's exposure to a broader issue, a large part of it is related to entering new industries and technologies and making smart development decisions while being aware of the effects of emissions on the environment. Through the adoption of sustainable green energy, cryptocurrencies can be established without adverse environmental consequences. In promoting carbon peaking and neutrality, it is crucial to develop feasible policies and appropriate interventions for Bitcoin mining and Bitcoin blockchain operations in the long run.

In addition to the discussions on the environmental impact of cryptocurrencies in social media forums (e.g., Browne, 2021; Huynh et al., 2020b; Namcios, 2021; Wang et al., 2018), the academic community is accelerating its efforts to investigate and address this urgent global issue. Most authors have found that Bitcoin mining generates a significant amount of CO_2 (e.g., Corbet et al., 2019). Jiang et al. (2021) show that in 2020, Bitcoin mining contributed approximately 1 % to the global CO_2 emissions and that the average CO_2 emissions per unit of power generation in China was approximately 570 g. They argue that if there are no feasible policies or government interventions, the total annualized energy consumption of the Bitcoin blockchain in China is expected to reach a peak of 296.59 TWh in 2024, with emissions of approximately 130.5 million metric tons of CO_2 equivalent. This accounts for approximately 5.41 % of China's total carbon emissions from power generation. At this scale, the emissions may exceed the total annual greenhouse gas emissions of the Czech Republic and Qatar combined. China accounts for 75 % of the Bitcoin network's total processing power mainly because of the availability of cheap electricity in the country. As China relies heavily on coal-fired power to generate electricity, its air pollution is on the rise (Wang et al., 2018). Yan et al. (2022) observe that 65 % of the energy sources used by cryptocurrency miners around the world are coal and that a positive linkage exists between coal price and Bitcoin price in the Asia Pacific region (e.g., Corbet et al., 2019; Akyildirim et al., 2021). Umar et al. (2020, 2021) also find similar results in the Chinese market. Several authors have highlighted the need for more data to form a true understanding of the impact of Bitcoin mining on climate change, especially because the Bitcoin mining industry is fragmented and scattered around the world (e.g., Baur and Oll, 2022; Umar et al., 2021; Yan et al., 2022).

Cryptocurrency markets consume a considerable amount of energy generated by conventional sources (e.g., coal), thereby causing tremendous environmental hazards. For example, Köhler and Pizzol (2019) provide a regional breakdown of China's internal emissions, explaining that hydropower (coal) has a positive (negative) influence on the reduction (increase) of total emissions in Sichuan Province (Inner Mongolia). Although several clean alternatives (e.g., biomass, geothermal, hydro, solar, and wind) can be adopted to combat global warming, the main challenge for businesses and citizens in implementing these low-carbon alternatives is the high investment cost (Lahiani et al., 2021). Hence, governments should develop and implement policies to encourage the transition from conventional energy to renewable energy (Huynh et al., 2020a).

2.2. *Cryptocurrencies as a financial asset and their impact on environmental quality*

A growing number of investors are recognizing cryptocurrencies' crucial role in combating climate change, along with the fact that climate issues have substantial implications for their investment portfolios (e.g., Baur and Oll, 2022; Corbet et al., 2021; Goodkind et al., 2020). For example, Baur and Oll (2022) study cryptocurrency investment sustainability using a mean-variance portfolio optimization framework and find a significant and positive relationship between the energy consumption of Bitcoin's blockchain networks and the non-sustainability of the investment. Corbet et al. (2021) investigate the impact of Bitcoin price volatility and cryptocurrency mining characteristics on energy markets and utility firms. They find that the increased energy usage of Bitcoin mining harms the profitability of utility firms. Expanding the study of Bitcoin, Goodkind et al. (2020) include three other prominent cryptocurrencies (i.e., Ethereum, Litecoin, and Monero) to estimate the relationship between cryptocurrency mining and the economic harm caused by air pollution emissions in China and the

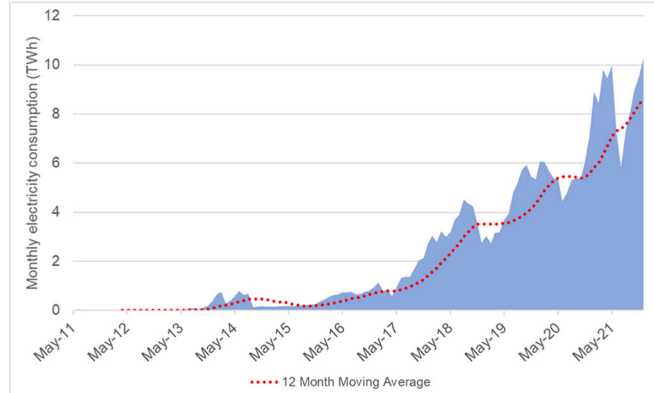

Fig. 1. Bitcoin electricity consumption.
Source: Data are obtained from the website of the Cambridge Bitcoin Electricity Consumption Index, which is constructed by the Cambridge Centre for Alternative Finance. The 12-month moving average is calculated by the author.

United States. They show that as electricity demands increase to produce each cryptocurrency, a cliff of negatives is almost inevitable. Therefore, reliable and accurate information regarding any company or country's carbon footprint should be readily available. This information would allow climate matters to be integrated into the investment decision-making process. Carbon information, however, and the corresponding emission estimates often lie outside investors' grasp because of their inaccuracy, unreliability, or even unavailability. Thus, it is difficult to analyze the causal consequences of climate investment because it is associated with considerable uncertainty (Baur and Oll, 2022; Talbot and Boiral, 2018). Consequently, the Bitcoin investment phenomenon is a particularly extreme example of an unresolved climate impact. It is more difficult to assess and report the actual footprint of the Bitcoin network because of its decentralized nature. This characteristic, which has been widely praised (Corbet et al., 2019; Jiang et al., 2021; Namcios, 2021; Truby, 2018), has led to adverse economic impacts from the perspective of climate change. The reader is referred to Corbet et al. (2019), who conduct an in-depth systematic literature review on cryptocurrency markets (Truby, 2018).

In summary, given that mining activities rely heavily on coal and nonrenewable energy as their primary energy sources, increasing levels of electricity consumption for mining activities are expected to drive up carbon emissions. Our study is distinct from the current literature given that we adopt daily CO_2 emission data to provide a more accurate picture of the environmental implications of cryptocurrency mining. More importantly, we are among the first to investigate the causality and predictability between Bitcoin mining and CO_2 emissions at different quantile levels and provide further empirical evidence on the dynamic connectedness among Bitcoin networks and climate change.

3. Empirical design

3.1. *Data*

This study employs daily data covering the period from January 1, 2019, to June 30, 2021, to investigate the relationship between climate change and the energy demand of Bitcoin networks. The data on daily world CO_2 emissions from residential sectors, as estimated by Liu et al. (2020), are obtained from the Carbon Monitor website.[2] The sample period is restricted by the availability of a series of CO_2 emissions. The Cambridge Centre for Alternative Finance constructs a range of Bitcoin electricity consumption comprising a hypothetical lower bound, a

[2] https://carbonmonitor.org/.

Table 1
Descriptive statistics.

	Obs.	Mean	Std. Dev.	Min	Max
CO_2	912	−0.0014	0.0398	−0.1378	0.1405
GUESS	912	0.0006	0.0197	−0.0852	0.0814
Bitcoin returns	912	0.0024	0.0322	−0.2263	0.1891
Bitcoin volatility	912	80.6932	330.9725	2.5547	5286.1120
Hash rate	912	0.0008	0.1159	−0.4972	0.4055
Blockchain size	912	0.0006	0.0001	0.0000	0.0010
Network difficulty	912	0.0014	0.0159	−0.1661	0.1196

hypothetical upper bound, and a best-guess estimate. In particular, the best-guess estimate is computed in a more realistic scenario to reflect the real electricity consumption of Bitcoin. Hence, the energy demand of the Bitcoin network in this study is proxied by the best-guess estimate of the CBECI, hereafter denoted as GUESS. Fig. 1 shows a 1000-fold increase in the best-guess estimate of Bitcoin electricity consumption on the basis of the comparison of the monthly consumption of 0.01 TWh in May 2011 with that of 10.29 TWh in December 2021. As indicated by the red dashed line of the 12-month moving average, the trend in Bitcoin electricity consumption is upward, and Bitcoin has been constantly experiencing record high energy usage. The unprecedented level of energy consumption and associated CO_2 emissions of Bitcoin mining can inhibit the fulfillment of the goal of net-zero transition. According to the estimation of Stoll et al. (2019), approximately 22–22.9 million metric tons of CO_2 emissions each year are related to Bitcoin mining activities; this range is equal to the CO_2 emissions from the annual power consumption of 2.6–2.7 billion households.

In addition, Bitcoin returns and price volatility series are obtained from Bitcointy.[3] For the blockchain-related data, we collect the total hash rate, blockchain size, and network difficulty from the Blockchain website.[4] All data are transformed into logarithm difference to ensure the stationarity of the series before conducting the econometric analysis.

Table 1 provides the descriptive statistics of the variables included in the analysis. As the sample period of the study ranges from January 1, 2019, to June 30, 2021, the number of observations for each variable is 912, and the total number of observations is 6384. All variables are converted into log differences. We can see that Bitcoin volatility has the largest mean value of 80.6932 while GUESS, hash rate, and blockchain size have similar mean values ranging from 0.00059 to 0.00084. As Bitcoin is a highly volatile digital currency, its volatility also has the greatest standard deviation and minimum and maximum values relative to the other variables in the dataset.

3.2. Methodology

3.2.1. Test for Granger causality in quantiles

Following Hong and Li (2005), we explore the nexus between Bitcoin and climate change by using a parametric tail dependence copula while considering the problems of structure and nonlinear breaks. As described in our empirical framework, Bitcoin electricity consumption resulting from Bitcoin mining contributes to the rise in CO_2 emissions and aggravates climate change. We are interested in testing the Granger causality in distribution tails between the pair of Bitcoin mining and electricity consumption, as well as between the pair of Bitcoin electricity consumption and CO_2 emissions.

Lee and Yang (2014) discuss the key merits of using a nonlinear approach. Theoretically, the problem with the conventional linear Granger causality test is that the test fails to model the asymmetric dependence between variables of interest owing to the possible nonlinear dependence structure of the multivariate distribution among variables and structural breaks. Therefore, the linear test is not powerful in detecting the causality link between variables, and it often accepts the null hypothesis of no causality, especially when the variables of Bitcoin electricity consumption and CO_2 emissions exhibit significant nonlinear structures.

The practical advantage of using a nonlinear approach (i.e., copulas in our case) to check the causality link between Bitcoin electricity consumption and CO_2 emissions from a practical perspective is that it enables researchers to test causal relations at the extremes of the variable's distributions rather than only at the center. The linear test cannot detect directional predictability from one variable to another at various quantile levels (e.g., the bullish market condition in the Bitcoin market may increase Bitcoin electricity consumption). The ability of Bitcoin electricity consumption to predict CO_2 emissions at different quantiles reinforces the fact that Bitcoin mining has significant environmental implications on climate change. Therefore, the motivation to check the nonlinear link between Bitcoin electricity consumption and CO_2 emissions is justified from the theoretical and practical perspectives.

For example, we investigate the Granger causality between the pair of Bitcoin electricity consumption of Bitcoin (GUESS) and CO_2 emissions by testing the null hypothesis that $CO_{2,t}$ in the distribution is not Granger caused by $GUESS_t$; that is,

$$H_0 : c(u, v) = 1 \tag{1}$$

$$H_1 : c(u, v) \neq 1 \tag{2}$$

where $c(u, v)$ denotes the conditional copula density function and u and v respectively represent the $CO2_t$ and $GUESS_t$ conditional probability integral transformations.

We respectively use Eqs. (3) and (4) to measure the conditional variances for $GUESS_t$ and $CO2_t$, $\widehat{h}_{Guess,t+1}$ and $\widehat{h}_{CO2,t+1}$:

$$\widehat{h}_{Guess,t+1} = \widehat{\beta}_{Guess0} + \widehat{\beta}_{Guess1} RAI_t^2 + \widehat{\beta}_{Guess2} \widehat{h}_{Guess,t} \tag{3}$$

$$\widehat{h}_{CO2,t+1} = \widehat{\beta}_{CO20} + \widehat{\beta}_{CO21} RBC_t^2 + \widehat{\beta}_{CO22} \widehat{h}_{CO2,t} \tag{4}$$

The cumulative distribution function values of $\widehat{u}_{t+1}$ and $\widehat{v}_{t+1}$ for $CO2_{t+1}$ and $GUESS_{t+1}$, respectively, are computed using the empirical distribution function (EDF). We estimate the nonparametric copula function by using the paired EDF values $\{\widehat{u}_{t+1}, \widehat{v}_{t+1}\}_{t=R}^{T-1}$ and the following quartic kernel function:

$$k(u) = \frac{15}{16}\left(1 - u^2\right)^2 I(|u| \leq 1) \tag{5}$$

3.2.2. Test for directional predictability by cross-quantilogram analysis

Linton and Whang (2007) first propose the quantilogram concept to investigate the time series predictability across a range of distributions. A key feature of the quantilogram is that it can be used to test the null hypothesis of no directional predictability from an individual time-series (Linton and Whang, 2007; Han et al., 2016). As the correlogram of quantile hits, the quantilogram is compared with the pointwise confidence interval to examine the predictability of time series. Under the multivariate quantilogram framework introduced by Han et al. (2016), the directional dependence structure between time series is analyzed using the cross-quantilogram method along with the application of conditional quantiles. Using cross-quantilogram to test for directional probability is advantageous as it is suitable for data with heavy-tailed distribution and does not require moment conditions to specify the quantile hits.

In our study, we apply Han et al. (2016)'s directional predictability test to use *GUESS* for predicting CO_2 emission changes. The null hypothesis is that there is no directional predictive power for GUESS in predicting CO_2 emissions. The quantile-to-quantile underlying relationship between *GUESS* and CO_2 emissions could be established using the cross-quantilogram:

[3] https://Bitcoinity.org/

[4] https://www.blockchain.com/

$$q_{\alpha(CO2_{t+1}|\mathscr{F}_t)} = \beta_{0,\alpha} + \beta_{1,\alpha}Guess_t + \beta_{2,\alpha}CO2q_\alpha(CO2_t|\mathscr{F}_{t-1}) + \beta_{3,\alpha}|CO2_t| \tag{6}$$

where $q_{\alpha(CO2_{t+1}|\mathscr{F}_t)}$ refers to the quantile estimate function of CO_2 emissions and $\mathscr{F}_t$ refers to the conditional quantile information set at time *t*. In this way, the directional predictability from GUESS to CO_2 emissions can be investigated. To address the nonsmooth functions in the estimation, we follow Han et al. (2016) and employ the methodology proposed by Koenker and Bassett (1978). The sample cross-quantilogram $\widehat{p}_\alpha(k)$ shows serial dependence at a range of conditional quantile levels. We define the sample cross-quantilogram $\widehat{p}_\alpha(k)$ as:

$$\widehat{p}_\alpha(k) = \frac{\sum_{t=k+1}^{T} \psi_{\alpha1}\left(CO2_t - \widehat{q}_{1,t}(\alpha_1)\right)\psi_{\alpha2}\left(Guess_{t-k} - \widehat{q}_{2,t-k}(\alpha_2)\right)}{\sqrt{\sum_{t=k+1}^{T} \psi^2{}_{\alpha1}\left(CO2_t - \widehat{q}_{1,t}(\alpha_1)\right)}\sqrt{\sum_{t=k+1}^{T} \psi^2\alpha_2\left(Guess_{t-k} - \widehat{q}_{2,t-k}(\alpha_2)\right)}} \tag{7}$$

where $\widehat{q}_{i,t}(\alpha_i) = x_{it}^T\widehat{\beta}_i(\alpha_i)$, with x_i representing the independent variable in the estimation framework. The directional predictability from GUESS to CO_2 emissions is measured by $\widehat{p}_\alpha(k)\forall k = 0, \pm1, \pm2, \ldots$, which evaluates the conditional quantile dependence structure with regard to the direction of the deviation. The situation of no directional predictability is indicated by $\widehat{p}_\alpha(k)$=0 while a high dependence between two variables is illustrated by a nonzero value of $\widehat{p}_\alpha(k)$. In addition, $\psi_\alpha \equiv 1[m < 0] - \beta$, where the indicator function is represented by 1[.]. The quantile exceedance process for CO_2 emissions is denoted by $1[s_{i,t} \le q_i(\alpha_i)]$, where $q_i(\alpha_i) = \inf(v : M_i(v) \ge \alpha_i)$ represents the quantile of GUESS, with $M_i(.)$ denoting the distribution function of $s_{i,t}$.

We start by investigating the directional predictability between, $x_{1,t}$ and $x_{2,t}$, which refer to CO_2 emissions and GUESS, respectively. Specifically, a range of α_1, 0.05, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9, and 0.95 for CO_2 emissions $q_1(\alpha_1)$ quantiles is examined. We consider the value of 0.3 for α_2 in GUESS $q_2(\alpha_2)$. To complement the empirical findings, we report 95 % bootstrapped confidence intervals from 10,000 replications. The number of lags (k) is set to 60 days. In addition, we estimate the critical values by using a nonparametric estimation approach in line with the properties of the stationary bootstrap introduced by Politis and Romano (1994). Finally, we examine the directional predictability from the Bitcoin trading (Bitcoin returns, Bitcoin volatility) and mining (hash rate, blockchain size, network difficulty) variables to GUESS in the same manner.

3.2.3. Measurement of dynamic connectedness

The dynamic connectedness between the Bitcoin network and climate change is examined following the connectedness measurement framework of Diebold and Yilmaz (2012), which is constructed on the basis of the generalized forecast variance decomposition of a vector autoregressive (VAR) model. Following Diebold and Yilmaz (2012), we write the stable VAR model with *p* lags as follows:

$$Z_t = \sum_{i=1}^{p} \mu_i Z_{t-i} + \varepsilon_t, \varepsilon_t \sim (0, \Sigma) \tag{8}$$

where Z_t is a vector of the variables of interest, μ_i *for* $i = 1, 2\ldots p$ are the matrices of the VAR parameters, and ε_t represents the independently and identically distributed error vector. Eq. (8) can be converted to the vector moving average as follows:

$$Z_t = \sum_{i=0}^{\infty} \Theta_i \varepsilon_{t-i} \tag{9}$$

where Θ_i is measured by the recursion specified in Eq. (10):

$$\Theta_q = \mu_1\Theta_{q-1} + \mu_2\Theta_{q-2} + \ldots \mu_p\Theta_{q-p} \tag{10}$$

where Θ_0 is an identity matrix and Θ_q equals zero for $q < 0$.

In the next step, $\beta_{ij}(Q)$ denotes the components of a Q-step-ahead generalized forecast error variance decomposition matrix:

$$\beta_{ij}(Q) = \frac{\sigma_{jj}^{-1}\sum_{q=0}^{Q-1}\left(e_i'\Theta_q \sum e_j\right)^2}{\sum_{q=0}^{Q-1}\left(e_i'\Theta_q \sum \Theta_q' e_i\right)}, i,j = 1, 2\ldots, N \; for \; all \; i \ne j \tag{11}$$

where σ_{jj} is the diagonal component of the *jth* equation in $\sum$ and e_i represents the selection vector with 1 as the *i*th component. Each entry of the variance decomposition matrix is normalized by the row sum as follows:

$$\widetilde{\beta}_{ij}(Q) = \frac{\beta_{ij}(Q)}{\sum_{j=1}^{N}\beta_{ij}(Q)} \tag{12}$$

$$\sum_{j=1}^{N}\widetilde{\beta}_{ij}(Q) = 1 \tag{13}$$

$$\sum_{i,j=1}^{N}\widetilde{\beta}_{ij}(Q) = N \tag{14}$$

The total spillover is computed as follows:

$$FL(Q) = \frac{\sum_{\substack{i,j=1 \\ i\ne j}}^{N}\widetilde{\beta}_{ij}(Q)}{\sum_{i,j=1}^{N}\widetilde{\beta}_{ij}(Q)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i\ne j}}^{N}\widetilde{\beta}_{ij}(Q)}{N} \times 100 \tag{15}$$

The directional spillover transmitted from variable *i* to *j* is computed as follows:

$$FL(Q)_{from} = \sum_{\substack{j=1 \\ i\ne j}}^{N}\widetilde{\beta}_{ij}(Q) \times 100 \tag{16}$$

Table 2
Testing for Granger-causality in quantiles.

	40 %	50 %	60 %	70 %	80 %	90 %	95 %	99 %
GUESS to CO_2	0.106	0.533	0.000	0.000	0.000	0.000	0.000	0.000
Bitcoin returns to GUESS	0.218	0.522	0.052	0.049	0.489	0.000	0.000	0.000
Bitcoin volatility to GUESS	0.024	0.612	0.118	0.039	0.022	0.003	0.000	0.015
Hash rate to GUESS	0.323	0.318	0.001	0.000	0.000	0.000	0.000	0.000
Blockchain size to GUESS	0.488	0.521	0.006	0.000	0.000	0.000	0.000	0.000
Network difficulty to GUESS	0.341	0.338	0.006	0.000	0.000	0.000	0.000	0.000

Notes: Granger-causality in quantile is tested by forecasting the conditional quantiles through the inverse of conditional copula distribution functions. Six copula models including Gaussian, Frank, Clayton, Clayton Survival, Gumbel, and Gumbel Survival are applied. We calculate the baseline quantile forecasts by utilising the independent copula which indicates that there is no Granger-causality in quantile. The null hypothesis is that no copula model among the six copula functions performs better quantile forecast than the independent copula function, thereby indicating that no Granger-causality in quantile. The corresponding bootstrapped *p*-values are reported. See Lee and Yang (2014) for detailed estimation technique.

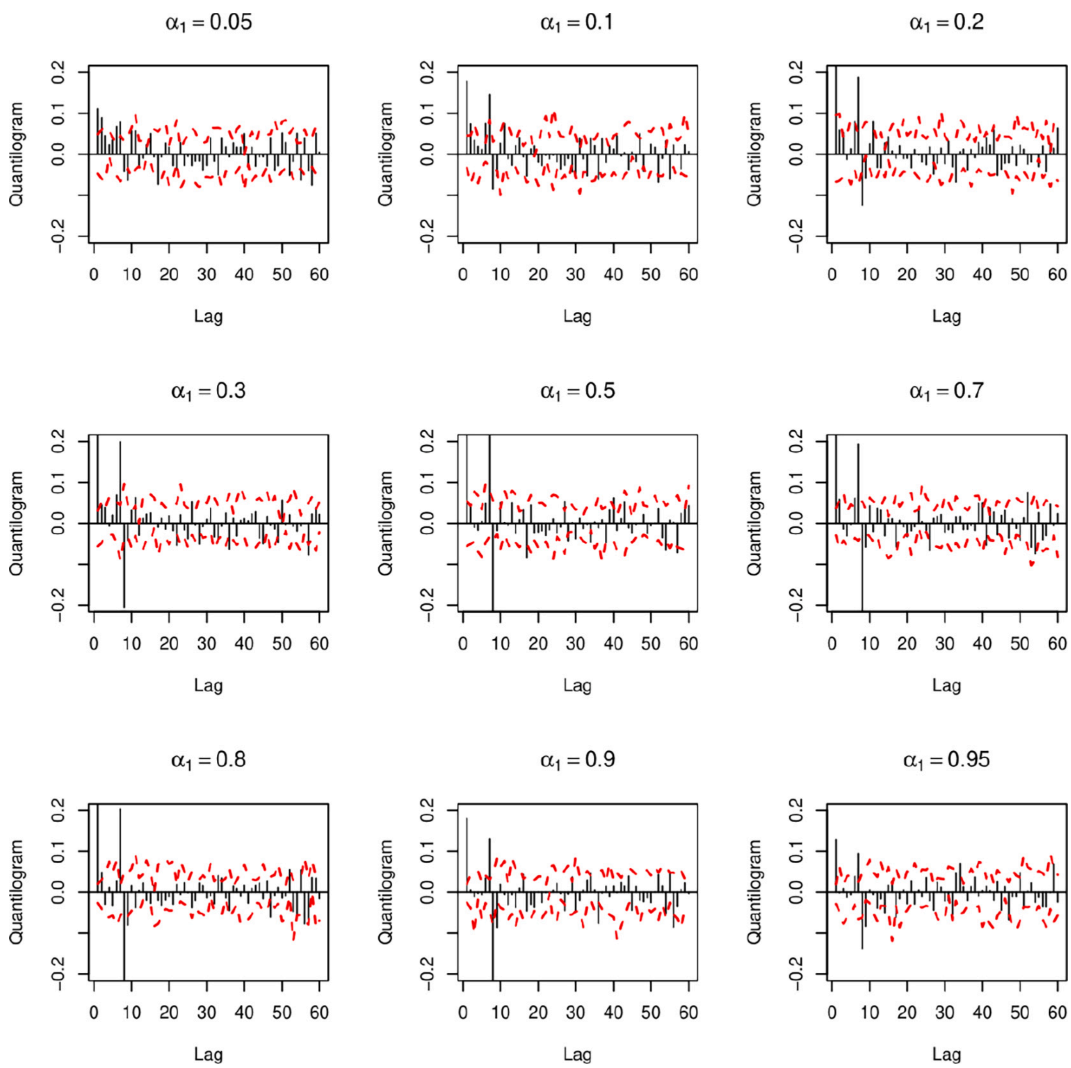

Fig. 2. Directional predictability in quantiles from hash rate to GUESS
Notes: This figure consists of the cross-quantilograms *when* α2 is taken as 0.3. The bar graphs represent the cross-quantilograms. The red dotted lines refer to the 95 % bootstrap confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The directional spillover transmitted from variable *j* to *i* is computed as follows:

$$FL(Q)_{to} = \sum_{\substack{j=1 \\ i \neq j}}^{N} \widetilde{\beta}_{ji}(Q) \times 100 \tag{17}$$

The net spillover transmitted from the network to variable *i* can be calculated as

$$FL(Q)_{net} = FL(Q)_{to} - FL(Q)_{from} \tag{18}$$

Finally, the net pairwise connectedness from variable *i* to *j* is measured by

$$NPC_{ij}(Q) = \left[\widetilde{\beta}_{ji}(Q) - \widetilde{\beta}_{ij}(Q)\right] \times 100 \tag{19}$$

During the formal econometric analysis, we select the optimal lag length of 7 for the VAR model based on the Akaike information criterion and Schwarz criterion. In addition, we choose the 20-step-ahead forecast horizon and a rolling window size of 200 following Diebold and Yilmaz (2012).

4. Empirical findings

4.1. Analysis of granger causality in quantiles

Table 2 presents the results of examining the Granger causality in quantiles. The small *p*-values in relation to the null hypothesis of no Granger causality provide evidence that a copular model is identified for Granger causality in quantiles, thereby indicating a strong predictor of CO_2 emissions based on the electricity consumption of Bitcoin mining activities (GUESS). Our main finding regarding this quantile forecasting model is that the null hypothesis of no Granger causality is rejected in the upper quantile phases. The evidence of Granger causality concentrated on the right tail implies that when the CO_2 emission is in its high distribution, the predictive content of electricity consumption from Bitcoin mining is significant.

The right-tail dependence between CO_2 emissions and Bitcoin energy consumption indicates that high CO_2 emissions can be attributed to the energy usage of Bitcoin mining. This can be explained by the theoretical underpinning of the EKC hypothesis (Grossman and Krueger, 1991, 1995), which documents an inverted U-shaped relationship between economic growth and pollution. The current literature extends the application of the EKC hypothesis to consider the impact of financial innovation (Chishti and Sinha, 2022), technological innovation (Wang

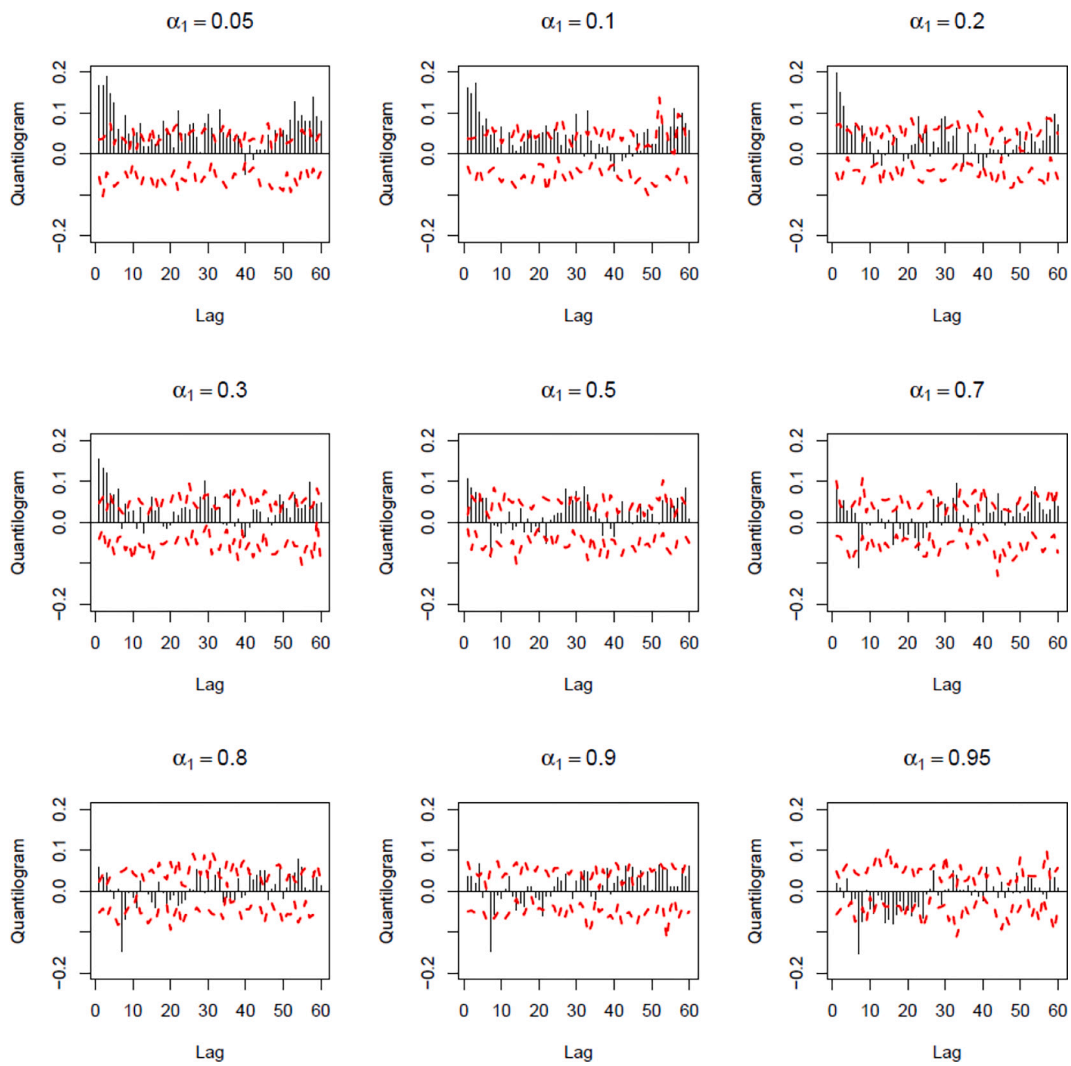

Fig. 3. Directional predictability in quantiles from blockchain size to GUESS
Notes: This figure consists of the cross-quantilograms when α2 is taken as 0.3. The bar graphs represent the cross-quantilograms. The red dotted lines refer to the 95 % bootstrap confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

et al., 2022), and financial development (Youssef et al., 2020) on environmental degradation. As a revolutionary innovation in the financial sector, cryptocurrencies such as Bitcoin are characterized by decentralized finance (DeFi) technology. Relative to the long history of traditional currencies and centralized finance, the development of cryptocurrencies is still in its infancy. At such an early stage, cryptocurrency expansion tends to aggravate the pollution level proxied by CO_2 emissions. Based on the EKC hypothesis, our findings further suggest that the period during which Bitcoin market development can help reduce the level of CO_2 emissions has yet to come and that the potential of DeFi technology architecture to alleviate environmental degradation has yet to be realized.

Relative to Bitcoin volatility, Bitcoin returns are shown to significantly Granger cause Bitcoin electricity consumption in higher quantiles. As Bitcoin is mainly considered a speculative asset (Baur et al., 2018), the demand for it is driven by its associated returns. Consequently, higher demand leads to higher electricity consumption, which is a key production input in Bitcoin mining.

Turning to the blockchain technology-related variables in Table 2, the very small *p*-values at 60 % and above indicate that strong Granger causality exists between Bitcoin electricity consumption and hash rate, blockchain size, and network difficulty in higher quantiles. This finding implies that when electricity consumption is above the median, an increase in hash rate, blockchain size, and network difficulty is found to increase Bitcoin electricity usage. This is in accordance with the findings of Lei et al. (2021) regarding the energy use of blockchain systems. The underlying cause for such statistically significant Granger causality in higher quantiles may be the energy-intensive feature of the blockchain consensus mechanism adopted in the Bitcoin network.

4.2. *Directional predictability analysis*

The directional predictability between the Bitcoin market and climate change is investigated through the cross-quantilogram method, as shown in Fig. 2-7. Specifically, Fig. 2-6 illustrates the predictability in quantiles from Bitcoin variables to the electricity consumption of Bitcoin mining activities while Fig. 7 demonstrates the predictability from the electricity usage of Bitcoin to CO_2 emissions.

By observing the cross-quantilograms in Fig. 2, we find significant directional predictability from hash rate to Bitcoin electricity consumption (GUESS) at all quantile levels. In particular, the cross-quantilogram from hash rate to GUESS consistently reaches the peak level at day 1 across the low, median, and high quantiles. This reveals that the ability of hash rate to predict GUESS lies in the immediate future. Moreover, the cross-quantilograms are positive and significant within the first seven days spanning quantile levels from 0.05 to 0.95,

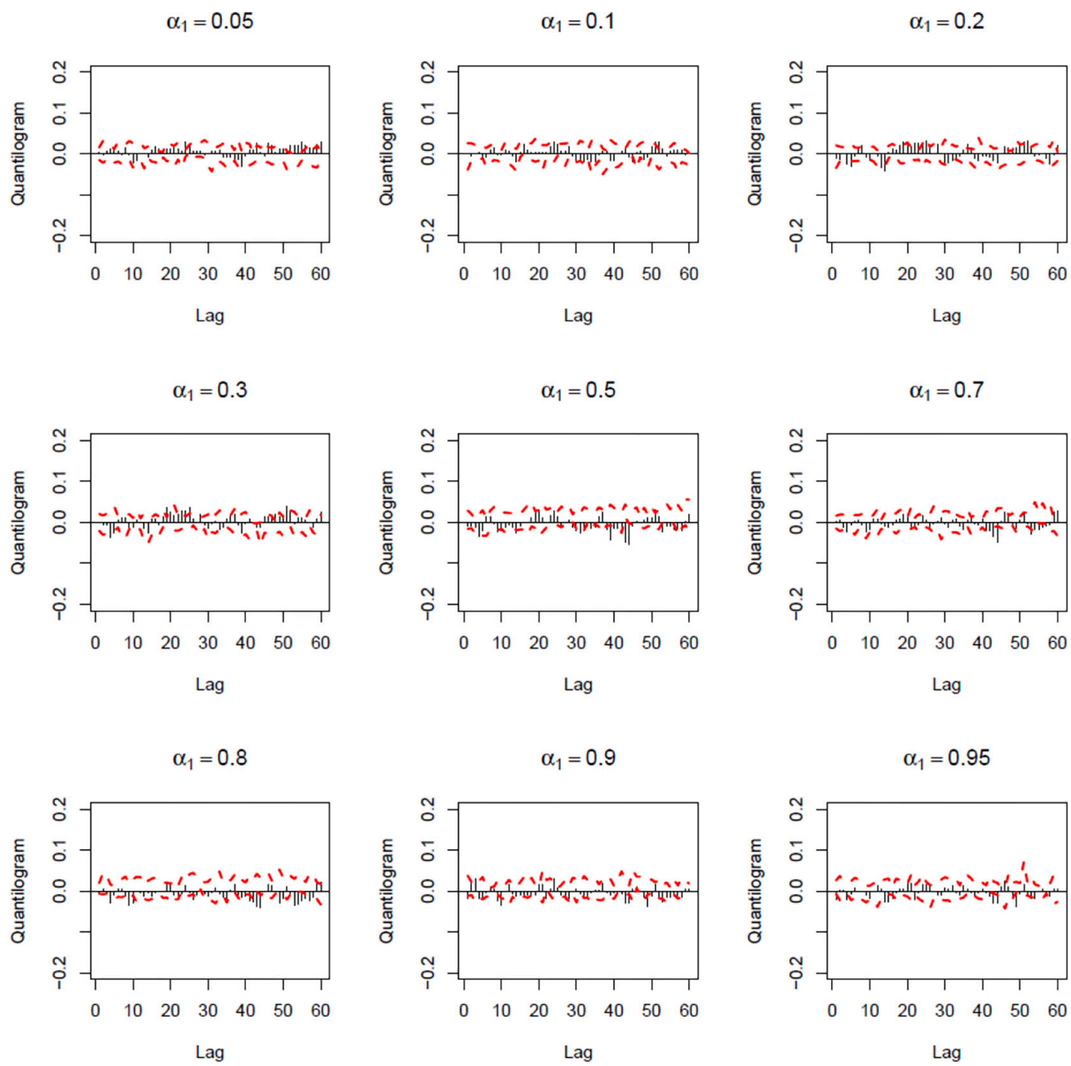

Fig. 4. Directional predictability in quantiles from network difficulty to GUESS
Notes: This figure consists of the cross-quantilograms when α2 is taken as 0.3. The bar graphs represent the cross-quantilograms. The red dotted lines refer to the 95 % bootstrap confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

indicating that there is a growing likelihood of a large positive increase in Bitcoin electricity consumption. As hash rate refers to the computing power in processing blockchain transactions and a higher hash rate is usually associated with better chances of obtaining Bitcoin as a reward, we can see that the additional computational power required by Bitcoin mining plays a significant role in predicting the energy usage of Bitcoin.

A different pattern of directional predictability is found between blockchain size and GUESS, as shown in Fig. 3. The cross-quantilograms in the extreme low quantile (0.05) are positive and statistically significant for most of the lags. Similarly, the cross-quantilograms for $\alpha_1 = 0.1$, 0.2, and 0.3 demonstrate that there is persistent directional predictability from blockchain size to GUESS for smaller lags, indicating that the likelihood of GUESS experiencing sizeable positive changes is increased if there are considerable positive changes in blockchain size. Relative to the results in Fig. 2, hash rate and blockchain size have a significant ability to predict Bitcoin electricity consumption over the next seven days. By contrast, the cross-quantilograms for $\alpha_1 = 0.5$, 0.7, 0.8, 0.9, and 0.95 show that the directional predictability from blockchain size to GUESS is beyond the first week. For example, as the lag number increases, the directional predictability from blockchain size to GUESS is detected to be significant at day 33 for $\alpha_1 = 0.5$ and 0.7, signifying a strong quantile dependence between the time series. As the scale of the Bitcoin blockchain has been continuously increasing since its launch in 2009, the corresponding electricity usage has been rising. Overall, blockchain size can be used to predict Bitcoin electricity consumption while the predictive content varies depending on different lags and quantiles.

As depicted in Figs. 4 and 5, the cross-quantilograms fluctuate between positive and negative values and do not show a consistent pattern, thereby suggesting that there is no significant directional predictability from network difficulty or Bitcoin volatility to GUESS. Furthermore, Fig. 6 shows significant directional predictability from Bitcoin returns to GUESS according to the cross-quantilograms for all quantile levels. This result indicates that remarkable positive changes in Bitcoin returns are very likely to increase Bitcoin electricity consumption. It also confirms that higher Bitcoin returns stimulate a wider interest in mining activities and add to the already large environmental burden of cryptocurrencies.

Fig. 7 illustrates the directional predictability from GUESS to CO_2 emissions. On the basis of the cross-quantilogram for the extremely low quantile (0.05), we find that significant directional predictability exists from GUESS to CO_2 emissions at day 60. This result indicates that when CO_2 emissions are very low, there is an increased likelihood that positive changes in Bitcoin electricity consumption can lead to a large increase in CO_2 emissions. A similar pattern is found when the cross-quantilogram is in the low quantile (0.1, 0.2, and 0.3); it confirms the existence of a significantly positive directional predictability from GUESS to CO_2

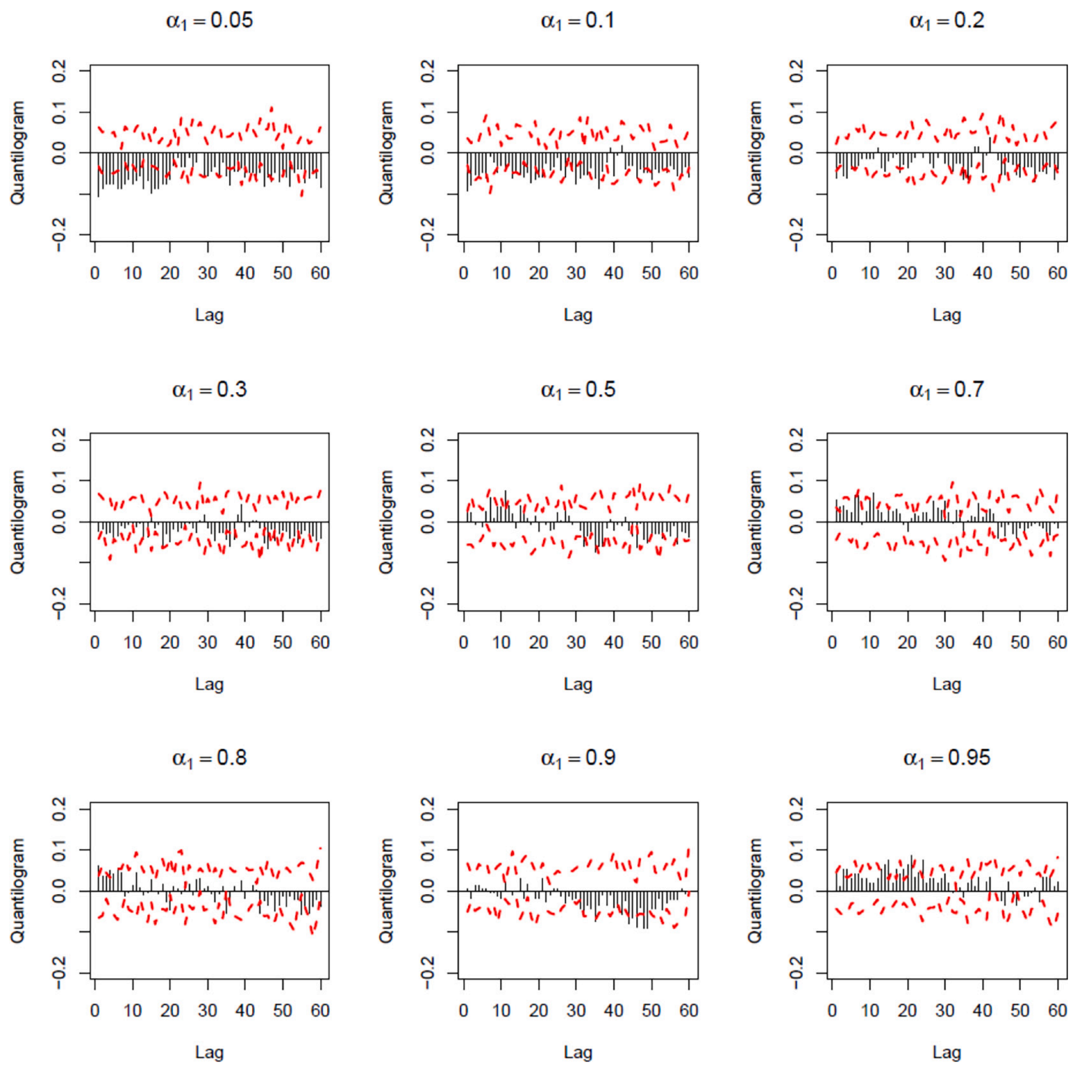

Fig. 5. Directional predictability in quantiles from Bitcoin volatility to GUESS
Notes: This figure consists of the cross-quantilograms when α2 is taken as 0.3. The bar graphs represent the cross-quantilograms. The red dotted lines refer to the 95 % bootstrap confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

emissions at approximately day 50.

Moreover, the cross-quantilograms for $\alpha_1 = 0.5$, 0.7, 0.8, 0.9, and 0.95 show that Bitcoin electricity consumption is informative in forecasting CO_2 emissions for several lags. For instance, in the case of $\alpha_1 = 0.8$, the cross-quantilogram turns out to be significantly positive at around days 10 and 40. This indicates that the likelihood of Bitcoin electricity consumption being able to project CO_2 emissions increases for different time scales. The findings from the directional predictability analysis illustrate a more comprehensive association between the Bitcoin network and CO_2 emissions. The ability of Bitcoin electricity consumption to predict CO_2 emissions at different quantiles reinforces the idea that Bitcoin mining has significant environmental implications on climate change. This finding is consistent with that of Mora et al. (2018), who document that the projected power consumption of Bitcoin can result in sufficient CO_2 emissions that would drive global warming above 2 °C in <30 years.

Overall, the two statistical tests of Granger causality in quantiles and directional predictability in quantiles follow the research lines of the bivariate modeling approach in the literature (Demir et al., 2018; Aysan et al., 2019; Dastgir et al., 2019; Bouri et al., 2018a). One of the motivations for using the bivariate modeling approach is that the multivariate Granger causality test cannot detect causal relationships between the related variables, with the exception of the central distributions, and a causal relationship indeed exists mainly in the left and right tails of the distribution, as supported by many studies. Moreover, the multivariate modeling approach of dynamic connectedness in Section 4.3 complements the bivariate analysis by providing a complete causality network analysis and evaluating all variables in a multivariate modeling framework.

4.3. Dynamic connectedness analysis

As shown in Table 3, the off-diagonal elements exhibit directional pairwise connectedness among the CO_2 emissions, Bitcoin, and blockchain variables. Hash rate has the largest spillover effects transmitted to CO_2 emissions, indicating that 9.21 % of the forecast error variance of CO_2 emissions is due to shocks from the hash rate. Table 3 also shows that the contribution of hash rate to Bitcoin electricity consumption is the greatest, amounting to 65.88 %, followed by Bitcoin returns at 7.9 %. The strong connectedness between hash rate and energy usage of the Bitcoin network corroborates the cross-quantilogram results shown in Fig. 2. Furthermore, the bottom row of Table 3 shows that Bitcoin electricity consumption receives the highest amount of net directional spillovers from the system, that is, 82.92 %. It is worth noting that spillovers from others to CO_2 emissions (30.53 %) are greater than those transmitted to others from CO_2 emissions (26.34 %), resulting in CO_2

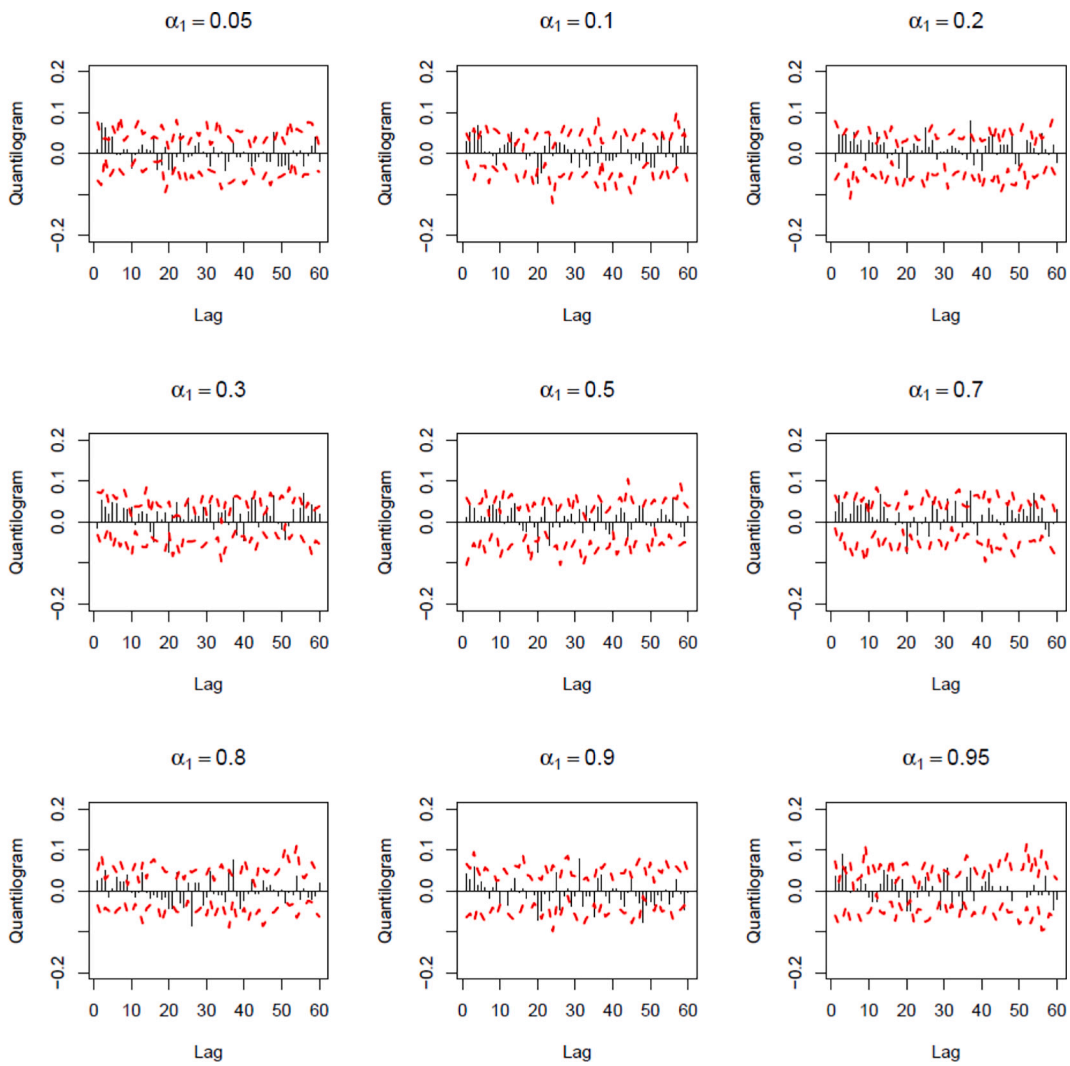

Fig. 6. Directional predictability in quantiles from Bitcoin returns to GUESS
Notes: This figure consists of the cross-quantilograms when α2 is taken as 0.3. The bar graphs represent the cross-quantilograms. The red dotted lines refer to the 95 % bootstrap confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

emissions acting as a net receiver of spillovers (4.19 %) from the system. Conversely, hash rate transmits the greatest amount of net directional connectedness to the system at 97.5 %. This implies that hash rate, as typically determined by the number of blocks and mining difficulty, has a considerable impact on the energy consumption of the Bitcoin network.

We visualize the directional net pairwise connectedness between the Bitcoin network and CO_2 emissions through a network analysis graph, as shown in Fig. 8. The interpretation of the graph can be summarized as follows: First, the edge thickness represents the pairwise directional connectedness. The thicker size and deeper colour of the edges indicate a higher degree of connectedness. Second, the arrows of the edges represent the direction of the pairwise connectedness, and the size of the nodes represents the weighted average net total directional connectedness. As shown in Fig. 8, hash rate, Bitcoin returns, and volatility act as the net transmitters of shocks in the system, whereas CO_2 emissions, Bitcoin electricity consumption, blockchain size, and network difficulty act as net receivers. In particular, hash rate is found to play a dominant role in determining the energy consumption of Bitcoin mining. Moreover, the net pairwise directional connectedness between CO_2 emissions and hash rate corroborates the existence of spillover effects from the Bitcoin blockchain to the global CO_2 emissions. This result is consistent with the evidence provided by Krause and Tolaymat (2018) for quantifying the carbon costs of cryptocurrencies and blockchains. The main finding drawn from the network analysis is that hash rate exhibits strong connectedness and plays a pivotal role in influencing Bitcoin electricity usage and CO_2 emissions.

4.4. Robustness checks

The robustness of the baseline results is examined in two ways. First, we check whether our main findings hold for an alternative forecast horizon by increasing the number of forecast steps from 20 to 30. As shown in Table 4, hash rate contributes the largest directional dynamic connectedness to CO_2 emissions (9.66 %) and Bitcoin electricity consumption (64.22 %). This is in accordance with the main results that hash rate is identified as the largest contributor of directional spillover effects to the energy usage of Bitcoin and climate change proxied by CO_2 emissions. Although the net dynamic connectedness from hash rate to the Bitcoin–climate change network has reduced marginally from 97.5 % in Tables 3 to 96.12 % in Table 4, hash rate remains the largest net transmitter of spillovers to the system. Moreover, the total connectedness index increases from 43.16 % (Table 3) to 44.47 % (Table 4), indicating stronger connectedness between the Bitcoin network and climate change. Therefore, the main results hold after adjusting the forecast horizon.

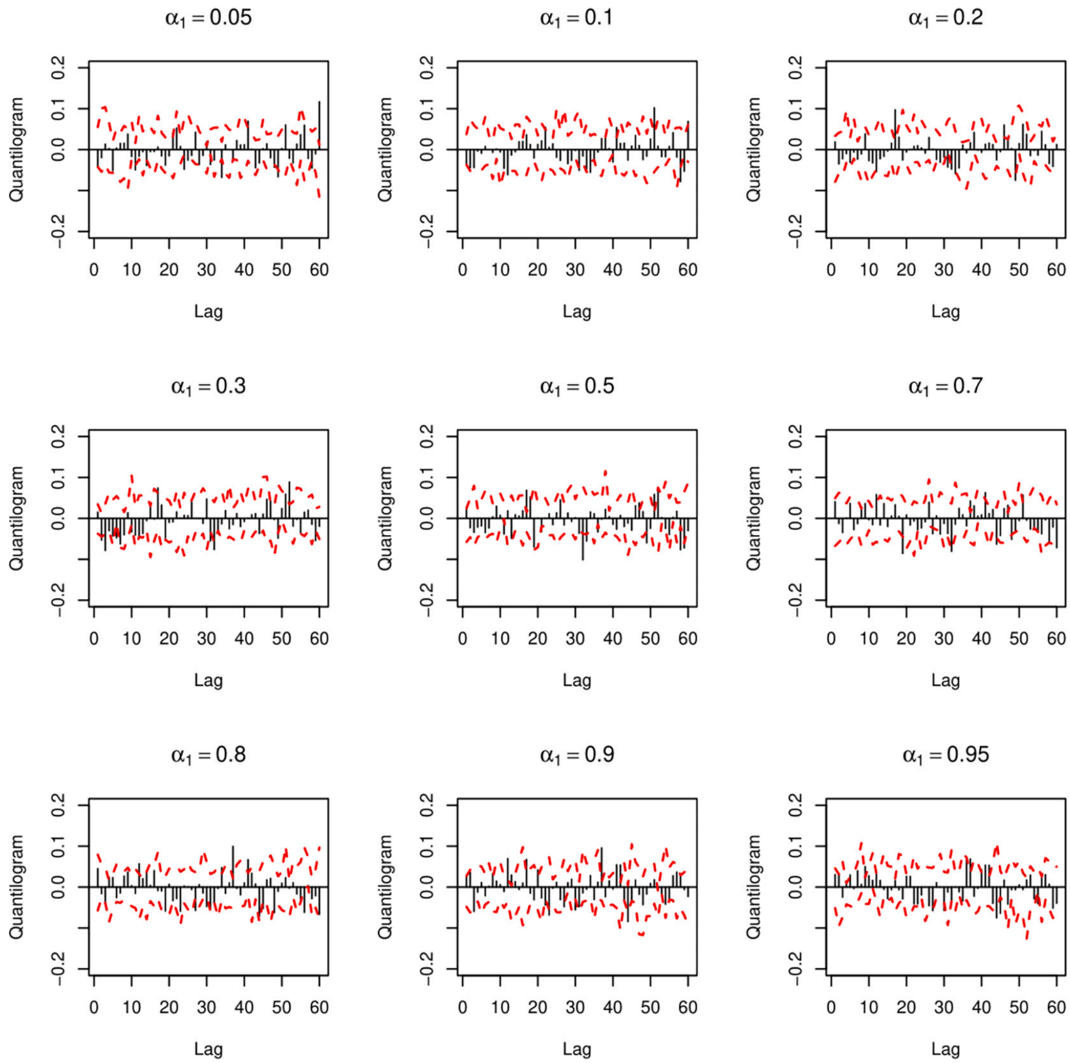

Fig. 7. Directional predictability in quantiles from GUESS to CO_2 emissions
Notes: This figure consists of the cross-quantilograms when α2 is taken as 0.3. The bar graphs represent the cross-quantilograms. The red dotted lines refer to the 95 % bootstrap confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Dynamic connectedness table.

	CO_2	GUESS	Bitcoin returns	Bitcoin volatility	Hash rate	Blockchain size	Network difficulty	FROM others
CO_2	69.47	1.38	5.19	5.94	**9.21**	5.1	3.71	30.53
GUESS	4.09	6.88	7.9	7.52	**65.88**	3.62	4.11	93.12
Bitcoin returns	4.61	1.47	67.89	10.47	7.22	3.51	4.83	32.11
Bitcoin volatility	4.53	1.07	15.23	66.06	5.12	4.63	3.36	33.94
Hash rate	4.46	2.91	6.34	5.88	73.27	3.17	3.97	26.73
Blockchain size	3.93	1.99	5.98	7.03	26.45	48.97	5.65	51.03
Network difficulty	4.73	1.38	5.61	6.26	10.36	6.31	65.35	34.65
TO others	26.34	10.2	46.26	43.1	124.24	26.34	25.64	302.12
Inc. own	95.81	17.08	114.15	109.15	197.5	75.31	90.99	TCI
NET	**−4.19**	**−82.92**	14.15	9.15	**97.5**	−24.69	−9.01	43.16

Notes: FROM others refers to the directional spillovers from the network to variable i. TO others refers to the directional spillovers from variable i to the network. Contribution including own refers to the directional spillovers from variable i to the network, including contribution from own innovations to variable i. NET refers to the net spillovers calculated as the difference between TO others and FROM others. The rest of this table reports the net pairwise spillovers.

Second, we test whether the baseline results are robust to an alternative specification of the rolling sample. Table 5 reports the robustness test results obtained by modifying the rolling window size from 200 days to 100 days. We find that hash rate still stands out as the largest transmitter of spillover effects to CO_2 emissions and Bitcoin electricity consumption. Table 5 also shows that hash rate contributes the largest spillovers to the system at 64.33 % and that Bitcoin electricity consumption receives the largest spillovers at 66.54 %. This finding corroborates the baseline dynamic connectedness results presented in Table 3. Furthermore, we find that CO_2 emissions consistently act as a net receiver of spillovers in the Bitcoin–climate change network in the robustness checks. This result is in line with the main findings.

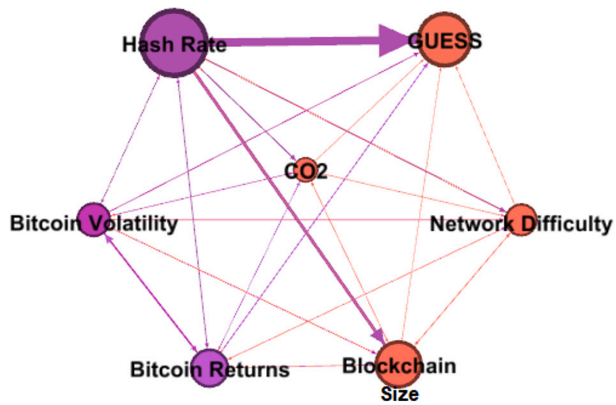

Fig. 8. Net pairwise directional connectedness.

Accordingly, our baseline results remain robust to the alternative width of the rolling window.

4.5. Discussion

The empirical evidence presented in this study helps us better understand the environmental implications of cryptocurrencies on climate change. First, our results provide novel insights by demonstrating significant Granger causality between Bitcoin mining and CO_2 emissions at higher quantiles. That said, a strong right-tail causal dependence exists between cryptocurrency energy usage and climate change, implying that more intense activities in the cryptocurrency market may result in higher CO_2 emissions and thus exacerbate climate change. This finding is consistent with that of Polemis and Tsionas (2021), who document a stronger interlinkage between Bitcoin and CO_2 emissions at higher than lower quantiles. It also highlights that regulatory regimes with respect to the cryptocurrency market should be enhanced to reduce the environmental burden of cryptocurrencies and alleviate climate change.

Second, the cross-quantilogram analysis shows that the directional predictability from the Bitcoin network to climate change is heterogeneous. By disentangling the cross-quantile dependence structure between Bitcoin trading conditions, blockchain technology, Bitcoin electricity consumption, and CO_2 emissions in a granular manner, we find that hash rate, blockchain size, and Bitcoin returns demonstrate positive directional predictability for Bitcoin electricity consumption, which, in turn, is shown to forecast CO_2 emissions. This result is supported by the findings of Mora et al. (2018) and Jana et al. (2022). More importantly, it should raise awareness about the environmental consequences of the cryptocurrency market. In this regard, it is imperative to accelerate the transition from fossil fuels to renewables as primary energy sources for mining cryptocurrencies. It is also important to promote the energy efficiency of mining hardware and blockchain technology to reduce CO_2 emissions and tackle the issue of climate change.

Third, we find that hash rate acts as the largest net transmitter of spillover effects to Bitcoin electricity consumption and CO_2 emissions. This finding may be underpinned by the fact that hash rate is a fundamental component of PoW consensus mechanisms, which are competitive but energy-intensive protocols for validating cryptocurrency transactions (Stoll et al., 2019; De Vries et al., 2022). The inherent design of PoW algorithms requires high computational power and energy consumption. Consequently, we argue that progress in the underlying distributed ledger technology may allow for the rise of a more energy-efficient and decentralized financial infrastructure and cryptocurrency. By optimizing energy usage and improving the environmental efficiency of the decentralized consensus mechanism, advances in blockchain technological innovations will play a pivotal role in ensuring the sustainable development of the cryptocurrency ecosystem.

Table 4
Robustness test using 30-step ahead forecasting horizon.

	CO_2	GUESS	Bitcoin returns	Bitcoin volatility	Hash rate	Blockchain size	Network difficulty	FROM others
CO_2	67.99	1.45	5.46	6.23	**9.66**	5.43	3.79	32.01
GUESS	4.24	7.29	8.28	8.05	**64.22**	3.71	4.21	92.71
Bitcoin returns	4.81	1.61	66.27	10.91	7.7	3.71	5	33.73
Bitcoin volatility	4.55	1.14	15.86	63.94	5.68	5.35	3.46	36.06
Hash rate	4.59	3.38	6.43	6.21	71.9	3.4	4.09	28.1
Blockchain size	4.02	2.39	6.04	7.57	26.13	47.82	6.03	52.18
Network difficulty	4.89	1.58	5.88	6.81	10.83	6.51	63.5	36.5
TO others	27.08	11.56	47.96	45.78	124.21	28.12	26.57	311.29
Inc. own	95.08	18.85	114.22	109.73	196.12	75.93	90.07	TCI
NET	**−4.92**	**−81.15**	14.22	9.73	**96.12**	−24.07	−9.93	**44.47**

Notes: FROM others refers to the directional spillovers from the network to variable i. TO others refers to the directional spillovers from variable i to the network. Contribution including own refers to the directional spillovers from variable i to the network, including contribution from own innovations to variable i. NET refers to the net spillovers calculated as the difference between TO others and FROM others. The rest of this table reports the net pairwise spillovers.

Table 5
Robustness test using 100-day rolling window size.

	CO_2	GUESS	Bitcoin returns	Bitcoin volatility	Hash rate	Blockchain size	Network difficulty	FROM others
CO_2	42.89	3.69	10.77	10.52	**12.22**	10.72	9.18	57.11
GUESS	8.56	7.56	11.97	10.83	**43.96**	8.27	8.85	92.44
Bitcoin returns	9.08	4.17	41.17	14.57	12.51	8.43	10.08	58.83
Bitcoin volatility	6.91	3.69	17.17	41.65	11.21	10.16	9.22	58.35
Hash rate	9.76	5.62	10.19	10.3	47.31	8.34	8.49	52.69
Blockchain size	8.31	4.96	9.97	11.35	23.02	32.39	10.01	67.61
Network difficulty	9.61	3.77	10.2	10.84	14.11	11.68	39.78	60.22
TO others	52.22	25.9	70.27	68.41	117.03	57.6	55.83	447.26
Inc. own	95.11	33.46	111.44	110.06	164.33	89.98	95.61	TCI
NET	**−4.89**	**−66.54**	11.44	10.06	**64.33**	−10.02	−4.39	**63.89**

Notes: FROM others refers to the directional spillovers from the network to variable i. TO others refers to the directional spillovers from variable i to the network. Contribution including own refers to the directional spillovers from variable i to the network, including contribution from own innovations to variable i. NET refers to the net spillovers calculated as the difference between TO others and FROM others. The rest of this table reports the net pairwise spillovers.

5. Conclusions

5.1. Concluding remarks

The fast-growing cryptocurrency market generates a tremendous amount of power demand, which poses a threat to the fulfillment of climate objectives and the transition to a net-zero world. Cryptocurrency mining is becoming more difficult as the network of encrypted assets continues to grow, leading to a sharp rise in computing power requirements for handling mining machines and the amount of energy required to generate digital tokens (Yan et al., 2022; Umar et al., 2021; Baur and Oll, 2022). Given the growing concerns about the environmental impacts of Bitcoin mining, we examine the implications of the cryptocurrency ecosystem on climate change and attempt to build a bridge between cryptocurrency energy consumption and corresponding policy reforms.

This study analyzes the association between Bitcoin mining and climate change by examining cross-quantile Granger causality, directional predictability, and dynamic connectedness. Specifically, we show that significant Granger causality exists between Bitcoin electricity consumption and CO_2 emissions in the upper quantiles, indicating that the causal dependence between cryptocurrency energy usage and climate change is asymmetric. We also find significant yet heterogeneous directional predictability from the Bitcoin network and blockchain variables to the global carbon footprint. In addition, the dynamic connectedness analysis suggests that hash rate acts as the largest net transmitter of spillover effects in the network that links the Bitcoin market to climate change. Overall, our results reaffirm the notion that hash rate is the underlying reason for the energy-intensive nature of Bitcoin mining.

5.2. Policy implications

These findings have practical implications for policymakers and other stakeholders. The empirical evidence provides valuable implications for monitoring environmental degradation caused by cryptocurrency energy usage. Drawing on the environmental impacts of Bitcoin mining on climate change, this study calls for the design and implementation of regulations and strategic plans to stimulate the transformation toward sustainable cryptocurrency mining and thereby decrease the carbon footprint and mitigate the environmental concerns of the cryptocurrency ecosystem (Huynh et al., 2021).

Moreover, this study suggests that it is critical to nurture carbon-neutral blockchain transactions by encouraging institutional cryptocurrency investors to seek environmental, social, and governance (ESG) compliance to offset the carbon footprint of cryptocurrencies. To alleviate the environmental consequences of cryptocurrencies, technological innovations in renewable energy and their applications in the cryptocurrency market should be promoted (Huynh et al., 2020a; Browne, 2021; Wang et al., 2018).

Finally, this study highlights the necessity of overcoming the technical and operational complexities in developing more environmentally friendly consensus algorithms and blockchain technology to curtail the energy demand of the cryptocurrency network (Bouri et al., 2018b). Meanwhile, the promotion of less energy-intensive distributed ledger technology systems, such as proof of stake (PoS), can contribute to the decarbonization of cryptocurrencies. Relative to the PoW consensus mechanism adopted by the Bitcoin blockchain network, PoS-permissioned crypto assets benefit from energy-efficient network architectures and require significantly less energy to process transactions (Lei et al., 2021).

5.3. Future research

The empirical evidence presented in this study highlights the environmental implications of cryptocurrency energy usage on climate change. This topic can be further explored in future research. For instance, future studies can be extended to a wide range of cryptocurrencies by including alternatives to Bitcoin, such as Ethereum, Litecoin, and Dogecoin. It would also be interesting to examine whether decentralized financial instruments can bring additional environmental benefits relative to traditional financial products. Furthermore, future research analyzing the linkage between cryptocurrency energy consumption and climate change can incorporate other quantile-based approaches, including the quantile heterogeneous autoregressive model and quantile coherency. In addition, scenario-based evaluation can be conducted to quantify the dynamic interlinkage between the trajectory of the technological development of cryptocurrencies and climate change.

CRediT authorship contribution statement

Dongna Zhang: Data curation, Formal analysis, Methodology, Software, Writing - original draft, Writing - review & editing. **Xihui Haviour Chen:** Project administration, Writing - original draft. **Chi Keung Marco Lau:** Supervision, Writing – review & editing, Conceptualization, Software. **Bing Xu:** Project administration, Writing - review & editing.

Data availability

Data will be made available on request.

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Dongna Zhang is an Assistant Professor at Northumbria University. Dr. Zhang holds a PhD in Economics from the University of York, UK. Her research interests include financial economics, energy economics, the interactions between finance and macroeconomic activity, and firm behaviour. Her research findings shed light on the UK under-investment puzzle and provide policy implications on industrial strategy. Her publication has bee appeared in journals such as Economic Letters.

Xihui Chen is an Assistant Professor of Accounting and Finance at Edinburgh Business School, Heriot-Watt University, UK. She has been a Senior Lecturer in Accounting and Finance at the Department of Finance, Performance & Marketing, Teesside University International Business School until May 2022. She joined Teesside in 2019 after completing her PhD in Corporate Governance from Nottingham Trent University. She has presented her research at a large number of top international conferences (e.g., BAM, BAFA, EAA and ICGS), workshops and research seminars in various countries. She is a Visiting Scholar of the University of Economics in Katowice, Poland. She is the first Chinese international student president of all UK Students' Union and she was awarded the Highly Commended International Student of the Year in the UK in 2013. She is working toward her CIMA professional qualification and Senior Fellow of HEA.

Chi Keung Marco Lau is an Associate Professor at The Hang Seng University of Hong Kong. Most of his recent research has been in Digital Finance, Financial Economics, International Finance, and Energy Economics. He published over 120 papers in SSCI/SCI peer review journals, with a current h-index = 33. His publications have appeared in ABS4* and ABS3* journal. He also served as the Founding Associate Editor of Eurasian Business Review (ABS/SSCI listed), and the current Associate Editor of Asian Economics Letters. According to RePEc (Research Papers in Economics) Professor Lau sit in the top 7 % of economist in Europe. Professor Lau has been featured in the list of top 2 % scientists in the world published by Stanford University in 2021 (ranked 211th in the category of Finance)

Bing Xu is a Professor of Finance at Edinburgh Business School, Heriot-Watt University, UK. She holds a MA (Hons) in Business Studies & Accounting and a PhD in Management both from the University of Edinburgh. Her current research interests are financial modelling for energy systems, sustainable finance and multi-criteria decision making analysis. She has worked on a portfolio of external funded multidisciplinary projects on low carbon fuels, sustainable cold-chains, and circular chemical economy which are recognised as central to achieving carbon neutrality. Bing is currently leading on "Policy, Society and Finance" theme of work on several multidisciplinary UKRI funded projects to address non-technological barriers around business and finance models, social dynamics, and policy, such as Zero Emission Cold-Chain (EP/V042548/1); UKRI Interdisciplinary Centre for Circular Chemical Economy (EP/V011863/1); Digital Circular Electrochemical Economy (EP/V042432/1).