Assessing the Carbon Footprint of Cryptoassets: Evidence from a Bivariate VAR Model

Hany Fahmy

1 Introduction

On September 7, 2021, El Salvador became the first country to adopt bitcoin as legal tender.[1] A few days later, on September 24, 2021, the central bank of China, one of the world's largest cryptocurrency markets, declared all virtual currency-related business activities illegal. This declaration effectively banned digital tokens such as bitcoin, the first and most popular cryptocurrency. Governments are not alone in their mixed feelings regarding cryptocurrencies and the blockchain technology that scaffolds them. While blockchain technology has many advantages in various fields such as smart contracts (Kosba et al., 2016), insurance (Gatteschi et al., 2018), and education (Turkanovic et al., 2018), among many others, Bitcoin's energy hunger has recently triggered a heated debate in the academic literature about its massive consumption

[1] Through the text, Bitcoin with a capital "B" represents the network while bitcoin with a small "b" represents units of the network's digital currency.

H. Fahmy (✉)
Royal Roads University, Victoria, BC, Canada
e-mail: hany.fahmy@royalroads.ca

T. Walker et al. (eds.), *Big Data in Finance*,
https://doi.org/10.1007/978-3-031-12240-8_11

and its carbon footprint (e.g., De Vries, 2018; Hayes, 2017; Kraus & Tolaymat, 2018; Mora et al., 2018; Stoll et al., 2019; Zade et al., 2019). Despite the inconsistencies and the large variations in the results of previous studies when measuring the electricity consumption of Bitcoin itself and, consequently, its carbon footprint, the importance of this topic is seeing a significant increase among policymakers, regulators, and investors, who are becoming acutely aware of climate change risks, especially after the Paris Agreement (Fahmy, 2022b). This topic is also relevant for stakeholders of the new emerging clean energy sector (Fahmy, 2022a).

The main objective of this chapter is to provide a sensible economic approximation and a meaningful economic forecast of the carbon footprint of cryptoassets following Bitcoin's alarming energy consumption. To this end, we examine the relationship between cryptocurrencies' trading volumes and Bitcoin's energy consumption using a vector autoregression (VAR) framework. More specifically, we use the VAR framework to test the directional Granger causality (Granger, 1969) from cryptocurrencies' trading volumes to Bitcoin's electricity consumption. Furthermore, from the VAR estimates, we conduct an impulse-response analysis to investigate the impact of one standard deviation shock (also known as innovation) in bitcoin's trading volume on the network's energy consumption. Finally, we use the results of our impulse-response analysis to provide an approximation of the carbon footprint of bitcoin, and to compute a sensible five-year economic forecast of the environmental impact of such digital currency.

We contribute to the existing literature in several ways. First, by examining the correlation between the top five cryptocurrencies' trading volumes, as proxies of investors' demand for digital currency, and Bitcoin's electricity consumption, we find that the network's electricity consumption correlates highly with trading volumes. This high correlation is robust for all cryptocurrencies. In the case of bitcoin, the correlation coefficient between the currency's average trading volume and the network's electricity consumption is 0.89. This strong positive correlation suggests a similar co-movement of both variables. Our Granger causality tests confirm this fact. Our results show, as expected, the existence of *one-way* directional causality from cryptocurrencies' trading volume to the network's electricity consumption.

Second, after revealing the main economic driver of Bitcoin's electricity consumption, i.e., bitcoin's trading volume, we conduct an impulse-response analysis within the proposed VAR model to measure the impact of a shock in trading volume on electricity consumption. We find that one standard deviation shock in bitcoin's trading volume has a *persistent* impact on Bitcoin's electricity consumption of about 8.8% per month on average over a period of twelve months. This result, which is robust across all cryptocurrencies under investigation, indicates that shocks do not die out in the long run, i.e., after a few months. This result, in turn, means that the network's electricity consumption increases exponentially following increased demand for cryptoassets.

Third, building on the previous dynamic forecast of the impulse–response analysis, we estimate the bitcoin's carbon footprint using reasonable assumptions about the Bitcoin's share of fossil fuels sources, i.e., coal and natural gas, and their carbon intensity. We find that bitcoin mining produced approximately 43 million metric tons of carbon from using coal and natural gas in 2020. This amount represents 0.14% of the world's total carbon emissions of that year. While this figure might not sound high, a deeper look at the progression of Bitcoin's electricity consumption following a shock in its trading volume (as suggested by our impulse–response analysis) reveals a rather disturbing statistic. We find that Bitcoin's average monthly electricity growth of 8.8%, as predicted by our impulse–response analysis, is equivalent to a 63% growth rate per year. This electricity growth means that over five years, i.e., by the end of 2026, and assuming a constant growth of 63% per year, the total electricity consumption of Bitcoin is expected to generate 492 million metric tons of carbon. This electricity consumption translates to approximately 1.6% of today's total carbon emissions worldwide. Indeed, this is a significant environmental impact.

Finally, despite the axiomatic limitations of our predictions, we believe that they are sensible enough to warrant the attention paid to the negative environmental implications of such digital currencies. It is worth noting that our analysis predicts the carbon footprint of bitcoin only. However, bitcoin accounts for two-thirds of the cryptocurrency's total energy consumption, and understudied cryptocurrencies represent the remaining one-third. Understudied currencies add nearly 50% on top of bitcoin's energy hunger (Gallersdörfer et al., 2020). This statistic means that including the remaining cryptocurrencies and the hundreds of other mineable coins and tokens would further increase the share of energy consumption beyond bitcoins. Therefore, further investigation of the carbon footprints of the crypto sector is essential for regulators and policymakers to understand and mitigate the environmental impacts of cryptoassets and the blockchain technology behind them.

The remainder of the chapter is organized as follows: Sect. 2 reviews the literature; Sect. 3 describes the data used in this study; Sect. 4 introduces the VAR methodology and discusses the causality tests and the impulse–response analysis; Sect. 5 documents the environmental impact of Bitcoin's energy consumption; Finally, Sect. 6 concludes the chapter.

2 Literature Review

A cryptocurrency is a decentralized digital monetary and payment system. Most cryptocurrencies utilize blockchain technology, a publicly shared ledger data technology enforced by a network of computers to record transactions continuously among decentralized nodes (Zheng et al., 2017). A blockchain is a distributed database that is continuously updated and verified by its users. Each added record forms a block of data on the chain and becomes part of a growing list of records. Network members surveil all records through a secure database.

The decentralized nature of blockchain technology allows participants to make joint transactions in a shared digital platform without assigning market power to a platform operator. In this respect, this technology contributes to increase competition, lower barriers to entry, and lower privacy risk (Catalini & Gans, 2016). Blockchain technology enables the transfer of assets and secure recording of transactions, and thus, offers innovative advantages in the supply chain, business, healthcare, and other fields, including climate change. A news report by the United Nations Climate Change (UNCC) suggests that blockchain technology can play a major role in the fight against climate change by improving the system of carbon asset transactions, i.e., improving carbon emission trading, promoting peer-to-peer clean energy trading, and enhancing climate finance flow by developing crowdfunding peer-to-peer financial transactions in support of climate action.[2] Sanderson (2018) studies the connection between blockchain and bond markets and suggests that blockchain technology can be a potential solution to enhance the reporting standards of this market. Harris (2018) documents

[2] More details are found here: https://unfccc.int/news/how-blockchain-technology-could-boost-climate-action.

how blockchains can improve environmental goals consistent with the Paris Agreement.

Despite the previously suggested climate benefits of blockchain technology, another strand of the literature warns about the negative environmental impact of using blockchain technology in creating cryptoassets. All bitcoin and most other cryptocurrencies need an algorithmic validation through the resolution of a cryptographic problem to add blocks to the chain, which results in the creation of new cryptocurrency. New bitcoins are created as a reward for transaction processing work in which users offer their computing power to verify and record payments into the public ledger. Individuals or firms engage in this process, which is also known as "mining," in exchange for the chance to earn newly created blocks of bitcoins (Hayes, 2017). While only the node which solves the problem gets the reward, the cryptographic problem is sent to all computer nodes in the network for algorithmic consensus (Dupont, 2019). This situation generates a context where all other computer nodes consume energy without any reason/reward. In fact, this mining process is so computation-intensive that the Bitcoin network has been estimated to consume as much energy (22 terawatt-hours per year) as Ireland in 2018 (De Vries, 2018). Several studies (e.g., De Vries, 2018; Stoll et al., 2019) suggest that the increasing trend in Bitcoin's energy use could seriously increase global temperature. Some studies even suggest that this increase could reach 2 °C by 2034 (e.g., Mora et al., 2018).

In this chapter, we argue that Bitcoin's energy consumption, which is triggered by the continuous increase in cryptocurrencies' trading volumes, is expected to have a severe negative environmental impact. We intend to test this hypothesis and provide a sensible forecast of these impacts. It is worth noting, however, that it is difficult to measure the actual electricity consumption of Bitcoin for various reasons. First, it is difficult to identify the individual miners who operate on Bitcoin's blockchain. Second, miners use different hardware equipment with various degrees of energy efficiency. Third, hashing facilities vary significantly in terms of how effectively they use electric power.[3] For instance, how much electricity is used by miners for cooling as opposed to just running the machines can vary significantly between facilities. For all these reasons, the electricity consumption of Bitcoin cannot be precisely

[3] A hashing facility, also known as "mining farm," is a physical data center dedicated to cryptocurrency mining activities.

determined by researchers. It can, however, be estimated based on theoretical models that rely on specific assumptions. In the literature on the subject, there are many examples of empirically attempting to analyze the electricity consumption of the Bitcoin network and to compute its environmental footprint (e.g., De Vries, 2018; Hayes, 2017; Kraus & Tolaymat, 2018; Mora et al., 2018; Stoll et al., 2019; Zade et al., 2019). As mentioned above, the previous studies produce significantly inconsistent estimates that lead to different assessments of the network's carbon footprint. This inconsistency is due to the different approaches and assumptions used by the authors in their calculations. However, aside from these variations, the previous studies agree that the increasing trend in Bitcoin's energy use has negative environmental implications that warrant further investigations.

3 Data Description

In this chapter, we use the Cambridge Bitcoin Electricity Consumption Index (CBECI) as an estimate of the Bitcoin network's daily electricity load. The monthly CBECI, which is measured in terawatt-hours (TWh), is a bottom-up economic model that provides a best-guess estimate of Bitcoin's actual electricity consumption within the boundaries of a hypothetical lower bound (floor) and a hypothetical upper bound (ceiling) estimate (https://ccaf.io/cbeci/index/methodology). The lower bound estimate is based on the best-case assumption that all miners always use the most energy-efficient equipment available on the market. The upper bound estimate is based on the worst-case assumption that all miners always use the least energy-efficient hardware available on the market. The best-guess estimate, or the CBECI, is based on the more realistic assumption that miners use a basket of profitable hardware rather than a single model. The reason we choose the CBECI approach to compute Bitcoin's electricity consumption is twofold. First, the CBECI model was designed after carefully reviewing the various methodologies and practices used in the literature. Second, except for De Vries' (2018) Bitcoin Energy Consumption Index, which approaches energy consumption from an economic perspective founded on the relation between miners' incomes

Table 1 Summary statistics

Stats	*CBECI (TWh)*	$ATV_{bitcoin}$	$ATV_{ethereum}$	ATV_{ripple}	$ATV_{stellar}$	$ATV_{litecoin}$
Mean	3.8	16.5	8	1.9	0.3	1.8
Maximum	10.3	81	48.7	16.1	2.6	9.2
Minimum	0.2	0	0	0	0	0
S.D	2.9	19.2	10.5	3	0.6	2.2
N	77	77	77	77	77	77

CBECI is the monthly Cambridge Bitcoin Electricity Consumption Index measured in terawatt-hours (TWh)
ATV_j is the monthly average trading volume of cryptocurrency j measured in billions of US dollars
S.D. is the standard deviation
N is the number of observations. The sample period is between August 2015 and December 2021

and costs, the CBECI is the only live index tracking Bitcoin's electricity load and consumption in real-time.[4]

For data on cryptocurrencies, we use daily trading volume data from August 2015 to December 2021 on the five leading cryptocurrencies: Bitcoin, Ethereum, Ripple, Stellar, and Litecoin. These five currencies represent more than 78% of the overall cryptocurrency market and attract more than 82% of the 24-h trade volume (Ji et al., 2019). All daily trading volume series are converted into monthly averages over the analysis period to be consistent with the monthly frequency of the CBECI that is used as a proxy for the cryptocurrency energy consumption. The monthly average trading volumes of the previous currencies are denoted in the text by $ATV_{bitcoin}$, $ATV_{ethereum}$, ATV_{ripple}, $ATV_{stellar}$, and $ATV_{litecoin}$, respectively, and are measured in billions of U.S. dollars. The data is sourced from the Coinmarketcap website (https://coinmarketcap.com). The starting point of the analysis, August 2015, is dictated by data availability for cryptocurrencies. Table 1 gives a summary statistic of the previous variables.

Figure 1 plots the monthly CBECI in TWh and the average trading volume of Bitcoin, Ethereum, Ripple, Stellar, and Litecoin in tens of billions of U.S. dollars over the analysis period (August 2015–December 2021). The average trading volumes of the five cryptocurrencies behave similarly. Bitcoin's average trading volume correlates highly with Ethereum's average trading volume as the correlation coefficient

[4] More details on the methodology and its limitations can be found here: https://digiconomist.net/bitcoin-energy-consumption.

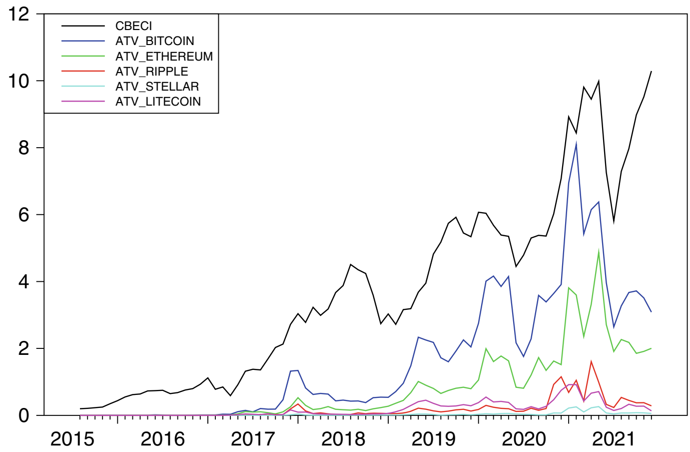

Fig. 1 Monthly Cambridge Bitcoin Electricity Consumption Index (BCECI) and the monthly average trading volume (ATV) of Bitcoin, Ethereum, Ripple, Stellar, and Litecoin (*Note* Monthly Cambridge Bitcoin Electricity Consumption Index [BCECI] measured in terawatt-hours [TWh] and monthly average trading volume [ATV] of cryptocurrencies measured in tens of billions of US dollars between August 2015 and December 2021)

between the two series is 0.96. In fact, all pairwise correlation coefficients between the average trading volumes of all five cryptocurrencies are very high and significant at the 1% level of significance, as shown from the test statistics of Ljung and Box's (1978) Q test of no cross-correlation, which are displayed in brackets beneath the cross-correlations values in the correlation matrix in Table 2. Also notable is the very high and significant correlation between the CBECI and the trading volumes of all cryptocurrencies. This preliminary investigation justifies the similar behavior of these series and points to the existence of causal relation between cryptocurrencies' energy consumption and their trading volume. We expect, of course, one-way directional causality from cryptocurrencies' trading volume to energy consumption and not the other way round. As we demonstrate below, the Granger causality tests within our proposed VAR framework confirm this fact.

4 Empirical Methodology

We use a bivariate vector autoregression (VAR) framework to investigate the relationship between each cryptocurrency's trading volume and

Table 2 Cross-correlations between the Cambridge Bitcoin Electricity Consumption Index (CBECI) and the average trading volumes of the top five cryptocurrencies

Variables	*CBECI*	$ATV_{bitcoin}$	$ATV_{ethereum}$	ATV_{ripple}	$ATV_{stellar}$	$ATV_{litecoin}$
CBECI	1					
$ATV_{bitcoin}$	0.89*** (61.95)	1				
$ATV_{ethereum}$	0.87*** (60.57)	0.96*** (72.95)	1			
ATV_{ripple}	0.73*** (41.67)	0.82*** (53.70)	0.82*** (52.83)	1		
$ATV_{stellar}$	0.75*** (44.16)	0.88*** (62.32)	0.92*** (66.82)	0.87*** (60.21)	1	
$ATV_{litecoin}$	0.77*** (47.48)	0.93*** (67.66)	0.86*** (58.18)	0.82*** (53.65)	0.84*** (56.52)	1

The figures between brackets underneath the pairwise correlation coefficients are the test statistics of Ljung and Box's (1978) robust Q test of zero cross-correlation

***, **, and * denote a test statistic is statistically significant at the 1, 5, and 10% level of significance, respectively

energy consumption. To reduce any unwanted variability (heteroskedasticity) in the data, we transform all series into their natural logarithms. To simplify the notation, let $Y = \ln(\text{CBECI})$, $X^b = \ln(ATV_{bitcoin})$, $X^e = \ln(ATV_{ethereum})$, $X^r = \ln\left(ATV_{ripple}\right)$, $X^s = \ln(ATV_{stellar})$, and $X^l = \ln(ATV_{litecoin})$. In a VAR framework, each variable depends on the lagged values of all the variables in the system. For instance, in a VAR system of order p that consists of two variables Y and X^j, for any cryptocurrency j, i.e., a bivariate VAR of order p, Y depends on its p lags and the p lags of X^j, and similarly, X^j depends on its own p lags and the p lags of Y; that is, a bivariate VAR system of order p that consists of the Bitcoin electricity consumption and cryptocurrency j's trading volume is defined as:

$$Y_t = \phi_1 Y_{t-1} + \ldots + \phi_p Y_{t-p} + \theta_1 X^j_{t-1} + \ldots + \theta_p X^j_{t-p} + \varepsilon_t,$$

$$X^j_t = \psi_1 X^j_{t-1} + \ldots + \psi_p X^j_{t-p} + \lambda_1 Y_{t-1} + \ldots + \lambda_p Y_{t-p} + \nu_t, \quad (1)$$

for $t = 1, \ldots, N$, where ϕ_i, θ_i, ψ_i, λ_i, for $i = 1, \ldots, p$, are system parameters, and ε_t, ν_t are error terms that are assumed to be independent and identically distributed with a zero mean and a constant variance.[5] One of the advantages of using the previous VAR framework is that it allows us to test the Granger directional causality (i.e., whether the lags of one variable help to explain the current value of the other variable) and describe the dynamic of the data (i.e., the response of one variable to a one standard deviation shock in another). For instance, from the first equation in the previous system, we can test whether the lags of the trading volume of cryptocurrency X^j are jointly causing the current value of the Bitcoin network's electricity consumption by simply testing the null hypothesis $H_{01} : \theta_1 = \ldots = \theta_p = 0$. Similarly, the other directional causality can be tested by testing the null hypothesis $H_{02} : \lambda_1 = \ldots = \lambda_p = 0$ from the second equation in the system. Rejecting H_{01} and accepting H_{02} is indicative of a one-way directional causality from cryptocurrency trading volume to electricity consumption.

Another advantage of the rich data structure of the VAR system is that the model dynamic can be studied using impulse–response functions. A linear impulse–response function within a VAR framework shows the impact of one standard deviation shock in one variable on another variable's current and future values. Using the Cholesky decomposition, we compute the orthogonalized impulse–response functions. We choose these functions over the conventional linear impulse–response functions because, unlike the linear type, this type forces the innovation in one time series to have no contemporaneous effect on the other series. An orthogonalized impulse–response function requires an ordering of the variables such that the first variable in the ordering is not contemporaneously affected by shocks to the second variable. However, the first variable is the only one with a potential immediate impact on the second. This setup, which is consistent with the (Granger) causality from cryptocurrency j's trading volume, X^j, to Bitcoin's electricity consumption, Y, is particularly suitable here as it allows us to easily trace the impact of a shock in trading volume (first variable in the ordering) on electricity consumption (second variable in the ordering). The results of this analysis will subsequently allow us to assess the environmental footprint of cryptocurrencies' energy consumption using sensible assumptions.

We begin the analysis by selecting an appropriate lag length p for the VAR system in Eq. (1). Determining the proper lag length in a VAR

[5] The order p in each equation refers to the number of lags of each variable.

system depends on the purpose of fitting such a model. If the objective is to test the directional (Granger) causality among the variables, then using a selection criterion like the Akaike information criterion, or AIC for short (Akaike, 1974), is advisable. If, however, the objective is to study the dynamics of the data using impulse–response functions, then selecting a reasonable lag length for the data (such as $p = 4$ for quarterly and $p = 12$ for monthly data) is recommended. It is also recommended to ensure that the maximum lag length is reasonable for the model's size, i.e., the number of observations. In the present analysis, we will use the AIC to determine the lag length of the VAR model to test the directional causality from cryptocurrencies' trading volume to energy consumption. As for the dynamic analysis, we will use a lag length $p = 12$ to study the impact of one standard deviation shock in trading volume on energy consumption. This lag length is reasonable here since we have a total number of $N = 77$ monthly observations.

4.1 Causality Tests

We begin with the directional causality analysis. Guided by the AIC, which is minimized at a lag length of order 1 for the bivariate VAR system for Y and X^j for each j, we fit the following VAR model of order $p = 1$ to each pair of variables for each j:

$$Y_t = \phi_1 Y_{t-1} + \theta_1 X^j_{t-1} + \varepsilon_t,$$

$$X^j_t = \psi_1 X^j_{t-1} + \lambda_1 Y_{t-1} + \nu_t, \tag{2}$$

where $t = 1, \ldots, N$, and everything else is defined as before.

The estimation results suggest that the bivariate VAR model for each pair Y and X^j, for every j, fits well. Table 3 documents the results. Consider the Y-X^b pair, for instance. The adjusted coefficient of determination (adjusted R^2) is 0.982 for the Y equation and 0.980 for the X^b equation. Similar values are reported for the other four pairs of equations. These values are remarkably high and demonstrate the goodness of fit of the bivariate VAR models. The standard error of each equation measures how different the dependent variable's predicted values are from the actual values. Smaller standard error values are better because they imply less dispersion about the regression line. This smaller standard error, in turn, means a tighter fitting model. All equations' standard error values obtained are small, which is another indication of the goodness of fit ofall fitted bivariate VAR models. The standard error of the equation expressed as a percentage of the mean of the dependent variable also confirms that each equation fits very well. Finally, we test the goodness of fit for each equation by adding a constant term to each equation in the VAR system and testing the null hypothesis that all coefficients (except the constant term) of the explanatory variables on the right-hand side are zeroes. Judging by the F statistic of this test, we reject this null hypothesis at the 1% level of significance for each equation and conclude that the overall fit of each equation is significant.

Next, we perform Granger causality tests on each bivariate VAR system ($\mathrm{Y} - \mathrm{X}^j$ for each j) and report the results in Table 4. Judging by the F statistic of the tests, the null hypothesis that the trading volume of cryptocurrency j, X^j_{t-1}, does not Granger cause the Bitcoin network's electricity consumption, Y_t, is rejected at the 1% level of significance for all five cryptocurrencies, whereas the null hypothesis that electricity consumption does not cause trading volume is accepted. Therefore, the previous tests confirm the existence of one-way directional (Granger) causality from cryptocurrency trading volume to energy consumption.

4.2 Impulse–Response Analysis

Finally, for each pair ($\mathrm{Y} - \mathrm{X}^j$), we compute the orthogonalized impulse–response functions over a period of a twelve-month time horizon. For each shock, we construct 95% Monte Carlo bands to confirm the statistical significance of its impact. Figure 2 depicts the response of the natural logarithm of Bitcoin's electricity consumption, Y, to one standard deviation shock in the natural logarithm of bitcoin's trading volume, X^b, over twelve months. The immediate impact of the shock on electricity consumption is about 5%. The shock then surges to about 6–10% monthly magnitude (or an average of 8.8% per month) and *persists* over the entire year. Judging by the orthogonalized impulse–response functions for the remaining four cryptocurrencies in Fig. 3, the average persistence of 8% impact on electricity consumption due to one standard deviation shock in trading volume seems to be a common impulse–response for all cryptocurrencies.

Table 3 Goodness of fit of the bivariate vector autoregression (VAR) models

Stats	Y	X^b	Y	X^e	Y	X^r	Y	X^s	Y	X^l
Adjusted R^2	0.982	0.980	0.980	0.970	0.983	0.956	0.982	0.947	0.982	0.963
S.E. equation	0.138	0.357	0.144	0.543	0.135	0.685	0.139	0.883	0.137	0.543
Mean dependent	0.938	−1.003	0.938	−2.180	0.938	−3.845	0.938	−6.024	0.938	−3.468
S.E. (%)	0.147	−0.356	0.154	−0.249	0.144	−0.178	0.148	−0.147	0.146	−0.157
F statistic	2092.2***	1751.4***	1931.2***	1222.7***	2197.6***	827.2***	2069.4***	681.1***	2106.8***	995.5***

Adjusted R^2 is the adjusted coefficient of determination. S.E. denote standard error. S.E.(%) is the standard error of each equation expressed as a percentage of the mean of the dependent variable. *F* is the statistic of the overall *F* test of significance

***, **, and * denote a test statistic is statistically significant at the 1%, 5%, and 10% level of significance, respectively

Table 4 Results of Granger Causality tests

VAR system for currency j: $Y_t = \phi_1 Y_{t-1} + \theta_1 X^j_{t-1} + \varepsilon_t$ $X^j_t = \psi_1 X^j_{t-1} + \lambda_1 Y_{t-1} + \nu_t$	*Null hypothesis*: $H_{01} : \theta_1 = 0$ (X^j_{t-1} *does not Granger cause* Y_t) $H_{02} : \lambda_1 = 0$ (Y_{t-1} *does not Granger cause* X^j_t)	$F(n_1, n_2)$	*p-value*
$j = b$	Reject H_{01}	$F(1, 74) = 8.79^{***}$	0.004
	Accept H_{02}	$F(1, 74) = 0.03$	0.862
$j = e$	Reject H_{01}	$F(1, 74) = 10.91^{***}$	0.001
	Accept H_{02}	$F(1, 74) = 0.57$	0.452
$j = r$	Reject H_{01}	$F(1, 74) = 8.463^{***}$	0.004
	Accept H_{02}	$F(1, 74) = 0.037$	0.847
$j = s$	Reject H_{01}	$F(1, 74) = 10.447^{***}$	0.002
	Accept H_{02}	$F(1, 74) = 0.064$	0.801
$j = l$	Reject H_{01}	$F(1, 74) = 8.462^{***}$	0.005
	Accept H_{02}	$F(1, 74) = 0.085$	0.771

$F(n_1, n_2)$ is the F statistic of the test, where n_1 and n_2 are the degrees of freedom of the numerator and denominator of the statistic, respectively. ***, **, and * denote a test statistic is statistically significant at the 1%, 5%, and 10% level of significance, respectively

5 Environmental Impact of Cryptoassets

We have established the existence of a one-way directional causality between cryptocurrency trading and electricity consumption. Furthermore, we have demonstrated that a trading shock has a persistent impact of about 8.8% on average per month on electricity consumption. In this section, we intend to use the previous results to assess the environmental footprint of Bitcoin. In this context, it is essential to remember that Bitcoin's electricity consumption refers to the total amount of electricity used by the Bitcoin mining process. However, what ultimately matters for the environment is not the total amount of electricity consumption; instead, it is the *carbon intensity of the energy source* used to generate this amount of electricity. For instance, one TWh of coal station-generated electricity has a significantly worse carbon footprint than one TWh of wind- or solar farm-generated electricity. Thus, to assess the environmental footprint of cryptoassets, we should investigate the energy sources used in their mining. So, what energy sources do Bitcoin miners use? Unfortunately, we do not have accurate data on either the type or the

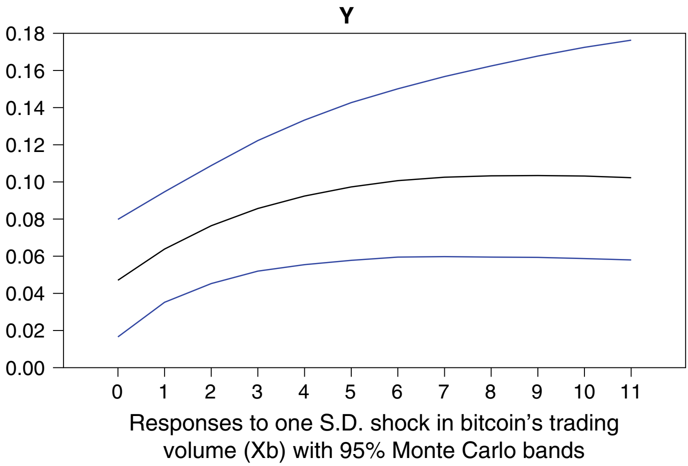

Fig. 2 Orthogonalized response of Bitcoin's electricity consumption to a one standard deviation impulse (shock) of Bitcoin's trading volume (*Note* Orthogonalized response and impulse shock in the natural logarithm. Blue lines represent 95% Monte Carlo bands)

number of energy sources used by Bitcoin miners. What we do know, however, is that Bitcoin miners use a wide variety of power sources, including coal, natural gas, hydroelectric power, nuclear power, and oil. In a recent industry survey, Blandin et al. (2020) find that hydroelectric power, coal, and natural gas are the dominating power sources. The survey also finds that Bitcoin miners use renewable power sources (wind, solar, and geothermal).

Against the previous backdrop, it is clear that until better data on the network's power mix become available, the only way to assess the environmental footprint of cryptoassets is by making assertions about the type and the quantity of the network's source power mix. These assertions, however, should be reasonable to avoid radical misleading predictions. As a guide, we will use the U.S. power mix distribution to compute the total electricity generated from polluting power sources. Although China's share of the global hash rate, which measures the total computational power that is dedicated to mining, amounted to roughly 76% in September 2019, the country's recent ban on all cryptocurrencies' related activities has significantly increased the U.S.'s share of global Bitcoin

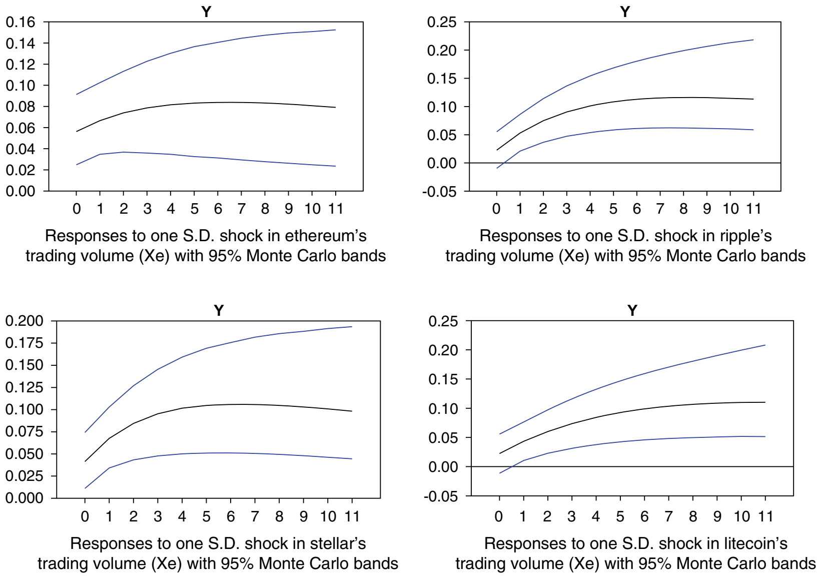

Fig. 3 Orthogonalized response of Bitcoin's electricity consumption to one standard deviation impulse (shock) of the monthly average trading volume (ATV) of Ethereum, Ripple, Stellar, and Litecoin (*Note* Orthogonalized response and impulse shock in the natural logarithm. Blue lines represent 95% Monte Carlo bands)

hash rate from 4.1% in 2019 to 35.4% in 2021, per Table 5. Thus, using the U.S. data as a guide for the network's source power mix is sensible. More specifically, we use the power mix distribution of total electricity net generation for all U.S. sectors from the most recent Monthly Energy Review report issued by the U.S. Energy Information Administration (EIA) in December 2021 (https://www.eia.gov/totalenergy/data/monthly/pdf/sec7.pdf). Table 6, which is reproduced from Table 7.2a of the 2021 EIA's Monthly Energy Review report, documents the last five years of complete annual data on the total electricity net generation from fossil fuels (coal, petroleum, natural gas, and other gases), nuclear electric power, and renewable energy (hydroelectric power, biomass, geothermal,

Table 5 Global hash rate by country

Country	*Share of global hash rate as of September 2019 (%)*	*Share of global hash rate as of August 2021 (%)*
U.S	4.1	35.4
Kazakhstan	1.4	18.1
Other	6.1	13.5
Russia	5.9	11.2
Canada	1.1	9.6
Malaysia	3.3	4.6
Germany	0.9	4.5
Iran	1.7	3.1
China	75.5	0.0

Source This data is obtained from the mining map of the Cambridge Bitcoin Electricity Consumption Index (CBECI), which is housed by the University of Cambridge: https://ccaf.io/cbeci/mining_map

solar, and wind) in million kilowatt-hours (kWh).[6] Taking the average net generation of each source relative to the total average electricity generation, we find that, on average, 63% of total electricity generation comes from fossil fuels (mainly 26% from coal and 36% from natural gas), 20% is coming from nuclear electric power, and 17% is coming from renewable energy sources as documented in the third column of Table 7.

The next step is to find an estimate of the carbon emissions of fossil fuels—the polluting source of electricity generation. Again, we will revert to the EIA's recent U.S. data on carbon emissions by fuel type in 2020 (https://www.eia.gov/tools/faqs/faq.php?id=74&t=11). According to the EIA, the 2020 carbon emissions in million metric tons ($MtCO_2$) per million kWh for coal, petroleum, and natural gas are 0.00101219, 0.000952032, and 0.000410713, respectively.

Finally, we compute the most recent annual Bitcoin electricity consumption in 2021 by simply aggregating the monthly data of the CBECI in 2021. This data aggregation yields approximately a total electricity consumption of 104 TWh (or 104,000 million kWh). If we entertain the previous U.S. energy mix distribution and carbon emissions

[6] The report has only 9 months of data in 2021. For that reason, this year is excluded from the analysis.

Table 6 Total electricity net generation from all sources and sectors in the United States

Year	*Fossil Fuels*				*Nuclear Electric Power*
	Coal	*Petroleum*	*Natural Gas*	*Other Gases*	
2016	1,239,148.654	24,204.806	1,378,306.934	12,807.432	805,693.948
2017	1,205,835.276	21,389.945	1,296,442.491	12,468.967	804,949.635
2018	1,149,487.339	25,225.618	1,469,132.682	13,462.749	807,084.477
2019	964,956.812	18,340.743	1,585,814.174	12,591.094	809,409.262
2020	773,392.897	17,341.014	1,624,049.997	11,818.478	789,878.863
Average	1,066,564.2	21,300.425	1,470,749.26	12,629.744	803,403.237

Year	*Renewable Energy*					*Totals*
	Hydro-electric Power[a]	*Biomass*[b]	*Geo-thermal*	*Solar*	*Wind*	*Total*[c]
2016	261,126.026	62,760.458	15,825.807	36,054.121	226,992.562	4,076,674.984
2017	293,838.382	62,733.412	15,926.774	53,286.865	254,302.695	4,034,270.559
2018	286,619.45	61,831.924	15,967.134	63,825.315	272,667.454	4,178,277.344
2019	282,612.987	57,506.953	15,472.717	71,936.822	295,882.484	4,127,855.214
2020	279,952.69	54,703.01	15,889.697	89,198.715	337,938.049	4,007,018.595
Average	280,829.907	59,907.1514	15,816.426	62,860.368	277,556.649	4,084,819.34

[a]This category includes both the hydroelectric pumped storage and the conventional hydroelectric power. The hydroelectric pumped storage is the pumped storage facility production minus energy used for pumping

[b]This includes wood, wood-derived fuels, municipal solid waste from biogenic sources, landfill gas, sludge waste, agricultural by-products, and other biomass

[c]The total electricity generation figures is slightly larger than the exact total of all categories since it includes other minor sources that are not listed in the table

statistics, then the carbon emissions from the 26% share of coal are:

$$0.26 \times 104,000\text{millionkWh} \times \frac{0.00101219\text{millionMtCO}_2}{1\text{millionkWh}} \approx 27.4\text{millionMtCO}_2, \tag{3}$$

and the carbon emissions from the 36% share of natural gas are

$$0.36 \times 104,000\text{millionkWh} \times \frac{0.000410713\text{millionMtCO}_2}{1\text{millionkWh}} \approx 15.4\text{millionMtCO}_2. \tag{4}$$

Thus, the total carbon emissions from the two main fossil fuel sources (coal and natural gas) used to generate the electricity needed for Bitcoin

Table 7 Average proportion of total electricity net generation from fossil fuels, nuclear power, and renewable energy between 2016 and 2020 in the United States

Type of energy source used for electricity generation	*Average net electricity generation per source between 2016 and 2020 (million kWh)*	*Average proportion of net energy generation per source*
Coal	$a = 1066564.2$	$(a/h) \times 100 = 26\%$
Petroleum	$b = 21300.425$	$(b/h) \times 100 = 0.5\%$
Natural Gas	$c = 1470749.26$	$(c/h) \times 100 = 36\%$
Other Gases	$d = 12629.744$	$(d/h) \times 100 = 0.3\%$
Fossil Fuels	$e = a + b + c + d = 2571243.62$	$(e/h) \times 100 = 63\%$
Nuclear Electric Power	$f = 803403.237$	$(f/h) \times 100 = 20\%$
Renewable Energy	$g = 696970.501$	$(g/h) \times 100 = 17\%$
Total	$h = e + f + g = 4084819.34$	100%

mining are approximately 43 million $MtCO_2$. This estimate is consistent with Stoll et al. (2019)'s figures except for the minor discrepancy in the estimate of Bitcoin's energy consumption. The authors find that Bitcoin's annual electricity consumption adds up to 45.8 TWh in 2018 and the corresponding annual carbon emissions range from 22.0 to 22.9 $MtCO_2$. In our analysis, we use the CBECI model to compute electricity consumption. According to this model, electricity consumption in 2018 was 52.18 TWh. Plugging this value in Eqs. (3) and (4) and adding up the resulting carbon emissions yield a total of 21.4 $MtCO_2$, which is very close to the lower bound of the reported range of Stoll et al. (2019). What is the significance of 22 million tons of carbon emissions in 2018 or 43 million tons of carbon emissions in 2020? Stoll et al. (2019) document that a level of 22 million $MtCO_2$ sits between the levels produced by the nations of Jordan and Sri Lanka. Obviously, 43 million $MtCO_2$ in 2020 is almost double this amount. For a more global perspective, a recent IEA study finds that the global energy-related carbon emissions amounted to around 31,500 million $MtCO_2$ in 2020.[7] Thus, our calculations of

[7] More details are found here: https://www.iea.org/articles/global-energy-review-co2-emissions-in-2020.

Bitcoin's carbon footprint in 2020 account for roughly $\frac{43}{31500} \approx 0.14\%$ of the world's total yearly emissions.

A carbon footprint amounting to 0.14% of the world's total emissions might not seem alarming. However, a deeper look at the progression of electricity consumption following a shock in cryptoassets' trading volume is indeed eye-opening. To demonstrate this, we use our earlier prediction from the impulse–response analysis in Sect. 4 to forecast the impact on electricity consumption following one standard deviation shock inbitcoin's trading volume over a time horizon of 12 months. We began with the CBECI's most recent recorded value in December 2021. The index shows that the total cumulative electricity consumption of Bitcoin (from January to December 2021) is 103.72 TWh. This obtained value is our initial forecasting value, which is recorded in the intersection of the first row and column *a* of Table 7. Next, we transform this initial value to its natural logarithm value since the trading volume, $X^b = \ln(ATV_{\text{bitcoin}})$, and the electricity consumption, $Y = \ln(\text{CBECI})$, in the impulse–response analysis are in natural logarithms. We record the forecasted value of Y in column *b* of Table 8. We record the monthly responses of Y to one standard deviation impulse in X^b that is revealed by our previous impulse–response analysis in column *c* of Table 8. In column *d*, we isolate the marginal response (that is, the change in the monthly responses of Y following the shock in X^b). For instance, the first predicted response of Y in month 1 is 4.58%. The total response in two months is 6.18%. Thus, the marginal response of Y in month 2 is simply the difference between 6.18% and 4.58%, which is 1.6%. Next, in column *e*, we grow the initial value of Y in column *b* by the marginal monthly response values in column *d* to obtain monthly forecasted values of Y measured in natural logarithm TWh. Finally, we convert back the value of Y, i.e., the natural logarithm of CBECI, to just CBECI using the exponential (anti-log) function in column *f*. We repeat the previous exercise for every month over the one-year forecast horizon. We find that a shock in bitcoin's trading volume leads to an estimated increase in Bitcoin's electricity consumption from approximately 104 TWh at the beginning of the year to 169 TWh by the end of the year. This increase means that the predicted surge in electricity consumption is about 63% per year. This result is indeed a significant number. If we entertain the oversimplified assumption that this increase in electricity will remain constant over the next five years (provided that cryptocurrency remains appealing to investors and other stakeholders), then the total electricity consumption of Bitcoin by the end of 2026 is expected to be $169 \times (1 + 0.63)^5 = 1196,662$ million kWh. Plugging this value back in Eqs. (3) and (4) yields a total of 492 million metric tons of carbon emissions from coal and natural gas usage as:

$$0.26 \times 1196,662\text{millionkWh} \times \frac{0.00101219\text{millionMtCO}_2}{1\text{millionkWh}} \approx 315\text{millionMtCO}_2 \quad (5)$$

and

$$0.36 \times 1196,662\text{millionkWh} \times \frac{0.000410713\text{millionMtCO}_2}{1\text{millionkWh}} \approx 177\text{millionMtCO}_2 \quad (6)$$

Table 8 One year prediction of Bitcoin's electricity consumption

Column	*a*	$b = \ln(a)$	*c*	$d = \Delta c$	$e = b \times \left(1 + \frac{d}{100}\right)$	$f = \exp\{e\}$
Time horizon (month)	*Forecasted value of CBECI (TWh)*	*Forecasted value of* $Y = \ln(CBECI)$ *(ln TWh)*	*Response of* $Y = \ln(CBECI)$ *to shock in* X^b *(%)*	*Marginal response of Y to shock in* X^b *(%)*	*Forecasted value of Y (ln TWh)*	*Forecasted value of CBECI (TWh)*
1	103.72	4.64	4.585632	4.585632	4.85454601	128.32
2*	128.32	4.85	6.185784	1.600152	4.93509081	139.09
3	139.09	4.94	7.413921	1.228137	4.99570048	147.78
4	147.78	5.00	8.341742	0.927821	5.04205164	154.79
5	154.79	5.04	9.027479	0.685737	5.07662685	160.23
6	160.23	5.08	9.518419	0.49094	5.10155005	164.28
7	164.28	5.10	9.85295	0.334531	5.11861631	167.10
8	167.10	5.12	10.062226	0.209276	5.12932835	168.90
9	168.90	5.13	10.171518	0.109292	5.13493429	169.85
10	169.85	5.13	10.201323	0.029805	5.13646476	170.11
11	170.11	5.14	10.168251	−0.03307	5.13476603	169.82
12	169.82	5.13	10.085753	−0.0825	5.13052995	169.11

This table reads from left to right row wise beginning with the first row. The value 103.72 TWh at the intersection of month 1 and Column *a* is the CBECI's value of total electricity consumption of the Bitcoin network as of December 2021. This is the initial forecast value

*The values starting in month 2 in Column *a* are the one-month lagged values of Column *f* respectively. These results yield an estimated value of Bitcoin's carbon footprint in 2026 of roughly $\frac{492}{31500} \approx 1.6\%$ of the world's total yearly emissions.

6 Concluding Remarks

A prediction that Bitcoin's carbon footprint in 2026 amounts to 1.6% of today's total carbon emissions worldwide is disturbing. Even worse, this analysis does not include the carbon footprint of several factors that could potentially make this figure even larger. First, our analysis does not include the carbon footprint of Bitcoin's entire hardware supply chain from production to delivery. Second, it does not include the carbon footprint from the e-waste that the disposal of older models generates. Third, the analysis does not include other understudied cryptocurrencies, which could add 50% on top of bitcoin's energy hunger (Gallersdörfer et al., 2020).

We acknowledge several limitations of the present analysis. First, we use the CBECI model to estimate Bitcoin's electricity consumption. This model, like any other model, has its limitations. However, the estimates seem reasonable and consistent with other studies (e.g., Stoll et al., 2019). Second, due to data unavailability, we use the power mix distribution of total electricity net generation for all U.S. sectors from the EIA as a proxy for the proportions of fossil fuel sources, i.e., coal and natural gas, that generate the total electricity of Bitcoin. We also use carbon emissions data on these energy sources from the EIA to estimate the carbon footprint of the network. Having said that, we consider the prediction that this chapter presents as a cause for reasonable concern about the environmental impact of Bitcoin. Although our results may differ from the actual carbon emissions figures, we believe that our assumptions are sensible enough to warrant attention to the negative environmental implications of such digital currency.

In closing, despite this study's data and axiomatic limitations, it is clear that a continuous increase in demand for cryptocurrencies, as reflected in the currencies' trading volumes, will create persistent and tremendous growth in the network's energy consumption, and in turn, its carbon footprint. This observation alone, without an actual or predicted figure for carbon emissions, warrants two courses of action. First, regulators and policymakers should design climate mitigation policies that effectively address the environmental impacts of cryptoassets. A carbon tax, for instance, is not an effective policy because it does not eliminate the carbon emissions from mining. However, a policy that forces miners to generate electricity only from green energy sources, e.g., solar, wind, and geothermal, is more effective in eliminating the carbon footprint of this sector. Second, regulators and policymakers should carefully assess the societal costs (including the alarming carbon footprint) and benefits of cryptocurrencies as a decentralized monetary system. Even if bitcoin mining became totally green, one must not ignore the opportunity cost of Bitcoin's tremendous electricity consumption, i.e., the benefit that otherwise could have been obtained from alternative use of Bitcoin's renewable energy sources. Do we need bitcoins as a currency? Do we need to exhaust green energy sources to generate this digital currency? Do the costs of doing so exceed the benefits? These are all interesting future research questions on this critical topic.

Acknowledgements The author would like to thank the editing team and two anonymous reviewers for their helpful comments. This paper is financially supported by a research grant from Royal Roads University.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control, AC-19*, 716–723.

Blandin, A., Pieters, G., Wu, Y., Eisermann, T., Dek, A., Taylor, S., & Njoki, D. (2020). *3rd global cryptoasset benchmarking study*. Judge Business School, University of Cambridge.

Catalini, C., & Gans, J. S. (2016). *Some simple economics of the blockchain* (NBER Working Paper No. 22952, NBER).

De Vries, A. (2018). Bitcoin's growing energy problem. *Joule, 2*, 801–805.

Dupont, Q. (2019). *Cryptocurrencies and blockchains*. Polity Press.

Fahmy, H. (2022a). Clean energy deserves to be an asset class: A volatility-reward analysis. *Economic Modelling, 106*, 105696.

Fahmy, H. (2022b). The rise in investors' awareness of climate risks after the Paris Agreement and the clean energy-oil-technolog prices nexus. *Energy Economics, 106*, 105738.

Gallersdörfer, U., Klaaßen, L., & Stoll, C. (2020). Energy consumption of cryptocurrencies beyond bitcoin. *Joule, 4*, 1843–1846.

Gatteschi, V., Lamberti, F., Demartini, C., Paranteda, C., & Santamaria, V. (2018). Blockchain and smart contracts for insurance: Is the technology mature enough? *Future Internet, 10*(2), 20.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica, 37*, 424–438.

Harris, A. (2018). A conversation with masterminds in blockchain and climate change. In A. Marke (Ed.), *Transforming climate finance and green investment with blockchains* (Ch. 2., pp. 15–22). Academic Press.

Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and Informatics, 34*, 1308–1321.

Ji, Q., Bouri. E., Roubaud, D., & Kristoufek, L. (2019). Information interdependence among energy cryptocurrency and major commodity markets. *Energy Economics*, 811042–811055. S0140988319301896 https://doi.org/10.1016/j.eneco.2019.06.005

Kosba, A., Miller, A., Shi, E., Wen, Z., & Papamanthou, C. (2016). Hawk: The blockchain model of cryptography and privacy-preserving smart contracts. In *Proceedings of the 2016 IEEE Symposium on Security and Privacy* (S.P.).

Krause, M. J., & Tolaymat, T. (2018). Quantification of energy and carbon costs for mining cryptocurrencies. *Nature Sustainability, 1*, 711–718.

Ljung, G. M., & Box, G. E. P. (1978). On a measure of a lack of fit in time series models. *Biometrika, 65*(2), 297–303.

Mora, C., Rollins, R. L., Taladay, K., Kantar, M. B., Chock, M. K., Shimada, M., & Franklin, E. C. (2018). Bitcoin emissions alone could push global warming above 2° C. *Nature Climate Change, 8*(11), 931–933.

Sanderson, O. (2018). How to trust green bonds: blockchain, climate, and the institutional bond markets. In A. Marke (Ed.), *Transforming climate finance and green investment with blockchains* (Ch. 20., pp. 273–288). Academic Press.

Stoll, C., Klaaßen, L., & Gallersdörfer, U. (2019). The carbon footprint of bitcoin. *Joule, 3*(1), 1647–1661.

Turkanovic, M., Hölbl, M., Košic, K., Hericko, M., & Kamišalic, A. (2018). EduCTX: A blockchain-based higher education credit platform. *IEEE Access, 6*, 5112–5127.

Zade, M., Myklebost, J., Tzscheutschler, P., & Wagner, U. (2019). Is Bitcoin the only problem? A scenario model for the power demand of blockchains. *Frontiers in Energy Research, 7*, 21.

Zheng, Z., Xie, S., Dai, H., Chen, X., & Wang, H. (2017). An overview of blockchain technology: Architecture, consensus, and future trends. *International Congress of Big Data (BigData Congress), 2017*, 557–564.