Bitcoin-Energy Markets Interrelationships - new evidence

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Abstract

The annual electricity consumption of cryptocurrency transactions has grown substantially in recent years, partially driven by the increasing difficulty in mining, but also driven by the large number of new market participants that have been attracted by the elevated prices of this developing financial asset. Total carbon production from mining now likely exceeds that generated by individual developed nations. This is now a prevailing and accepted feature in cryptocurrency markets, however unsustainable it may be. This paper investigates as to how Bitcoin's price volatility and the underlying dynamics of cryptocurrency mining characteristics affect underlying energy markets and utilities companies. Further analysis of potential side-effects within the market for Exchange Traded Funds are considered. The results show a sustained and significant influence of cryptocurrency energy-usage on the performance of *some* companies in the energy sector as separated by jurisdiction, emphasising the importance of further assessment of environmental impacts of cryptocurrency growth. Robustness testing presents evidence that dynamic correlations peaked during the sharp Bitcoin price appreciation of late-2017 as investors re-evaluated how this increased energy usage would influence the profitability of utility companies.

Keywords: Bitcoin; Cryptocurrencies; Volatility; Speculative Assets; Currencies; Energy Usage.
JEL Code: G10, Q43

1. Introduction

As cryptocurrency markets continue to develop, it is to be expected that solutions emerge to solve some substantial forthcoming issues. The energy use of Bitcoin mining has increased from 4.8Twh (Terrawatt hours) to 73.12Twh over the past two years, and the entire network is now estimated to consume more energy than Austria (October 2019). The energy footprint per Bitcoin transaction is estimated as 619 Kwt, which is equivalent to 350,000 visa transactions or to the power consumption of an average US household over 20.92 days. When considering energy usage, Bitcoin can be considered quite an expensive and inefficient transmission mechanism in its current form. Furthermore, most bitcoin mining is situated in China. The major fuel used by these networks is from coal-fired power plants, which results in an extensive embedded carbon footprint for each transaction. This raises questions about the environmental sustainability of cryptocurrencies. Within the scope of recent research on cryptocurrencies markets, we must consider as to what side-effects these new financial products can have on not only other financial markets through contagion effects, but also as to what effects can manifest physically through direct interactions. This paper sets out to establish as to what effects cryptocurrencies have had on energy markets and utility companies, specifically within the regions in which mining is most prevalent.

While Bitcoin is presented as the most famous of all cryptocurrencies, we must continue to remember that there exist thousands of other feasible, albeit not as reputable cryptocurrencies. Research by Li et al. [2019] presented evidence through data analysis and experiments, that the estimated electricity for Monero, could consume 645.62GWh of electricity in the world in a single year after the hard fork. If there is 4.7% mining activity happening in China, the consumption is at least 30.34GWh, contributing a carbon emission of between 19.12 and 19.42 thousand tons in a single year. Stoll et al. [2019] utilised a methodology for estimating the power consumption associated with Bitcoin mining based on IPO filings of major hardware manufacturers. The authors then translate the power consumption estimates into carbon emissions, using the localisation of IP-addresses. As of late 2018, the authors estimate the electricity consumption of Bitcoin to be 48.2TWh, and estimate that annual carbon emissions range from 23.6 to 28.8$MtCO_2$, similar to that produced by the nations of Jordan and Mongolia, a result that the authors consider to be conservative. Should other cryptocurrency markets such as Ethereum, Monero and zCash among others be considered, this figure could well double, a sum equivalent to that of Portugal. Further, Krause and Tolaymat [2018] had previously identified that that mining Bitcoin, Ethereum, Litecoin and Monero consumed an average of 17, 7, 7 and 14MJ of energy to generate one US$, respectively. While presenting results largely in line with Stoll et al. [2019], it was also estimated that it took four times more energy for mining 1 US$ of Bitcoin than it did to mine one US$ of copper and double that of either platinum or gold. Mora et al. [2018] showed that when basing their calculations on projected Bitcoin usage, under the assumption that it follows the rate of adoption of other broadly adopted technologies, this new cryptocurrency had the potential to create enough CO_2 emissions to push warming above 2 degrees Celsius within less than three decades.

While opponents of such estimates largely point towards the omission in such research of renewable energy usage, it is highly probable given the relatively small share of renewable in most countries with large mining pools that the net effects of the growth of cryptocurrency is carbon positive and detrimental to our environment at its current rate of growth. Recent research has focused on issues such as the sharp growth in cybercriminality (Corbet et al. [2019]), and the use of cryptocurrency for illicit purposes (Foley et al. [2019]), but little research to date has been done on the environmental impacts of cryptocurrencies (Truby [2018]; Easley et al. [2019]; Greenberg and Bugden [2019]; Li et al. [2019]).

Insert Figure 1 about here

Participation in the validation and mining process of Bitcoin requires both special hardware and a substantial amount of energy. Thus there is embedded carbon and ongoing carbon production. The computing power required to solve one Bitcoin as of 2019 has quadrupled compared to twelve months previous. Evidence of this substantial growth in difficulty is presented in Figure 1. NBER-denoted periods of crisis are presented in the shaded grey regions. This has led to some concern within the sector of the imminent need for broad international regulation in a bid to stall such exponential growth in energy usage. However, there are difficulties in providing definitive estimates and the argument has been even further muddied as cryptocurrency proponents have stated that the usage of renewable energy has not been appropriately accounted for.

This paper contributes to the previous literature in a number of ways. We primarily observe that there is a strong positive, significant relationship between Bitcoin returns and both Chinese and Russian electricity company price volatility, indicates that there exists evidence of interactions between Bitcoin and electricity companies in these key mining pool regions. Further, there is also evidence of a significant interlinkage in the pricing volatility of Bitcoin and the selected international utility ETFs, while Bitcoin is found to be negatively related to the price of Carbon Credits. We observe that the dynamic correlations between Bitcoin volatility and that of Chinese and Russian electricity companies that has grown sharply since early-2017, remaining substantially above its long-term value. It is the relationship between Bitcoin volatility and indexed utility ETFs that presents the most substantial evidence of sustained growing interactions since early 2016, peaking during 2018, indicating that the growth in Bitcoin price volatility is found to be positively correlated, and increasingly related to the volatility we have observed in energy and utility company markets. Further robustness tests are provided outlining the interactions between the selected variables and the underlying market conditions within cryptocurrency markets as determined by difficulty, the mining hashrate and mining difficulty, with evidence suggesting that dynamic correlation behaviour peaked across all analysed utility companies during the sharp Bitcoin price appreciation of late-2017 and early-2018.

The remainder of this paper is organised as follows. Section 2 outlines the key previous literature associated with the energy usage of cryptocurrency markets. Section 3 describes the data while 4 describes the econometric methods utilised. Section 5 presents the empirical results and Section 6 concludes and discusses the implications.

2. Previous Literature

Research by Stoll et al. [2019] utilised a methodology for estimating the power consumption associated with Bitcoin mining based on IPO filings of major hardware manufacturers, insights on mining operations, and mining pool compositions. The authors then translate the power consumption estimates into carbon emissions, using the localisation of IP-addresses. As of late 2018, the authors estimate the electricity consumption of Bitcoin to be 48.2TWh, and estimate that annual carbon emissions range from 23.6 to 28.8$MtCO_2$, similar to that produced by the nations of Jordan and Mongolia, a result that the authors consider to be conservative. Should other cryptocurrency markets such as Ethereum, Monero and zCash among others be considered, this figure could well double, a sum equivalent to that of Portugal. Krause and Tolaymat [2018] had previously identified that that mining Bitcoin, Ethereum, Litecoin and Monero consumed an average of 17, 7, 7 and 14MJ of energy to generate one US$, respectively. While presenting results largely in line with Stoll et al. [2019], it was also estimated that it took four times more energy for mining 1 US$ of Bitcoin than it did to mine one US$ of copper and double that of either platinum or gold. Mora et al. [2018] showed that when basing their calculations on projected Bitcoin usage, under the assumption that it follows the rate of adoption of other broadly adopted technologies, this new cryptocurrency had the potential to create enough CO_2 emissions to push warming above 2 degrees Celsius within less than three decades.

Although investors and cryptocurrency miners often ignore the environmental effects of networks' energy usage, the increased mining difficulty and costs of cryptocurrency mining affect the profitability of mining in countries with high electricity costs. This area also attracted attention by finance scholars who tried to establish a true value of Bitcoin, identify the linkages between Bitcoin price and costs of mining, as well as specifically, investigated the profitability of mining in different regions. The paper by Kistoufek [2020] employs combination of cointegration models and causality test to identify the relationships between Bitcoin Price Index and costs of mining/creating a single Bitcoin. The results show that Bitcoin price influences the costs of Bitcoin mining. This findings are not surprising since the increased popularity of this innovative asset and tremendous price growth, particularly, in the second half of 2017, attracted many investors and miners to this area and increased profitability of mining. However, according to Delgado-Mohatar et al. [2019] after June 2018, the Bitcoin mining was profitable only for professional miners located in those countries where electricity costs less than 0.14$/kWh. These findings are supported by Das and Dutta [2019] who report the decrease of miner's revenues due to the increase of electricity costs and energy consumption. From environmental viewpoint, these findings highlight a growing problem of concentration of the mining pools in areas with cheap energy, such as China. Thus, in contrast to the popular beliefs of crypto-enthusiasts that cryptocurrency usage will become more sustainable due to the renewable energy, it will not be practically achievable in the recent future. While it sounds like a great idea in theory to switch to green energy sources and decrease carbon footprint of Bitcoin, in practice we observe a high concentration of the mining pools in countries that rely heavily on coal-based power increasing the carbon footprint of cryptocurrency networks.

Some may argue that cryptocurrency investments not necessarily require mining of new Bitcoins, and furthermore, there are a number of digital currencies available that are non-mineable and consequentially less energy consuming. This position sounds reasonable at first glance, however, the recent research shows that even small allocation of assets to Bitcoin significantly deteriorate the sustainability of investment portfolios (Baur and Oll [2019]). Therefore, even if investors do not participate in mining process directly, or construct a portfolio containing only digital currencies, they still provide negative impact on the environment because even small Bitcoin allocations increasing the carbon footprints of their investment portfolios. Furthermore, according to the numerous findings Bitcoin remains its position as a market leader, and the price of other cryptocurrencies is dependent on changes of Bitcoin price (Corbet et al. [2018]). Therefore, the portfolios consisting only of non-mineable cryptocurrencies cannot be considered as ethically-cleansed from environmental effects of networks' energy usage, since the investment returns of those portfolios, as well as cryptocurrency market as whole, are increasing with Bitcoin price growth. Thus, any engagement with cryptocurrency implies in participating in its carbon emission and negative environmental effects.

Given the relatively small share of renewable energy in most countries with large mining pools the cryptocurrency market growth will continue negatively affect environment. There is much evidence to suggest that this new financial product has continued to progress with evidence provided of growing efficiency (Bariviera [2017]) and product and pricing enhancement through the use of related derivatives products (Corbet et al. [2018]; Akyildirim et al. [2019]). While the main stream of cryptocurrency research is currently focused on the dilemma as to whether this is a currency or speculative asset (Baur et al. [2018]); and conducting analysis of the multiple forms of pricing inefficiencies (Urquhart [2017]; Sensoy [2019]; Mensi et al. [2019]; Katsiampa et al. [2019]), Corbet et al. [2019] have provided a concise systematic review of the literature associated with cryptocurrency markets at large, and note that more research is needed to assess environmental and energy use issues.

Cryptocurrency research is vary vast, and there are a number of papers discussing specific issues associated with cryptocurrency market growth, such as cybercriminality (Corbet et al. [2019]), and illegal usage of cryptocurrencies (Foley et al. [2019]), however, the environmental impacts of cryptocurrencies has not been extensively analysed yet (Truby [2018]; Easley et al. [2019]; Greenberg and Bugden [2019]; Li et al. [2019]). This paper is motivated by the insights on Bitcoin pricing and mining costs/revenues provided by Das and Dutta [2019]; Schilling and Uhlig [2019]; Delgado-Mohatar et al. [2019]; Xiong et al. [2020], as well as recent papers analysed the relationship between electricity prices and Bitcoin energy consumption in the context of its dynamics and sustainability Kistoufek [2020];Baur and Oll [2019]; Krause and Tolaymat [2018], among others. However, in comparison to existing literature, our paper assesses the financial market impacts of Bitcoin energy usage. While the volatility generating effect of Bitcoin on fossil fuel and clean energy stocks in a long run has been confirmed by Symitsi and Chalvatzis [2018], we further hypothesise that increased energy consumption of Bitcoin affect utility companies, utility ETFs, and green ETFs. While the paper by Ji et al. [2019] uses Minimum Spanning Tree methods and finds bidirectional relationships between some energy commodities and cryptocurrencies, the analysis of green ETFs and utility companies offers novel insights. Furthermore, in contrast to Symitsi and Chalvatzis [2018] who conducted analysis using Bitcoin and three global indices, we utilise data specifically for China, Japan, and Russia since these countries are accountable for more than 80% of Bitcoin mining.

This paper contributes to existing literature in two main ways. First, this research sets out to specifically investigate as to whether the price volatility effects of such cryptocurrencies, proxied by Bitcoin, has generated dynamic correlations with electricity and utilities providers in countries that contain the largest international mining pools. Such increased demand through the cryptocurrency mining process should theoretically manifest in changing financial dynamics for these identified companies. Second, we have also selected to investigate as to whether any dynamic relationship exists between Bitcoin and the markets for green energy ETFs and the market for ICE EUX Carbon Credits, where one lot of 1,000 CO_2 EU Allowances provides an entitlement to emit one tonne of carbon dioxide equivalent.

3. Data

To investigate the relationship between Bitcoin's price volatility and the underlying dynamics of the cryptocurrency's mining characteristics and trading volume, we investigate: 1) mining difficulty; 2) hashrate; 3) the number of daily transactions; 4) the number of unique Bitcoin mining addresses and 5) block size. Each are presented in Figure 1. Mining difficulty reflects how difficult it is to find a new block compared to the easiest that it could be, recalculated every 2016 blocks to a value such that the previous 2016 blocks would have been generated in exactly two weeks had everyone been mining at the same difficulty. As more miners join, the rate of block creation will increase, which causes the difficulty to increase in compensation to push the rate of block creation back down. A hash is the output of a hash function, and the hashrate is the speed at which a compute is completing an operation in the Bitcoin code. A higher hashrate when mining increases your opportunity of finding the next block and receiving the reward. The increased difficulty in mining has led to a need for more powerful technology and increased energy usage to mine cryptocurrency. Of course, the source of this additional required energy is central to the issues that Bitcoin, among other cryptocurrencies, faces.

Insert Tables 1 through 3 about here

Due to the growing number of mining pools across the world, we focus specifically on the six largest. China accounts for 81% of mining pool concentration, the Czech Republic 10%, while Iceland, Japan, Georgia and Russia account for 2% respectively. After a thorough analysis, only China, Japan and Russia possess publicly traded electricity companies or core utility companies that trade primarily in energy. Further, there have been issues identified with the very nature of such concentration. Stoll et al. [2019] found that the four largest Chinese pools now provide almost 50% of the total hashrate, with Bitcoin operating three of such pools. To analyse the interactions between Bitcoin and selected energy sectors, we therefore create indices representing China (created using China Shenhua Energy, China Yangtze Power Co., China National Nuclear Power Co. and Hunaeng Power International), Japan (Chugoku Electric Power Co., Chubu Electric Power, Hokuriku Electric Power, Kyushu Electric Power, Kansai Electric Power Co., and the Okinawa Electric Power Co.) and Russia (Gazprom, Rosneft, Lukoil ,Surgutneftegas). Carbon credit market interactions are analysed through the use of ICE EUX Carbon Credit prices. To analyse interactions with international utility and power companies, we use largest ETFs ranked by market capitalisation (the selected tickers are XLE, VDE, XOP, IXC, OIH, IYE, IGE, KOL and FRAK). Finally interactions with green energy ETFs are analysed based on interactions with the largest funds ranked by market capitalisation. Associated summary statistics for our selected variables are presented in Table 1, with Tables **??** and 3 presenting the summary statistics relating to the NBER-denoted non-crisis and crisis periods respectively.

4. Selected Methodology

We utilise data from the Bitfinex exchange for Bitcoin. The log return, $r_t = ln(P_t/P_{t-1})$ is then estimated for the period 1 January 2010 through 31 May 2019. Structural data related to the functionality of Bitcoin was obtained from historical API (application programming interfaces). Figure 1 represents the price, price volatility, hashrate, mining difficulty, number of unique mining addresses and block size respectively. We considered the use of higher frequency data and even tick level data, however, the use of daily data was found to be most effective from a methodological standpoint. The selection of Bitfinex as a source eliminates such fears presented by Alexander and

Dakos [2019], who identified issues with data variation, widely dependent on the selected supplier. The selected indices relating to the examined international energy sectors are presented in Figure 2. NBER-denoted periods of crisis are presented in the shaded grey regions. Data was obtained from Thompson Reuters Eikon. As Bitcoin continues to trade throughout the weekends, we only utilise daily closing prices on days when traditional financial markets are denoted to be open.

Insert Figure 2 about here

We develop on the channels through which cryptocurrency volatility could potentially influence other, more traditional, energy markets such as electricity and utilities companies. China, Japan and Russian electricity companies are identified as a key source of analysis due to the large number of mining pools that currently operate within these jurisdictions. Changing correlation dynamics could also indicate that the company is being treated differently by investors due to their involvement in blockchain or cryptocurrency energy production and as to whether such a process is sustainable. While first focusing on the interactions and contagion between pricing behaviour, we also based investigated as to whether there were any interaction between our selected independent variables and other contingent dependent variables directly related to the estimation of the fundamental behaviour of Bitcoin as a leading cryptocurrency. We consider the hashrate, mining difficulty, number of individual Bitcoin wallet addresses and the Bitcoin blocksize. When blockchain becomes too large, nodes which are running full will have to extend their hardisk space. The impact of a large blockchain is quite substantial as network synchronisation takes a considerable amount of time for new node as they have to download whole blockchain locally. When considering the blocksize and the number of individual Bitcoin users have increased exponentially over time, it is easy to see as to how much processing power, and therefore energy usage can escalate with potential broader side-effects. To consider contagion effects, we use the popular DCC-GARCH model of Engle [2002]. We first let $r_t = [r_{1,t}, ..., r_{n,t}]'$ be the vector of financial time series returns and $\varepsilon_t = [\varepsilon_{1,t}, ..., \varepsilon_{n,t}]'$ be the vector of return residuals obtained after some filtration. Let $h_{i,t}$ be the corresponding conditional volatilities obtained from univariate GARCH process. We the assume that $E_{t-1}[\varepsilon_t] = 0$ and $E_{t-1}[\varepsilon_t \varepsilon_t'] = H_t$, where $E_t[\cdot]$ is the conditional expectation on $\varepsilon_t, \varepsilon_{t-1}, ...$ The asset conditional covariance matrix H_t can be written as:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{1}$$

where $R_t = [\rho_{ij,t}]$ is the asset conditional correlation matrix and the diagonal matrix of the asset conditional variances is given by $D_t = diag(h_{1,t}, ..., h_{n,t})$. Engle [2002] models the right hand side of the above equation rather than H_t directly and proposes the dynamic correlation structure:

$$R_t = \{Q_t^*\}^{-1/2} Q_t \{Q_t^*\}^{-1/2} \tag{2}$$

$$Q_t = (1 - a - b)S + au_{t-1}u'_{t-1} + bQ_{t-1} \tag{3}$$

where $Q_t \equiv [q_{ij,t}]$, $u_t = [u_{1,t}, ..., u_{n,t}]'$ and $u_{i,t}$ is the transformed residuals i.e. $u_{i,t} = \varepsilon_{i,t}/h_{i,t}$, $S \equiv [s_{ij}] = E[u_t u'_t]$ is the $n \times n$ unconditional covariance matrix of u_t, $Q^*_t = diag\{Q_t\}$ and a, b are non-negative scalars satisfying $a + b < 1$. The parameters of the model are estimated by using the quasi-maximum likelihood method with respect to the log-likelihood function, and according to the state two-step procedure. Cr_t represents the periods of recession as denoted by the National Bureau of Economic Research[1], indicative of substantial changes in correlation and pricing behaviours between crisis and non-crisis periods. One of the key benefits of this structure is that it allows for directly inferring the time-varying correlations between our selected markets as well as for dealing with a relatively large number of variables within its structure.

5. Results

The results of this DCC-GARCH analysis are presented in Table 4. We primarily observe that there is a strong positive, significant relationship between Bitcoin returns and both Chinese and Russian electricity company price volatility. However, although the relationship between Bitcoin price volatility and Japanese electricity companies is also positive, it is insignificant. This indicates that there exists evidence of interactions between Bitcoin and electricity companies in these key mining pool regions. There is also evidence of a significant interlinkage in the pricing volatility of Bitcoin and the selected international utility ETFs, although the scale of this relationship is quite minute (+0.0868). The price volatility of Bitcoin is found to be negatively related to the price of Carbon Credits, while no significant relationship is identified between the largest cryptocurrency market and the identified largest green energy ETFs. The effects of financial crises are measured through the addition of the variable Cr_t, indicating evidence of significant volatility effects during NBER-denoted crisis periods in all investigated methodological structures.

Insert Table 4 about here

The lack of significant linkages between Bitcoin returns and energy companies in Japan is particularly interesting observation. It can be explained by considering the energy mix data in the selected countries. In 2018, the percentage of renewables in electricity production in China, Japan, and Russia were 26.3%, 17.5% and 17.2% respectively, however, the respective share of coal in domestic consumption were 69% in China and 62% in Russia, and only 3% in Japan[2]. These

[1] Available at https://www.nber.org/cycles.html

[2] Source:https://yearbook.enerdata.net/

results further support the position of dependency of Bitcoin mining from coal energy, that is especially evident from China and Russia cases. A significant relationship of Bitcoin returns with international utility ETFs supports our hypothesis, that Bitcoin energy consumption is important channel of information transmission from cryptocurrency markets to utility ETFs. These findings are particularly interesting for investors building diversification and hedging strategy, since the financial effects of Bitcoin energy consumption is evident not only for energy markets, but exceeds to broader range of investments assets, such as international utility ETFs.

The analysis of interactions between Bitcoin returns and ICE EU Carbon Credit prices, and green ETFs, contributes to assessment of environmental impacts of Bitcoin growth. There is no positive linkages identified between Bitcoin and neither carbon credits nor green ETFs, suggesting that Bitcoin growth does not provide any positive externalities to tackle climate change. This contributes to previous work by Baur and Oll [2019], suggesting that carbon footprint of Bitcoin investments is high and its unsustainable investment. The use of renewable energy for electricity production in countries with high concentration of mining pools is still very low, and absence of financial effects and linkages between Bitcoin returns and green finance instruments, such as green energy ETFs, further highlight that renewables has limited linkages with cryptocurrency markets. This should concern both practitioners and financial regulators alike since the decentralised nature of this technology causes severe misusage and waste of electricity that can be used more efficiently elsewhere, and for potentially more useful purposes. While decrease of the carbon emission become a part of main global agenda to combat climate change, it is surprising how such a modern technology can be so unsustainable, thus further legislation is required to minimise its negative environmental effects.

In Figure 3 we observe the time-varying dynamic correlations between the selected products. We first observe the time varying interactions between Bitcoin and Chinese electricity companies, with a sharp elevation in dynamic correlations of pricing dynamics observed between late-2014 and early-2016. Japanese electricity markets present evidence of shared volatility dynamics during the period 2011 through 2013, however, this interaction does not appear to have sustained thereafter. However, Russian electricity companies appears to have experienced quite substantial elevations in dynamic interactions since late-2018. This situation is found to be somewhat replicated when observing interactions with both carbon credit markets and green energy ETFs, however, indexed utility ETFs present evidence of a sustained level of correlation that appears to mirror the timing of the price appreciation of Bitcoin, albeit, the correlations appear to be quite minimal in comparison to other analysed relationships. The selected ETFs represent the largest funds as ranked by market capitalisation. When considering the role of economic crisis, it is important to note that in five of the six analysed cases presented in Figure 3, there are distinct increases in the dynamic correlation relationships presented, with the exception of Chinese electricity companies. One potential explanation for this result surrounds the earlier physical outbreak of COVID-19 in China. Where evidence suggests that the international contagion of COVID-19 does not become official until the World Health Organisation announcement of 31 December 2019, physical evidence of the pandemic in China were evident as early as November 2019 [Corbet et al., 2020,?, Goodell, 2020].

Insert Figure 3 about here

We observe that the dynamic correlations between Bitcoin volatility and that of Chinese and Russian electricity companies that has grown sharply since early-2017, remaining substantially above its long-term value. It is the relationship between Bitcoin volatility and indexed utility ETFs that presents the most substantial evidence of sustained growing interactions since early 2016, peaking during 2018. This presents evidence that the growth in Bitcoin price volatility is found to be positively correlated, and increasingly related to the volatility we have observed in energy and utility company markets.

To provided add robustness to these results, the same methodology was repeated using a variation of underlying data representing the internal dynamics of Bitcoin's structural behaviour, such as the hashrate, mining difficulty, the natural logarithm of the number of unique Bitcoin wallet addresses and the blocksize of Bitcoin. While the dynamic correlations of the pricing behaviour between the Bitcoin and the selected assets under investigation is of particular interest when attempting to obtain an understanding of the interconnection of sentiment and the expectations of market participants, these selected dependent variables will shed further light on any physical interactions. Further, we utilise the log of the total number of individual Bitcoin wallets in existence and such interactions with the pricing dynamics of the selected companies (presented in Figure 4), and, the relationship between the same companies and the hashrate of Bitcoin (as per Figure 5). These latter two measures present substantial information, particularly as the energy consumption of Bitcoin is found to increase substantially, not only with more users, when considering as to how much power the Bitcoin network is consuming to generate, or to find blocks at the normal mean time of ten minute. These computations for finding the blocks are equivalent to mathematical puzzles that a miner must solve using substantial technological computation. The measure of mining difficulty establishes as to how difficult it is to find a hash below a given target. The Bitcoin network has a global block difficulty, therefore valid blocks must have a hash below this target.

Insert Figures 4 and 5 and about here

When considering that there existed a very sharp increase in the number of individual Bitcoin wallets as the price of the cryptocurrency appreciated substantially in both 2016 and again late-2017 in line with the worldwide publicity that cryptocurrencies had received due to the price appreciation of Bitcoin, the number of wallets appears to have maintained a level between 300 and 700 thousand users during this time. There is evidence to suggest that there was a sharp increase in the dynamic correlations between this increased number of Bitcoin users and the price appreciation of all of the selected energy companies with the exception of carbon markets and Green ETFs. Both Chinese and Japanese energy companies present evidence of increased dynamic correlations during both periods of sharp worldwide focus on this developing cryptocurrency. Utility companies in these regions present evidence of short-term interactions with the substantial number of new entrants to this developing market. With regards to Bitcoin's hashrate, as per Figure 1, we observed that there was a substantial period of growth in late-2015 and early-2016, leading directly to the exponential growth in the level of both the hashrate and mining difficulty in the period throughout 2017 and 2018. In late-2018, both measures fell by approximately half, before sharply increasing in 2019. Considering Figure 5, we note an increasing level of dynamic correlation between the pricing behaviour of each of the regions analysed, the analysed utility companies and the hashrate of Bitcoin, indicating that not only has the price of this cryptocurrency had an influence on the prices of utility companies, but it would appear that market behaviour and perspective is incorporating information that further Bitcoin mining requires further generation of electricity in these regions. There is particular evidence to suggest that the effects of such behaviour was most substantial during the sharp Bitcoin price appreciation of late-2017, suggesting market participants had identified the potential gains that utility companies would experience.

6. Conclusions

This paper discusses the cryptocurrency growth as an important factor to consider in the debate between fossil fuels and renewable energy. With emphasis on Chinese, Russian and Japanese electricity markets, and broad international utility companies, this study shows that continued cryptocurrency energy-usage demonstrates influence on the pricing of large electricity and utilities markets. These results are important for both policy makers and for academics, since they highlight an imminent need for research addressing key issues such as the growth of carbon produced in the creation of this new digital currency. The results are also important for investors concerned with ethical implications and environmental impacts of their investment choices.

While Blockchain technology has a number of useful implications and great potential to transform several industries, a high electricity consumption of Bitcoin has become one of the main areas of criticism raising several questions of sustainability of cryptocurrency as a new form of money and investment assets. Although cryptocurrencies are largely considered to be one of the most significant financial innovations in recent times and investment asset that offer high returns to the inventors, we must assess whether it justifies high electricity consumption stemming from its mining and transactions. There are two alternative positions which have been discussed in the literature and media. The first position is that cryptocurrency markets do not provide any significant value to society and economies, that it is simply a new speculative asset used to achieve abnormal returns for a relatively small proportion of the population, therefore, its high energy consumption can be argued to be unnecessary, wasteful and unsustainable. It relies heavily on coal as its main energy source, and thus contributes to the growing climate change problem. This energy could be used more wisely to support more important and critical services in society. Additionally, it increases pressure on power suppliers to produce and distribute more energy. The second position suggests that cryptocurrency is not only speculative asset and its usage as method of payment and money transfer is increasing. While the proponents of cryptocurrency do not deny its energy inefficiency, however, they claim that environmental effect is not the problem of the technology itself, but the sources of energy used to support the mining process. Thus, the transition to green renewable energy sources can decrease the carbon footprint of cryptocurrency usage and crypto investments.

The results reported in this paper provide some important empirical evidence to this debate. We specifically focus on three energy markets, i.e. China, Japan, and Russia, that are accountable for the majority of Bitcoin mining, and rely heavily on non-renewable energy sources. We found significant and positive relationships between Bitcoin returns and both Chinese and Russian electricity company price volatility. Furthermore, the results suggest a similar positive relationship between Bitcoin and utility companies in those countries. Robustness is added through the additional usage of the number of Bitcoin wallets and the hashrate of the developing cryptocurrency over time, indicating significant, albeit at times quite minute interactions, that peaked across all analysed utility companies during the sharp Bitcoin price appreciation of late-2017 and early-2018. These results display that popularity of Bitcoin as an investment asset provides a positive effect on the electricity sector and utilities. This mutually beneficial relationship indicates that energy companies benefit from a high Bitcoin price and mining process, therefore there is no financial motivation to switch to renewable energy sources to make Bitcoin more sustainable.Taking into account that Bitcoin mining is profitable only in countries with cheap energy (see for example Delgado-Mohatar et al. [2019]), there is no rational reason to believe that this change towards sustainability will be realistic in the near future without relevant legislation. Thus, for policy makers it is important to acknowledge the growing environmental problem of cryptocurrency energy usage, and impose sufficient regulation in this area.

The second important piece of evidence is a lack of positive linkages between Bitcoin and green ETFs and carbon credits. The growing Bitcoin price does not contribute to growth of green investment instruments, which further highlights that to date we do not have any evidence suggesting that cryptocurrency market growth has some positive impacts on renewable energy markets, that can somewhat compensate its current carbon footprint. These results should be of great interest to investors who want to create more sustainable portfolios and support solutions to climate change. In line with Baur and Oll [2019], we find that considering high energy consumption of the network as a whole, strong positive linkages with energy and utility providers, and lack of positive impacts on green ETFs, the investments in cryptocurrency markets are not sustainable.

We acknowledge that this research is one of the first studies in this area, and we explored this topic from a very narrow set of perspectives. Further research on the environmental sustainability of cryptocurrencies is highly essential. Specifically, we recommend the analysis of the environmental sustainability of cryptocurrency markets beyond Bitcoin, considering the differences between characteristics of various crypto assets. Other cryptocurrencies might have different carbon footprints and levels of energy consumption which will affect their interactions with energy and utility companies. It is important to analyse whether cryptocurrencies are sustainable in terms of their energy requirements, and to assess their contribution to climate change. Furthermore, a broader impact of cryptocurrency market growth on environmental sustainability should be considered, and we hope that future research can help to answer the question of how to make mineable cryptocurrencies more sustainable.

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Table 1: Summary Statistics of the Selected Data, Total Investigated Period

Type	Description	Mean	Variance	Skewness	Kurtosis	Maximum	Minimum	Observations
	Trading Volume	0.0000	0.0000	5.5381	44.6735	0.0000	0.0000	3,065
	Difficulty	0.0000	0.0000	2.0874	3.2044	0.0000	1.0000	3,065
	Block Size	0.4732	0.1972	0.3772	-1.4287	1.4218	0.0002	3,065
Crypto	Hashrate	0.0000	0.0000	2.1010	3.3312	0.0000	0.0000	3,065
	Addresses	0.0000	0.0000	0.4658	-1.0735	0.0001	0.0000	3,065
	Transactions per Day	0.0001	0.0000	0.4949	-0.9563	0.0001	0.0000	3,065
	Wallet Transactions	0.0001	0.0000	12.2092	226.9387	0.0000	0.0000	3,065
	China Shenhua Energy	-0.0002	0.0004	-0.2996	5.2996	0.0911	-0.1143	3,064
China Utilities	China Yangtze Energy	0.0001	0.0002	-0.5094	8.9176	0.0725	-0.1227	2,974
	China Nat. Nuclear Power	-0.0003	0.0004	-0.2708	11.1900	0.0915	-0.1112	1,392
	Huaneng Power Int.	-0.0004	0.0004	-0.0617	4.1754	0.1286	-0.1266	3,064
	Chugoku Electric Power	0.0000	0.0006	-0.1015	5.7680	0.1007	-0.1073	3,064
	Chubu Electric Power	-0.0001	0.0006	-0.2981	5.4654	0.1186	-0.1245	3,064
Japan Utilities	Hokuriku Electric Power	-0.0002	0.0007	-1.3133	19.8641	0.1252	-0.2714	3,064
	Kyushu Electric Power	-0.0002	0.0007	0.0541	8.4755	0.1776	-0.1553	3,064
	Kansai Electric Power	-0.0002	0.0008	-0.2384	7.2161	0.1500	-0.1729	3,064
	Okinawa Electric Power	0.0001	0.0006	0.3239	4.3935	0.1144	-0.0935	3,064
	Gazprom	-0.0001	0.0003	-0.0356	6.1230	0.1406	-0.1614	3,064
Russia Utilities	Rosneft	0.0002	0.0004	-0.3117	8.2343	0.1304	-0.2035	3,064
	Lukoil	0.0003	0.0003	-0.6175	13.1060	0.1336	-0.2293	3,064
	Surgutneftegas	0.0001	0.0004	-0.1316	7.1328	0.1317	-0.1856	3,064
	XLE	-0.0003	0.0003	-1.6980	24.0189	0.1382	-0.2522	3,064
	VDE	-0.0003	0.0003	-1.5106	20.6338	0.1359	-0.2473	3,064
	XOP	-0.0007	0.0007	-3.8945	89.3720	0.1793	-0.5840	3,064
	IXC	-0.0003	0.0003	-1.8412	26.8312	0.1476	-0.2415	3,064
Utility ETFs	OIH	-0.0012	0.0006	-3.4882	66.7031	0.1514	-0.4759	2,297
	IYE	-0.0003	0.0003	-1.7450	25.4513	0.1386	-0.2604	3,064
	IGE	-0.0002	0.0003	-1.3647	16.4029	0.1288	-0.2188	3,064
	KOL	-0.0004	0.0004	-0.5390	5.6696	0.1092	-0.1287	3,064
	FRAK	-0.0009	0.0006	-4.2860	94.9964	0.1531	-0.5048	2,257
Carbon Markets	Eux Carbon	-0.0004	0.0008	-1.7455	23.5852	0.1470	-0.4410	2,655
	iShares Cl. Energy	-0.0002	0.0003	-0.7274	7.6223	0.1266	-0.1469	3,064
	Invesco Cl. Energy	-0.0001	0.0004	-0.8332	7.3676	0.1263	-0.1693	3,064
Green ETFs	Nasdaq Cl. Energy	0.0003	0.0004	-0.7129	6.8713	0.1231	-0.1685	3,064
	Invesco Glob. Cl. Energy	0.0001	0.0003	-1.4573	17.3615	0.0989	-0.2241	3,064
	FT Nasdaq Cl Energy	0.0003	0.0004	-0.6494	6.6647	0.1249	-0.1628	3,064

Note: The table above presents the summary statistics for the selected indices used in this analysis. We utilise data from the Bitfinex exchange for Bitcoin. The log return, $r_t = ln(P_t/P_{t-1})$ is then estimated for the period 1 January 2010 through 31 May 2019. Structural data related to the functionality of Bitcoin was obtained from historical API (application programming interfaces). Traditional financial market data was obtained from Thompson Reuters Eikon.

Table 2: Summary Statistics of the Selected Data, Non-Crisis Denoted Period

Type	Description	Mean	Variance	Skewness	Kurtosis	Maximum	Minimum	Observations
Crypto	Trading Volume	0.0000	0.0000	5.0838	37.2480	0.0000	0.0000	2,508
	Difficulty	0.0000	0.0000	2.2054	4.1312	0.0000	11.8462	2,508
	Block Size	0.4840	0.1690	0.2844	-1.4669	1.3144	0.0003	2,508
	Hashrate	0.0000	0.0000	2.2226	4.2797	0.0000	0.0001	2,508
	Addresses	0.0000	0.0000	0.4169	-0.9279	0.0000	165.0000	2,508
	Transactions per Day	0.0001	0.0000	0.2625	-1.2276	0.0000	0.0000	2,508
	Wallet Transactions	0.0001	0.0000	11.3363	193.2444	0.0000	0.0000	2,508
China Utilities	China Shenhua Energy	-0.0003	0.0004	-0.3508	6.2556	0.0911	-0.1112	2,508
	China Yangtze Energy	0.0002	0.0001	-0.6400	10.8454	0.0725	-0.1227	2,508
	China Nat. Nuclear Power	-0.0002	0.0005	-0.2396	10.6712	0.0915	-0.1112	1,190
	Huaneng Power Int.	-0.0002	0.0004	-0.2613	4.0967	0.1286	-0.1266	2,508
Japan Utilities	Chugoku Electric Power	-0.0002	0.0003	-0.1686	5.2799	0.1007	-0.1073	2,508
	Chubu Electric Power	-0.0003	0.0003	-0.3216	5.2756	0.1186	-0.1245	2,508
	Hokuriku Electric Power	-0.0005	0.0004	-1.5332	21.4198	0.1252	-0.2714	2,508
	Kyushu Electric Power	-0.0005	0.0004	0.0120	7.9261	0.1776	-0.1553	2,508
	Kansai Electric Power	-0.0005	0.0005	-0.1748	6.4571	0.1500	-0.1729	2,508
	Okinawa Electric Power	-0.0001	0.0003	0.2958	4.6610	0.1144	-0.0935	2,508
Russia Utilities	Gazprom	0.0000	0.0003	0.0367	8.3660	0.1406	-0.1614	2,508
	Rosneft	0.0001	0.0003	0.0545	2.1174	0.0952	-0.0825	2,508
	Lukoil	0.0004	0.0002	-0.2092	3.4483	0.0883	-0.1083	2,508
	Surgutneftegas	0.0001	0.0003	0.4034	5.0290	0.1317	-0.1153	2,508
Utility ETFs	XLE	-0.0001	0.0002	-0.3907	3.1286	0.0586	-0.0930	2,508
	VDE	-0.0001	0.0002	-0.3971	2.9981	0.0605	-0.0933	2,508
	XOP	-0.0005	0.0004	-0.2990	2.8718	0.1037	-0.1445	2,508
	IXC	-0.0001	0.0002	-0.4535	3.6421	0.0533	-0.0930	2,508
	OIH	-0.0007	0.0003	-0.1233	1.7064	0.0960	-0.0978	2,095
	IYE	-0.0001	0.0002	-0.3762	2.8979	0.0594	-0.0912	2,508
	IGE	-0.0001	0.0002	-0.3933	2.9205	0.0566	-0.0834	2,508
	KOL	-0.0006	0.0003	-0.3484	3.8492	0.0907	-0.1068	2,508
	FRAK	-0.0006	0.0003	-0.1422	2.4560	0.0944	-0.1144	2,055
Carbon Markets	Eux Carbon	-0.0004	0.0008	-1.8739	26.3106	0.1470	-0.4410	2,453
Green ETFs	iShares Cl. Energy	-0.0002	0.0002	-0.3869	3.0137	0.0720	-0.0974	2,508
	Invesco Cl. Energy	-0.0003	0.0003	-0.3998	2.5578	0.0783	-0.1082	2,508
	Nasdaq Cl. Energy	0.0001	0.0002	-0.3605	1.9645	0.0679	-0.0840	2,508
	Invesco Glob. Cl. Energy	-0.0001	0.0002	-0.4549	4.2579	0.0795	-0.0972	2,508
	FT Nasdaq Cl Energy	0.0001	0.0002	-0.4011	2.2082	0.0737	-0.0840	2,508

Note: The table above presents the summary statistics for the selected indices used in this analysis. We utilise data from the Bitfinex exchange for Bitcoin. The log return, $r_t = ln(P_t/P_{t-1})$ is then estimated for the period 1 January 2010 through 31 May 2019. Structural data related to the functionality of Bitcoin was obtained from historical API (application programming interfaces). Traditional financial market data was obtained from Thompson Reuters Eikon.

Table 3: Summary Statistics of the Selected Data, Crisis Denoted Period

Type	Description	Mean	Variance	Skewness	Kurtosis	Maximum	Minimum	Observations
	Trading Volume	0.0000	0.0000	2.3379	7.3020	0.0000	0.0000	552
	Difficulty	0.0000	0.0000	0.6026	-1.5879	0.0000	1.0000	552
	Block Size	0.4246	0.3225	0.6309	-1.5337	1.4218	0.0002	552
Crypto	Hashrate	0.0000	0.0000	0.6352	-1.5055	0.0000	0.0000	552
	Addresses	0.0000	0.0000	0.6635	-1.4370	0.0001	0.0000	552
	Transactions per Day	0.0001	0.0000	0.7048	-1.3353	0.0001	0.0000	552
	Wallet Transactions	0.0001	0.0000	1.2501	0.9580	0.0001	0.0000	552
	China Shenhua Energy	0.0001	0.0006	-0.1797	2.7119	0.0909	-0.1143	551
China Utilities	China Yangtze Energy	-0.0004	0.0002	-0.0733	3.3847	0.0671	-0.0639	461
	China Nat. Nuclear Power	-0.0007	0.0002	-0.9043	8.5950	0.0442	-0.0948	202
	Huaneng Power Int.	-0.0011	0.0006	0.4316	3.6359	0.1207	-0.1149	551
	Chugoku Electric Power	0.0011	0.0020	0.6064	8.2439	0.0955	-0.0604	551
	Chubu Electric Power	0.0010	0.0020	-0.1066	5.0039	0.0748	-0.0749	551
Japan Utilities	Hokuriku Electric Power	0.0012	0.0021	0.3355	3.8663	0.0841	-0.0701	551
	Kyushu Electric Power	0.0013	0.0020	0.6270	7.4598	0.1024	-0.0663	551
	Kansai Electric Power	0.0009	0.0020	-1.2144	11.4479	0.0535	-0.1319	551
	Okinawa Electric Power	0.0009	0.0021	0.4482	3.3572	0.0860	-0.0560	551
	Gazprom	-0.0004	0.0007	-0.0825	1.7996	0.0933	-0.1010	551
Russia Utilities	Rosneft	0.0005	0.0009	-0.4944	5.3282	0.1304	-0.2035	551
	Lukoil	-0.0002	0.0009	-0.6745	8.6567	0.1336	-0.2293	551
	Surgutneftegas	0.0001	0.0009	-0.5821	4.5803	0.0937	-0.1856	551
	XLE	-0.0014	0.0009	-1.7013	14.0669	0.1382	-0.2522	551
	VDE	-0.0013	0.0009	-1.5611	12.7648	0.1359	-0.2473	551
	XOP	-0.0015	0.0017	-5.1010	74.3744	0.1793	-0.5840	551
	IXC	-0.0013	0.0008	-1.9002	16.6219	0.1476	-0.2415	551
Utility ETFs	OIH	-0.0063	0.0035	-2.6208	20.0766	0.1514	-0.4759	202
	IYE	-0.0014	0.0008	-1.8392	16.1318	0.1386	-0.2604	551
	IGE	-0.0006	0.0007	-1.5988	11.7824	0.1288	-0.2188	551
	KOL	0.0005	0.0009	-0.6267	2.9395	0.1092	-0.1287	551
	FRAK	-0.0045	0.0028	-4.0295	39.2420	0.1531	-0.5048	202
Carbon Markets	Eux Carbon	-0.0003	0.0012	-0.8010	5.7581	0.1196	-0.1967	202
	iShares Cl. Energy	0.0001	0.0008	-0.7720	4.2085	0.1266	-0.1469	551
	Invesco Cl. Energy	0.0009	0.0009	-1.0272	5.0053	0.1263	-0.1693	551
Green ETFs	Nasdaq Cl. Energy	0.0013	0.0009	-0.8804	4.7643	0.1231	-0.1685	551
	Invesco Glob. Cl. Energy	0.0007	0.0007	-1.7053	11.6737	0.0989	-0.2241	551
	FT Nasdaq Cl Energy	0.0013	0.0008	-0.7668	4.5880	0.1249	-0.1628	551

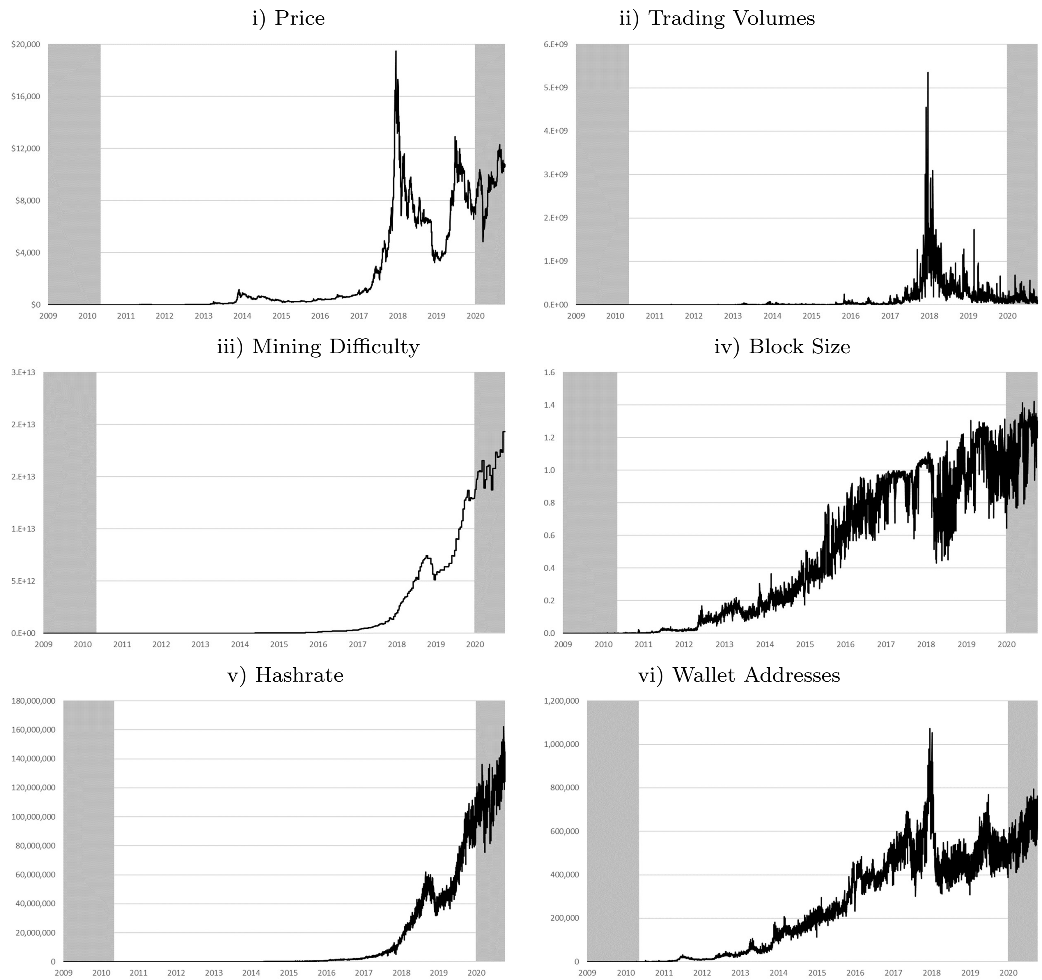
Note: The table above presents the summary statistics for the selected indices used in this analysis. We utilise data from the Bitfinex exchange for Bitcoin. The log return, $r_t = ln(P_t/P_{t-1})$ is then estimated for the period 1 January 2010 through 31 May 2019. Structural data related to the functionality of Bitcoin was obtained from historical API (application programming interfaces). Traditional financial market data was obtained from Thompson Reuters Eikon.

Table 4: DCC-GARCH Results for the Selected Variables

	China Elec.	Japan Elec.	Russia Elec.	Utility ETFs	Carbon	Green ETFs
Constant	0.0031***	0.0033***	0.0034***	0.0037***	0.0035***	0.0030***
	(5.51)	(5.61)	(5.39)	(5.77)	(5.81)	(4.81)
Bitcoin						
Constant	0.0001***	0.0003***	0.0002***	0.0002***	0.0001***	0.0002***
	(3.99)	(3.08)	(4.31)	(4.29)	(3.78)	(4.39)
ARCH	0.2806***	0.2699***	0.2181***	0.2085***	0.3019***	0.2909***
	(5.92)	(3.60)	(5.14)	(5.22)	(5.70)	(5.97)
GARCH	0.7046***	0.7013***	0.6611***	0.6741***	0.6733***	0.6500***
	(19.61)	(16.22)	(13.48)	(14.38)	(14.53)	(14.40)
Independent	China Elec.	Japan Elec.	Russia Elec.	Utility ETFs	Carbon	Green ETFs
Constant	0.0000**	0.0000**	0.0000**	0.0000***	0.0000**	0.0000**
	(2.48)	(2.55)	(1.97)	(2.64)	(2.19)	(1.99)
ARCH	0.1108***	0.1086***	0.0802***	0.1322***	0.0844***	0.0421***
	(4.67)	(3.60)	(3.37)	(4.89)	(4.98)	(4.51)
GARCH	0.8818***	0.8901***	0.8953***	0.8580***	0.9034***	0.9337***
	(37.10)	(39.76)	(25.67)	(31.10)	(48.61)	(67.62)
Correlation	+0.0529***	+0.0127	+0.0677***	+0.0868***	-0.0602**	+0.1437
	(-6.49)	(0.91)	(6.31)	(8.98)	(2.01)	(0.93)
Cr_t	0.0034***	0.0148***	0.0074***	0.0091***	0.0730***	0.0829***
	(6.68)	(7.00)	(6.68)	(6.67)	(13.66)	(13.01)
Adjustment						
λ_1	0.0003***	0.0001	0.0091***	0.0003***	0.0059***	0.0023***
	(4.22)	(0.15)	(3.44)	(4.14)	(4.29)	(3.58)
λ_2	0.9473***	0.9968***	0.9902***	0.9972***	0.3315***	0.9976***
	(11.13)	(132.82)	(39.82)	(193.12)	(3.34)	(313.47)

Note: The table above presents the DCC-GARCH-calculated correlations between Bitcoin and i) Chinese electricity companies; ii) Japanese electricity companies; iii) Russia electricity companies; iv) indexed utility ETFs ranked by market capitalisation; v) carbon credit markets; and vi) green energy ETFs ranked by market capitalisation respectively. T-statistics are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. Further calculations and results are available from the authors on request.

Figure 1: The Changing Characteristics of Bitcoin, 2010-2020



Note: The top two figures represent the price and volatility of Bitcoin between 2010 and 2020. The middle pair of figures presents the hashrate and mining difficulty respectively. The bottom figures represents the number of unique addresses used to mine Bitcoin and the block size respectively. The shaded grey areas indicate recessions as denoted by the National Bureau of Economic Research available at https://www.nber.org/cycles.html

Figure 2: Price Performance of Key International Energy Sectors, 2010-2020

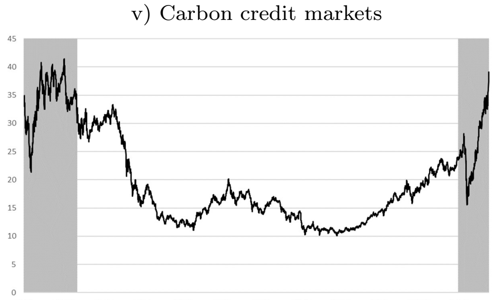
i) Chinese electricity companies

ii) Japanese electricity companies

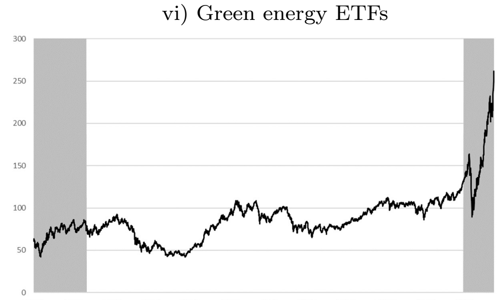
iii) Russia electricity companies

iv) Indexed utility ETFs

v) Carbon credit markets

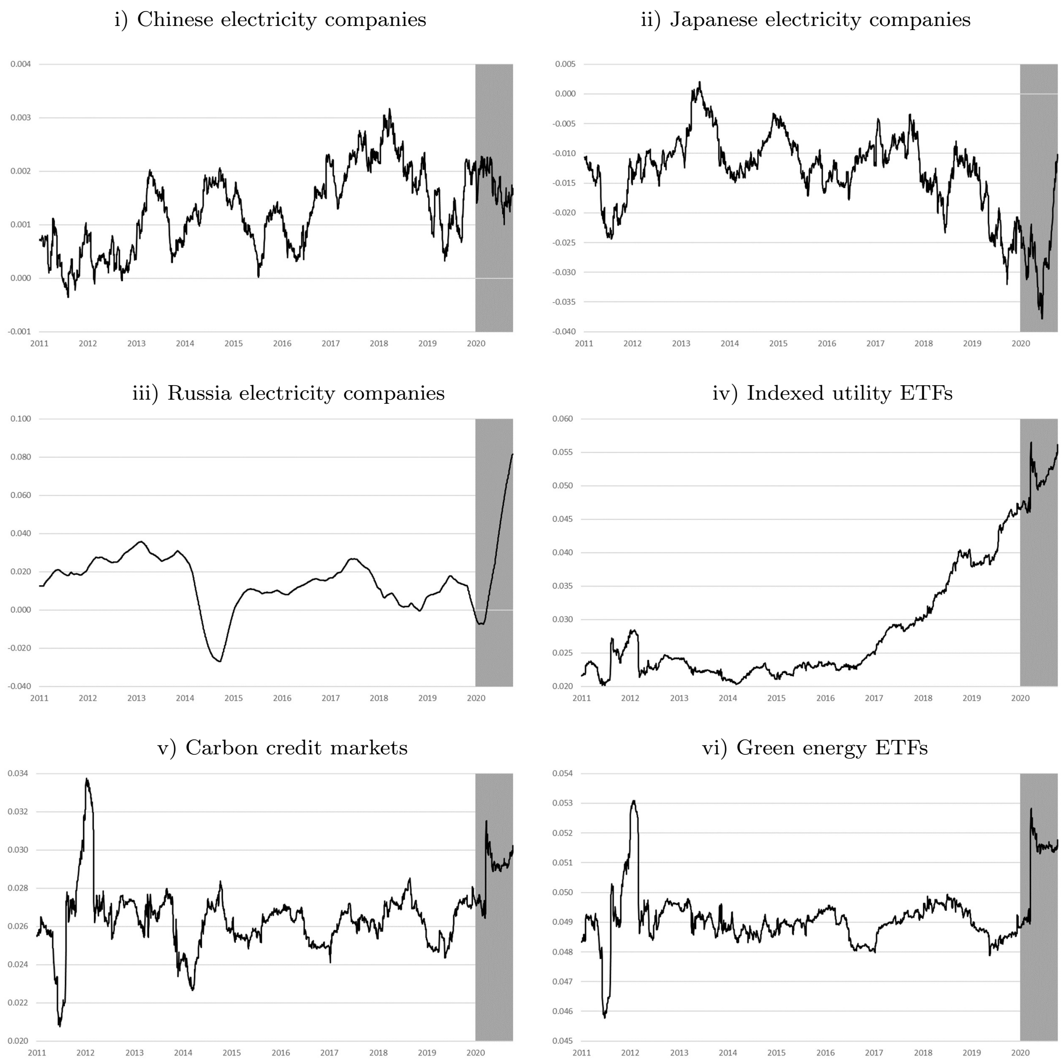


vi) Green energy ETFs



Note: The six identified figures represents the average price performance of Chinese, Japanese and Russian electricity companies respectively. Next we observe the average price performance of ten of the largest utlity company ETFs in the world as ranked by market capitalisation. The bottom figures represents the price performance of the International Carbon Credit Market (ICE EUX Carbon Credit) while the final figure represents the average price performance of the six largest green energy ETFs by market capitalisation. The shaded grey areas indicate recessions as denoted by the National Bureau of Economic Research available at https://www.nber.org/cycles.html

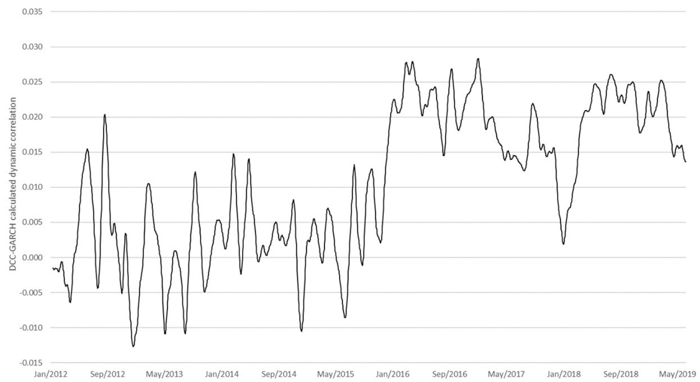
Figure 3: Selected DCC-GARCH-calculated relationships between Bitcoin price volatility and selected International Energy Sectors



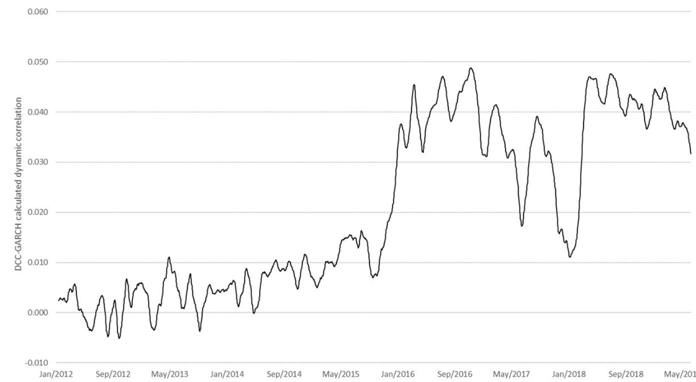
Note: The above figures present the 10-day moving average of DCC-GARCH-calculated correlations between Bitcoin and i) Chinese electricity companies; ii) Japanese electricity companies; iii) Russia electricity companies; iv) indexed utility ETFs ranked by market capitalisation; v) carbon credit markets; and vi) green energy ETFs ranked by market capitalisation respectively. Further calculations and results are available from the authors on request. The shaded grey areas indicate recessions as denoted by the National Bureau of Economic Research available at https://www.nber.org/cycles.html

Figure 4: Selected DCC-GARCH-calculated relationships between the number of unique Bitcoin wallet addresses (log) and selected International Energy Sectors

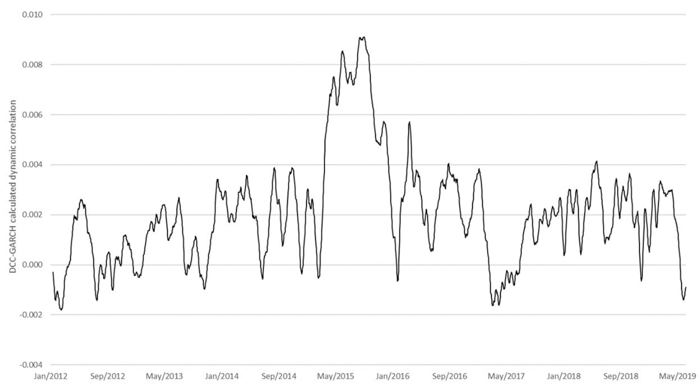
i) Chinese electricity companies



ii) Japanese electricity companies



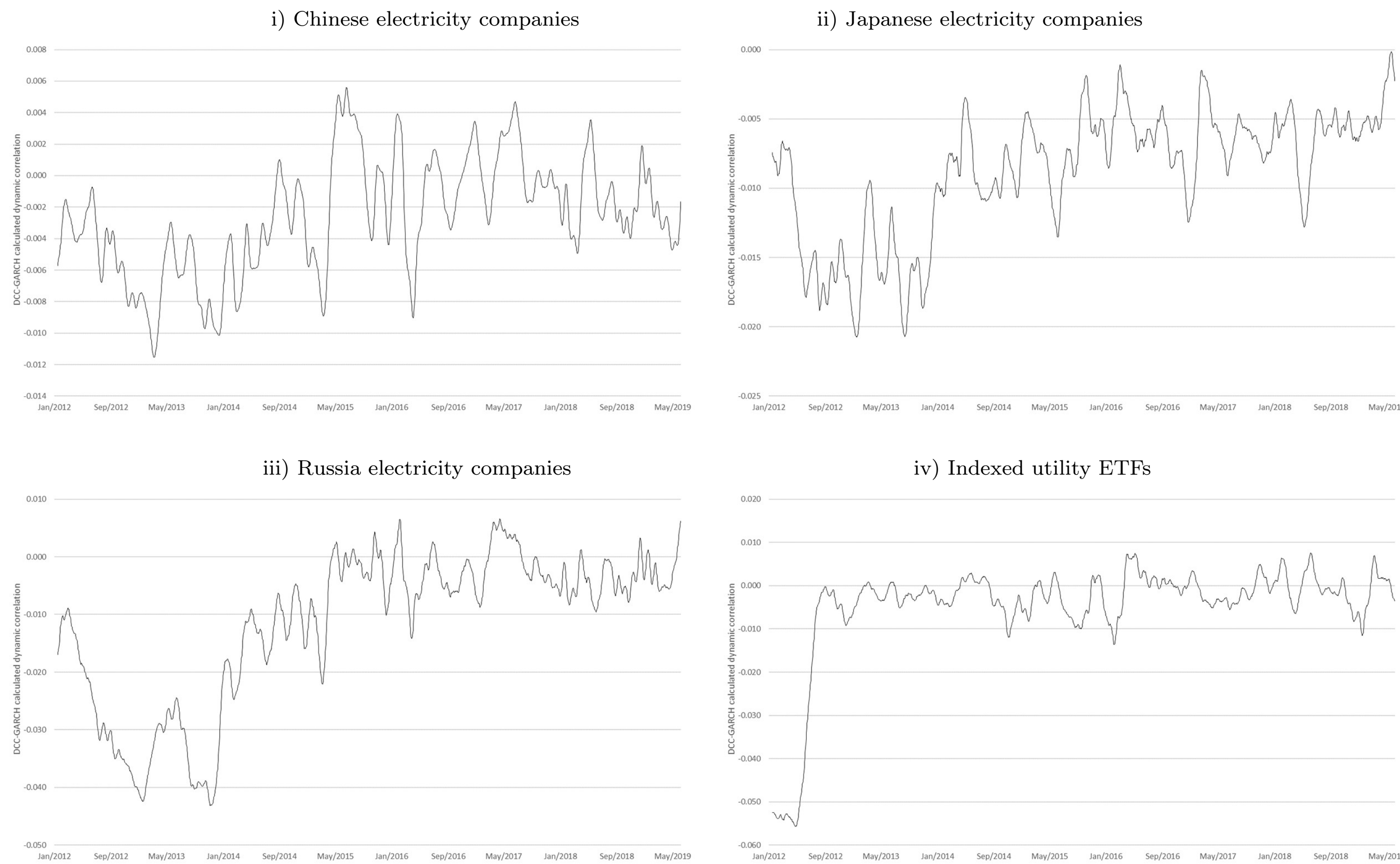
iii) Russia electricity companies



iv) Indexed utility ETFs

Note: The above figures present the 10-day moving average of DCC-GARCH-calculated correlations between Bitcoin and i) Chinese electricity companies; ii) Japanese electricity companies; iii) Russia electricity companies; iv) indexed utility ETFs ranked by market capitalisation; v) carbon credit markets; and vi) green energy ETFs ranked by market capitalisation respectively. Further calculations and results are available from the authors on request.

Figure 5: Selected DCC-GARCH-calculated relationships between Bitcoin hashrate and selected International Energy Sectors



Note: The above figures present the 10-day moving average of DCC-GARCH-calculated correlations between Bitcoin and i) Chinese electricity companies; ii) Japanese electricity companies; iii) Russia electricity companies; iv) indexed utility ETFs ranked by market capitalisation; v) carbon credit markets; and vi) green energy ETFs ranked by market capitalisation respectively. Further calculations and results are available from the authors on request.