The Pricing Implications of Cryptocurrency Mining on Global Electricity Markets: Evidence from Quantile Causality Tests

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Abstract

This paper examines the causal interactions between various measures of energy consumption due to mining activity and electricity return and volatility patterns across the power markets in the U.S., U.K. and Europe via a nonlinear causality model that accommodates structural breaks and regime shifts in the bivariate interactions. Our findings establish a causal relationship running from bitcoin mining activity, proxied by the Cambridge Bitcoin Electricity Consumption Index, to Phelix electricity price returns, the reference price for the power spot market for the German/Austrian market area. This suggests that mining activity can induce wealth effects in the real economy; however, the effect is heterogeneous across the different power markets examined. At the same time, we find that the effect of mining activity is focused on return volatility, consistently for all three proxies of bitcoin electricity consumption and all the electricity markets examined. Accordingly, our findings provide robust evidence of volatility effects of mining activity in power markets across both sides of the Atlantic, suggesting that the crypto mining-power market nexus primarily entails risk effects, an issue of particular concern for hedgers whose goal is to stabilize energy costs in their operations.

Keywords: Electricity market, Bitcoin, Quantile causality
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1. Introduction

The use of Bitcoin and associated cryptocurrencies is increasingly gaining relevance in recent years, fuelled by the rising cryptocurrency adoption rates among investors, particularly in developing countries in Asia and Africa, who tend to suffer from financial instability and barriers to traditional financial products. Naturally, the rise in adoption rates for crypto assets has resulted in a flurry of mining activity for these assets globally, overwhelmingly led by crypto miners in mainland China, followed by the U.S. and Russia, until 2011 when the Chinese government decided to ban all mining activities in June 2021 following major power disruptions experienced in the country, fuelled by the heavy energy consumption rates associated with cryptocurrency mining. In fact, an increasing number of studies published in the last several years present robust evidence regarding the non-virtual side of mining and trading of these assets, establishing a link to price fluctuations in the energy market (e.g. Karmakar, et al, 2021). The goal of this paper is to provide further evidence on the non-virtual effects of cryptocurrency mining activity on the real economy by examining the causal interactions between various measures of electricity consumption associated with bitcoin mining activity and power market dynamics from major electricity markets in Europe, U.K. and U.S. By doing so, we present novel insight to the price dynamics in global power markets with significant implications, both from an investment and policy making perspectives.

Bitcoin is owned and governed by series of autonomous individuals and cooperate organizations known as Bitcoin "Miners". These miners are authorities responsible for enforcing the credibility of the Bitcoin network in a decentralized manner. New Bitcoin are released to miners at a fixed but periodically declining rate. The process of creating new Bitcoin is hugely energy intensive as powerful computers are required to solve complex cryptographic puzzles and the trust-minimizing policy of Bitcoin mining is facilitated through its "proof-of-work algorithm" that this requires huge power-hungry machines for performance. In fact, it is estimated that Bitcoin consumes more energy than decent sized economies like Czech Republic, Netherlands and Ukraine, while it consumes around half as much energy as several G7 countries including Italy and the U.K.[1] In the U.S., the annual quantum of electricity usage of the Bitcoin network is estimated to be about the same as that of Washington State with an

[1] https://digiconomist.net/bitcoin-energy-consumption.

average Bitcoin transaction consuming an amount equivalent to six weeks of electricity consumption in a typical average American household (Tully, 2021).

Although Bitcoin is primarily mined in countries that enjoy the availability of relatively cheap and surplus energy supply – like China, U.S. and Russia, recent evidence shows that mining activity not only leaves a large carbon footprint as most mining facilities are powered by fossil fuels, but also has the potential to disrupt real economic activity as it puts tremendous pressure on energy consumption rates. In this regard, the recent ban in 2011 by the Chinese government on all crypto mining activity is a great example of why policy authorities need a better understanding on the effect of mining activity on the power market as the country decided to ban crypto mining after experiencing major disruptions and power shortages. Furthermore, considering that the Chinese crackdown on mining has led to a flurry of Chinese miners flocking into Kazakhstan to continue their operations, who in turn, reportedly caused major power disruptions in that country, a better understanding of the nexus between crypto mining and power market can help policy authorities to better coordinate their efforts to monitor and mitigate the non-virtual side effects of mining activity on their economies.

On the academic side, a growing number of works have examined the link between Bitcoin as a cryptocurrency and other asset markets as well as carbon emission patterns using various methodologies and in different contexts (e.g. Urquhart, 2016; Bouri et al., 2017; Bouri et al., 2018 Shahzad et al., 2019; Smales, 2019; Aalborg et al. 2019; Scharnowski, 2021; Jiang et al, 2021 among others). Separately, there is a large literature on the price and volatility dynamics in the electricity market, primarily focusing on modelling and forecasting electricity prices (e.g. Weron et al., 2004; Weron and Misiorek 2008; Escribano et al., 2011; Raviv et al., 2015; Karakatsani and Bunn, 2015; Foroni et al., 2019; Algieri et al., 2021). Weron (2014) provides a detailed review of the literature in this regard. In the strand of the literature that is more related to the focus of our analysis, a growing number of works in recent years have examined Bitcoin from an energy consumption perspective (e.g. Stoll et al., 2019; de Vries, 2020, 2021; Sedlmeir et al, 2020; Karmakar et al., 2021; Ante and Fiedler, 2021) although a formal econometric model that established a direct link between the two markets was only developed recently in Karmakar et al. (2021). Unlike these works, we examine the causal interactions between various measures of energy consumption due to mining activity and electricity return and volatility patterns across electricity markets in the U.S., U.K. and Europe via a nonlinear causality model that has been popularly utilized in different contexts in recent works.

Our findings establish a causal relationship running from bitcoin mining activity, proxied by the Cambridge Bitcoin Electricity Consumption Index, to Phelix electricity price returns, the reference price for the power spot market for the German/Austrian market area. This suggests that mining activity can induce wealth effects in the real economy; however, the effect is heterogeneous across the different power markets examined. At the same time, we find that the effect of mining activity is focused on return volatility, consistently for all three proxies of bitcoin electricity consumption and all the electricity markets examined. Accordingly, we provide robust evidence of volatility effects of mining activity in power markets across both sides of the Atlantic, suggesting that the crypto mining-power market nexus primarily entails risk effects which is an issue of particular concern for hedgers in the power market whose goal is to stabilize energy costs in their operations.

The rest of the paper is structured as follows. Section 2 presents a brief review of the literature on power market dynamics and the link to cryptocurrencies. Sections describes the data and methodology employed in our analysis. Section 4 presents the empirical results and Section 5 concludes with a discussion of the implications of the findings and directions for future research.

2. Literature Review

Various studies in the literature have attempted to quantify the energy consumption and resulting carbon emissions associated with the Bitcoin network (de Vries, 2018, 2020, 2021; Krause and Tolaymat, 2018; Stoll et al., 2019; Sedlmeir et al., 2020) and other proof-of-work blockchains (Li et al., 2019; Gallersdörfer et al., 2020). Given the popularity of the issue, particularly from a policy making perspective, the validity of the proposed models, assumptions and their implications have been heavily debated in public scientific platforms. These discussions have consequently led to the development of proxies that capture the Bitcoin network's electricity consumption at the regional and global levels. One of the popularly cited works in this regard include the Cambridge Bitcoin Electricity Consumption Index (CBECI) project maintained by the Digital Assets Programme (DAP) Team at the Centre for Alternative Finance at the University of Cambridge. The second is the Bitcoin Energy Consumption Index (BECI) maintained by Digiconomist that measures energy consumption of the Bitcoin network.

The bitcoin consumption indices have been utilized in different contexts in the literature and in studies that are more related to our focus. For example, focusing on the social costs associated with the energy consumption related to Bitcoin, Ante and Fiedler (2021) highlight the role of Bitcoin in the settlement of global transactions in a decentralized fashion by comparing energy consumption patterns associated with Bitcoin to the social benefits it offers over the centralized settlement layers such as the American FedWire, Clearing House Interbank Payments System (CHIPS) or the European TARGET2 system. The authors argue that even though the mining process involves exorbitantly high energy costs, miners are not necessarily irrational in their decision to absorb high energy expenditures as long as the potential reward from mining exceeds that cost. In other words, as long as the cost of electricity remains stable, while the value of Bitcoin rises, the profitability argument becomes a fuelling propensity for incessant mining with consequent increase in energy consumption (Steinmetz et al., 2020). Similarly, in another attempt to quantify the impact of Bitcoin mining on power consumption dynamics, Stoll et al. (2019) utilize a methodology to obtain an estimate for 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 estimates, using the localization of IP addresses.

In studies that aim to examine the possible effect of Bitcoin's energy usage on financial markets, Corbet et al. (2019) establish a link between the energy consumption patterns in the cryptocurrency market with the financial performance in the energy sector, particularly large electricity and utility markets. Their results confirm the earlier findings by Krause and Tolaymat (2018) that it costs more to mine $1 worth of Bitcoin than it did to mine $1 worth various precious metals including gold, platinum or copper. Furthermore, from a carbon emissions perspective, Mora et al. (2018) show that Bitcoin mining and trading activity has the potential to create enough CO_2 emissions to push warming above 2 degrees Celsius within less than three decades although Song and Aste (2020) find that the energy consumption cost of mining Bitcoin has remained stable since 2010. The direct link to price dynamics in the power, however, is provided recently in Karmakar et al (2021) who examine the effect of energy consumption due to Bitcoin mining and trading on the electricity prices in three prominent U.S. power markets. Utilizing the time-varying Regression+ GARCHX in volatility model, the authors document a significant volatility effect of Bitcoin mining activity in the electricity markets examined, with the volatility effect increasing over time, particularly with the widespread lockdowns enforced due to the COVID-19 pandemic. Despite the emerging evidence regarding the effect of crypto mining and trading activity on power market dynamics, however, the topic is still relatively understudied. In our application, to the best of our knowledge, we present the first evidence regarding the possible causal interactions between return and volatility dynamics in global electricity markets and various proxies of energy consumption due to Bitcoin mining.

3. Data and Methodology

3.1 Data

Our electricity price dataset covers major U.S. and European pricing benchmarks including the Northern Illinois hub, Western Hub, New England hub, Phelix electricity, French base load, Italian base load, Spanish base load, and the UK base load electricity prices, all of which are converted to log-returns. Specifically, we collect daily spot price data over the period Dec. 19, 2017–June 18, 2021, obtained from Commodity Systems Inc.[2] To capture bitcoin mining activity, we use the change in the Cambridge Bitcoin Electricity Consumption Index that measures the Bitcoin network's daily electricity load.[3] The electricity consumption index data is available in the form of a hypothetical range consisting of a lower bound, upper bound and best-guess estimate as the exact electricity consumption value cannot be determined. The lower (upper) bound assumes that all miners always use the most (least) energy-efficient equipment available on the market. The best-guess estimate is based on the more realistic assumption that miners use a basket of profitable hardware rather than a single model. For robustness checks, we perform our tests using each consumption index separately.

Table A1 in the Appendix provides the summary statistics of the data, and highlights the existence of non-normality, i.e., heavy-tails, and provides a preliminary motivation to rely on a quantiles-based approach. Figure A1 in the Appendix plots the variables of interest.

3.2 Methodology

Our empirical analysis utilizes a nonparametric, nonlinear causality test via a hybrid approach developed by Balcilar et al. (2018), based on the frameworks created by Nishiyama et al. (2011) and Jeong et al. (2012). Let y_t denote the electricity price returns for the various US, UK, and European hubs descried earlier and let x_t denote the daily growth in the Bitcoin consumption indexes (max, min, and guess), derived by taking the first difference of the natural

[2] https://www.csidata.com/.
[3] The data is publicly available at: https://cbeci.org/.

logarithms of the respective consumption series. Consider $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and let $F_{y_t|\cdot}(y_t| \bullet)$ denote the conditional distribution of y_t given $\bullet$. Defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we obtain $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. Subsequently, we test the hypotheses of (non)causality in the θ-th quantile as:

$$H_0: \ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{1}$$

$$H_1: \ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{2}$$

Jeong *et al*. (2012) show that the feasible kernel-based test statistics has the following formulation:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{3}$$

where $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile and $\mathbf{1}\{\bullet\}$ is the indicator function. The *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \tag{4}$$

with $L(\bullet)$ denoting the kernel function.

In an extension of the framework proposed by Jeong *et al*. (2012) that is based on Nishiyama *et al*. (2011), Balcilar *et al*. (2018) develop an extension to the K-th moment which allows us to test causality at higher moments. In our case, we focus on ($K = 2$) and examine the causal relationship between bitcoin electricity consumption and electricity return volatility captured by the *second* moment of the electricity return series. As a general description, causality at the K-th moment is tested via the null and alternative hypotheses given by:

$$H_0: \ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1, \quad k = 1,2, \dots, K \tag{5}$$

$$H_1: \ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1, \quad k = 1,2, \dots, K \tag{6}$$

As a special case, the causality-in-variance test is formulated by replacing y_t in Eqs. (3) and (4) with y_t^2. As pointed out by Balcilar *et al*. (2018) a rescaled version of $\hat{J}_T$ has the standard normal distribution. The testing approach is sequential and failing to reject the test for $k = 1$ does not automatically lead to no-causality in the *second* moment (i.e., non-causality in means does not imply that there is no causality in variances), meaning that one can still construct the test for $k = 2$.

The empirical implementation of causality testing via quantiles entails specifying three key parameters: the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We determine h by the leave-one-out least-squares cross validation. We use a lag order based on the Schwarz Information Criterion (SIC), which is 2 for max and 1 for min and guess. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

4. Results

Before examining the findings from the quantile-based causality tests, we begin our analysis by examining the linear Granger causality tests, presented in Table 1, where the null hypothesis is that bitcoin electricity consumption does not affect electricity prices. Note that we select the appropriate lag length in these tests by minimizing the Schwarz Information Criterion (2 lags for max and 1 for min and guess). As seen in Table A1, we find no statistical evidence of a linear causal relationship, consistently across all electricity price series and three alternative bitcoin electricity consumption indexes. Thus, the linear causality tests do not reject the null hypothesis, indicating no causation based on the linear specification.

[Please insert Table 1 here.]

Having observed no evidence of causality based on the linear specification, we next examine whether the finding of non-causality might be due to model mis-specification that assumes a linear predictability relationship. Therefore, in order to explore whether the linear model is mis-specified, we test for the presence of nonlinearity and regime changes (structural breaks) in the relationship between the bitcoin consumption indexes and the electricity return series. Specifically, we use the Brock et al. (1996, BDS) test on the residuals from the linear model used in the linear Granger causality tests and test the null hypothesis of *i.i.d.*residuals at various dimensions (m). Table 2 in the Appendix presents the results of the BDS nonlinearity tests. As shown in the table, the BDS test yields overwhelming evidence of nonlinearity, that is, we reject the null hypothesis of linearity at the highest level of significance, consistently across all electricity return series and bitcoin consumption indexes. Further examining the presence of possible structural breaks in the data via the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), we observe in Table 3 at least one structural break for all return series with the exception of Northern Illinois hub, New England hub and Spanish base load electricity prices, as well as the UK base load (for max and min bitcoin indexes only). These additional tests, thus yield strong evidence of nonlinearity and structural breaks in the relationship between the electricity price and bitcoin consumption index series, suggesting that the inferences from the linear causality model in Table 1 are not valid.

[Please insert Tables 1 and 2 here.]

Given the strong evidence of nonlinearity, we then proceed with the causality-in-quantiles test (for both causality-in-means and causality-in-variance) that builds on a data-driven framework, and as such, is robust against possible misspecification due to nonlinearity and/or regime changes. Figures 1 and 2 present the results for the causality-in-mean and causality-in-variance tests, respectively, examining causality running from each bitcoin consumption series to electricity returns (volatility) at a particular quantile. The horizontal (vertical) axis in the figure captures the various quantiles (test statistic). The lines corresponding to the various electricity prices show the rejection (non-rejection) of the null of no Granger causality from the various measures of Bitcoin electricity consumption index to electricity returns (volatility) at the 5 percent level, if the lines are above (below) 1.96 for a specific quantile.

[Please insert Figure 1 here.]

The tests for causality-in-means, reported in Figure 1, generally yield insignificant causal effects of bitcoin mining activity on electricity returns, implied by the test statistic values below the critical value at all electricity return quantiles. The only exception is the Phelix electricity prices, the reference price for the power spot market for the German/Austrian market area, for which we observe a significant causal effect of bitcoin mining on electricity prices. Interestingly, although the U.S. dominates the global share of mined bitcoins (China was the biggest miner until the mining ban imposed in 2021 when large scale power outages were experienced in the country), we do not observe any significant causal effects of mining activity on electricity prices. At the same time, although Germany contributes to about 5% of global mining activity, we observe significant causality running from mining activity to electricity returns in the Germany/Austria hub, possibly driven by the presence of heavy industrial zones in this region, consuming vast amounts of power and coupled with high energy prices, making the power market in this region particularly vulnerable to additional consumption pressures due to mining activity. Interestingly, this finding comes against the background that Germany has recently unseated Singapore as the most-crypto friendly country in the world.[4] Accordingly, our findings suggest that the policy authorities in that country should be carefully

[4] Coincub's global crypto ranking report, Q1 2022. https://coincub.com/crypto-ranking-guide-for-2022-q1/

monitoring mining activity and its contribution to power consumption trends as this could pose a serious threat for the real economic activity, particularly considering that the German economy is based on heavy industrial production that consumes vast amounts of power annually.

[Please insert Figure 2 here.]

Further examining the causality-in-variance tests reported in Figure 2, we observe that the real effect of bitcoin mining activity on the power market is focused on return volatility rather than returns, consistent with the recent evidence in Karmakar et al. (2021) for three prominent power markets in the U.S. We find that all three proxies of bitcoin electricity consumption have a significant causal effect on return volatility in all of the electricity markets examined. The causal effects are significant at the highest level of significance in all cases and strongest around the median quantiles. The robust volatility effect of mining activity on electricity returns is likely to create challenges for market participants who hedge their exposure to power market fluctuations, implying that hedgers need to carefully monitor mining proxies in order to determine optimal hedge positions to minimize their exposure to price uncertainty. Nevertheless, these findings provide further support to the growing evidence that relates mining activity by crypto miners to power market dynamics.

5. Conclusion

This paper contributes to the growing literature on the non-virtual effects of cryptocurrency mining activity on the real economy by examining the causal interactions between various measures of electricity consumption associated with bitcoin mining activity and power market dynamics from major electricity markets in Europe, U.K. and U.S. Utilizing a nonlinear, quantile-based causality test that can uncover quantile specific causality relationships, we document a significant causal effect running from bitcoin mining activity, proxied by the Cambridge Bitcoin Electricity Consumption Index, to Phelix electricity price returns, the reference price for the power spot market for the German/Austrian market area. While the causal effect on returns is not observed for the other power markets in the sample, we find that the effect of mining activity is focused on return volatility, consistently for all three proxies of bitcoin electricity consumption and all the electricity markets examined. Accordingly, we provide robust evidence of volatility effects of mining activity in power markets across both sides of the Atlantic.

The findings have significant implications for firms who aim to stabilize their energy costs by hedging price fluctuations in power prices. Given the evidence of nonlinear predictability in return volatility due to mining activity, the findings imply that conditional hedging strategies could be devised by firms in energy intensive industries by utilizing volatility forecasting models that employ measures of mining activity. In fact, a natural extension of our study would be to examine the wealth effects of improved volatility forecasts obtained from forecasting models that employ mining activity as a predictor. From a policy making perspective, our findings pave the way to institute a carbon tax on crypto miners to compensate firms and consumers for the increased volatility in power prices due to mining activity. Given that mining activity also plays a critical role from a carbon emissions perspective, our findings present a strong case for policy makers to consider taxing strategies justified both from a power market stability and climate perspectives. It will be interesting to extend our study to a full-fledged volatility forecasting exercise in future work and see if volatility models can indeed be improved by augmenting standard models with measures of mining activity.

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Table 1: Granger causality Tests

Electricity hub	Bitcoin price measure	$\chi^2(p)$	*probability*
Northern Illinois hub	Max	0.335507	0.8456
	Min	0.007924	0.9291
	Guess	0.077782	0.7803
Western Hub	Max	0.731127	0.6938
	Min	1.648939	0.1991
	Guess	0.898384	0.3432
New England hub	Max	0.734015	0.6928
	Min	0.235759	0.6273
	Guess	0.445944	0.5043
Phelix electricity	Max	0.400431	0.8186
	Min	0.060442	0.8058
	Guess	0.476983	0.4898
French base load	Max	0.327982	0.8487
	Min	0.019075	0.8902
	Guess	0.118434	0.7307
Italian base load	Max	0.407831	0.8155
	Min	0.338044	0.561
	Guess	0.199189	0.6554
Spanish base load	Max	0.74133	0.6903
	Min	0.060343	0.806
	Guess	0.088564	0.766
UK base load	Max	0.032838	0.9837
	Min	0.013032	0.9091
	Guess	0.268284	0.6045

Note: p is the lag-length chosen based on SIC.

Table 2: Brock et al., (1996, BDS) test of nonlinearity.

	Northern Illinois hub				
M	2	3	4	5	6
Max	4.3168***	5.8858***	6.2898***	6.7479***	7.2954***
Min	4.4888***	5.9105***	6.2685***	6.7596***	7.3267***
Guess	4.4570***	5.8502***	6.1986***	6.6776***	7.2240***
	Western Hub				
M	2	3	4	5	6
Max	6.9813***	9.8899***	11.2758***	12.3795***	13.4955***
Min	6.8867***	9.5509***	10.9679***	12.0890***	13.2110***
Guess	6.9257***	9.6563***	11.1055***	12.2810***	13.4384***
	New England hub				
M	2	3	4	5	6
Max	3.9538***	5.8426***	6.6573***	7.2399***	7.7598***
Min	3.6695***	5.7729***	6.6577***	7.2602***	7.7786***
Guess	3.6521***	5.7691***	6.6506***	7.25061***	7.7663***
	Phelix electricity				
M	2	3	4	5	6
Max	3.6295***	4.2736***	4.5033***	4.4884***	4.9369***
Min	3.5933***	4.1529***	4.4080***	4.4085***	4.8270***
Guess	3.6653***	4.2105***	4.4755***	4.4834***	4.9020***
	French base load				
M	2	3	4	5	6
Max	4.5191***	4.9600***	4.8870***	4.8304***	4.9855***
Min	4.7809***	5.2606***	5.1863***	5.1300***	5.1707***
Guess	4.7541***	5.2314***	5.1624***	5.1113***	5.1512***
	Italian base load				
M	2	3	4	5	6
Max	5.1572***	6.1971***	6.4847***	6.2976***	6.3295***
Min	5.5262***	6.5806***	6.9119***	6.6924***	6.5875***
Guess	5.5102***	6.5479***	6.8696***	6.6458***	6.5374***
	Spanish base load				
M	2	3	4	5	6
Max	5.0819***	6.2952***	6.5659***	6.4732***	6.7091***
Min	5.7296***	7.1283***	7.2790***	7.1077***	7.1896***
Guess	5.7208***	7.1429***	7.2881***	7.1095***	7.1735***
	UK base load				
M	2	3	4	5	6
Max	4.6689***	5.8592***	6.4593***	6.9316***	7.5992***
Min	4.6345***	5.8737***	6.4970***	7.0004***	7.6068***
Guess	4.5222***	5.7351***	6.3473***	6.8608***	7.4831***

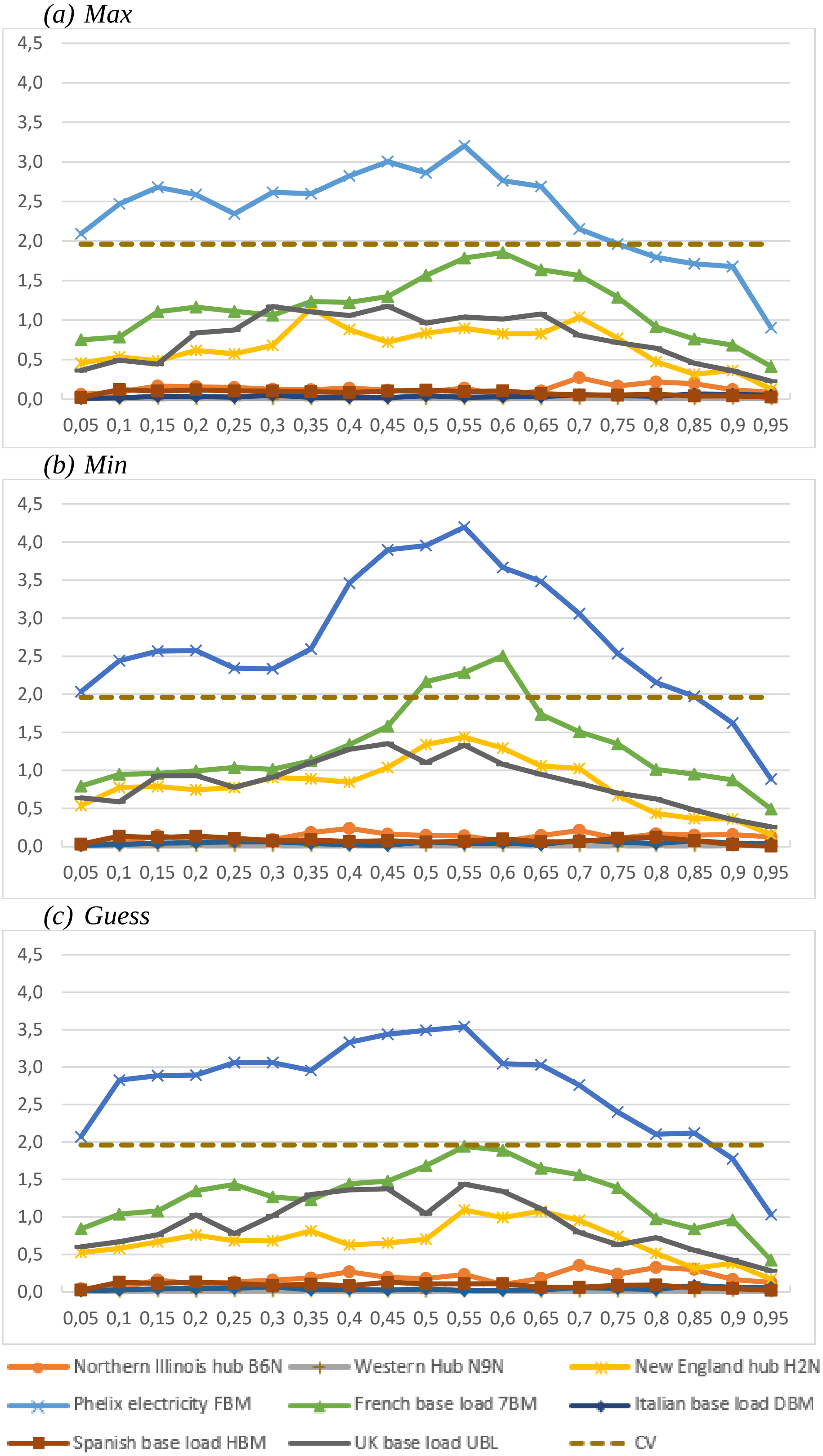
Note: The table reports the *z*-statistic of the BDS test corresponding to the null of *i.i.d.* residuals, with the test applied to the residuals recovered from the electricity returns equation used to test linear Granger causality. *** indicates rejection of the null hypothesis at the 1 percent level of significance.

Table 3: Bai and Perron (2003) multiple structural break test.

Break test	Northern Illinois hub	Western Hub	New England hub	Phelix electricity	French base load	Italian base load	Spanish base load	UK base load
Max		2/27/2018		11/07/2019, 6/05/2020, 12/08/2020	11/23/2018, 10/03/2019, 4/16/2020	5/26/2020		
Min		2/26/2018		9/17/2020, 11/16/2020	10/03/2019, 4/16/2020	5/26/2020		
Guess		2/26/2018		9/08/2020, 11/05/2020	10/03/2019, 4/16/2020	5/26/2020		9/11/2018, 4/03/2019, 10/17/2019, 4/30/2020, 11/06/2020

Note: The table reports the break dates obtained from the Bai and Perron (2003) test of multiple structural breaks, with the test applied to the electricity returns equation used to test linear Granger causality.

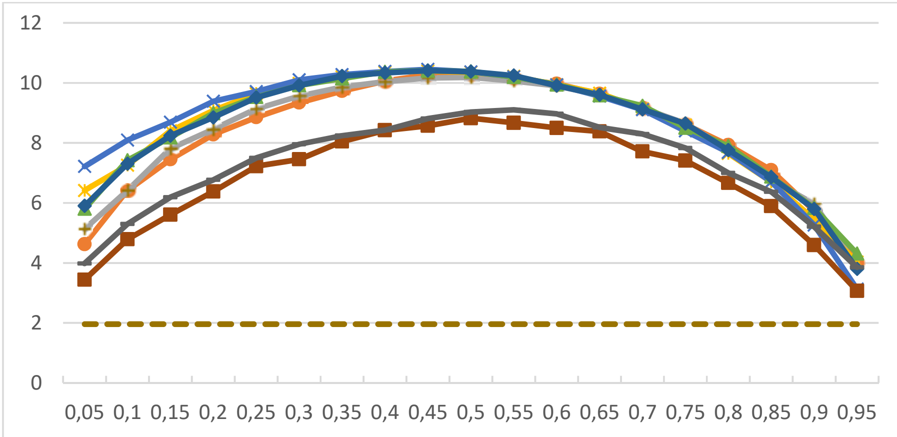
Figure 1: Causality-in-means tests.



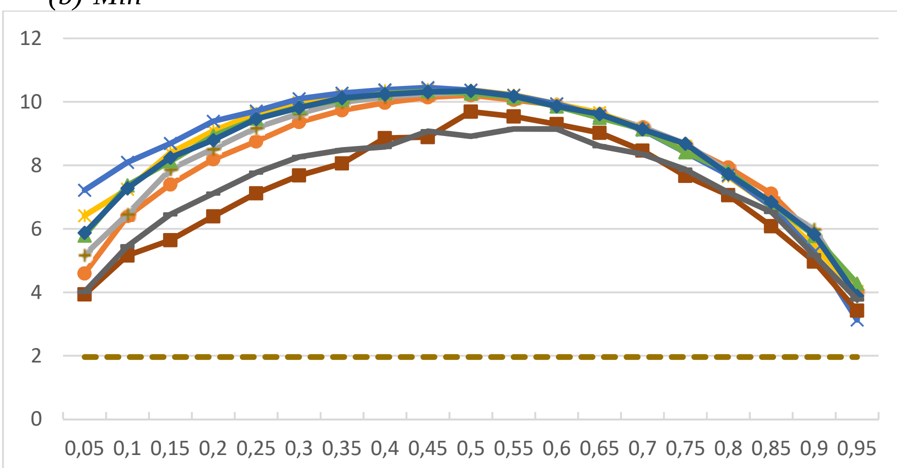
Note: The horizontal axis measures the various quantiles and the vertical axis captures the test statistic. The lines corresponding to the various electricity prices show the rejection (non-rejection) of the null of no Granger causality from the various measures of Bitcoin electricity consumption index growth to electricity returns at the 5 percent level, if the lines are above (below) 1.96 for a specific quantile. CV is the 5 percent critical value of 1.96.

Figure 2: Causality-in-variance tests.

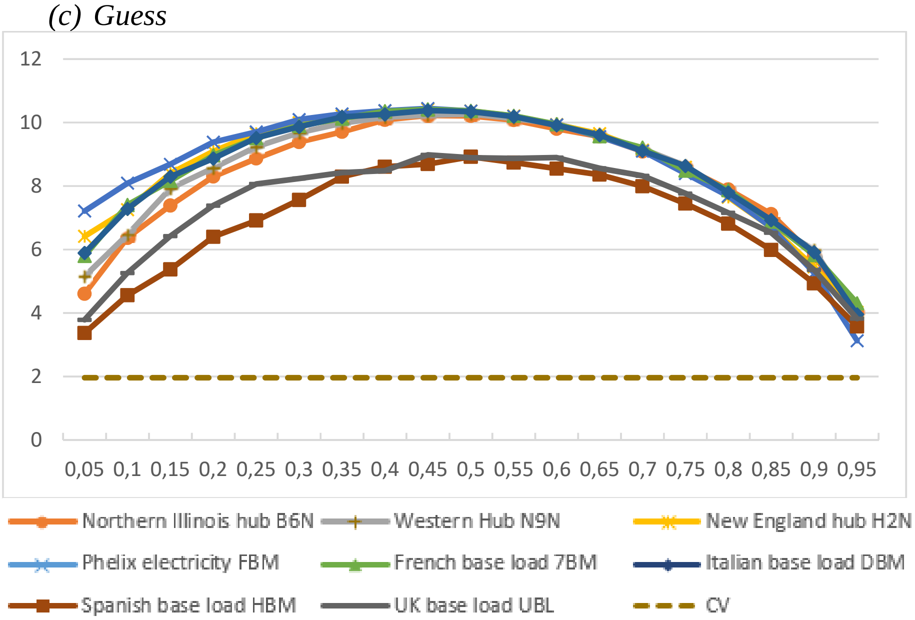
(a) Max



(b) Min



(c) Guess



Notes: The horizontal axis measures the various quantiles and the vertical axis captures the test statistic. The lines corresponding to the various electricity prices show the rejection (non-rejection) of the null of no Granger causality from the Bitcoin electricity consumption index to electricity return volatility at the 5 percent level, if the lines are above (below) 1.96 for a specific quantile. CV is the 5 percent critical value of 1.96.

APPENDIX:

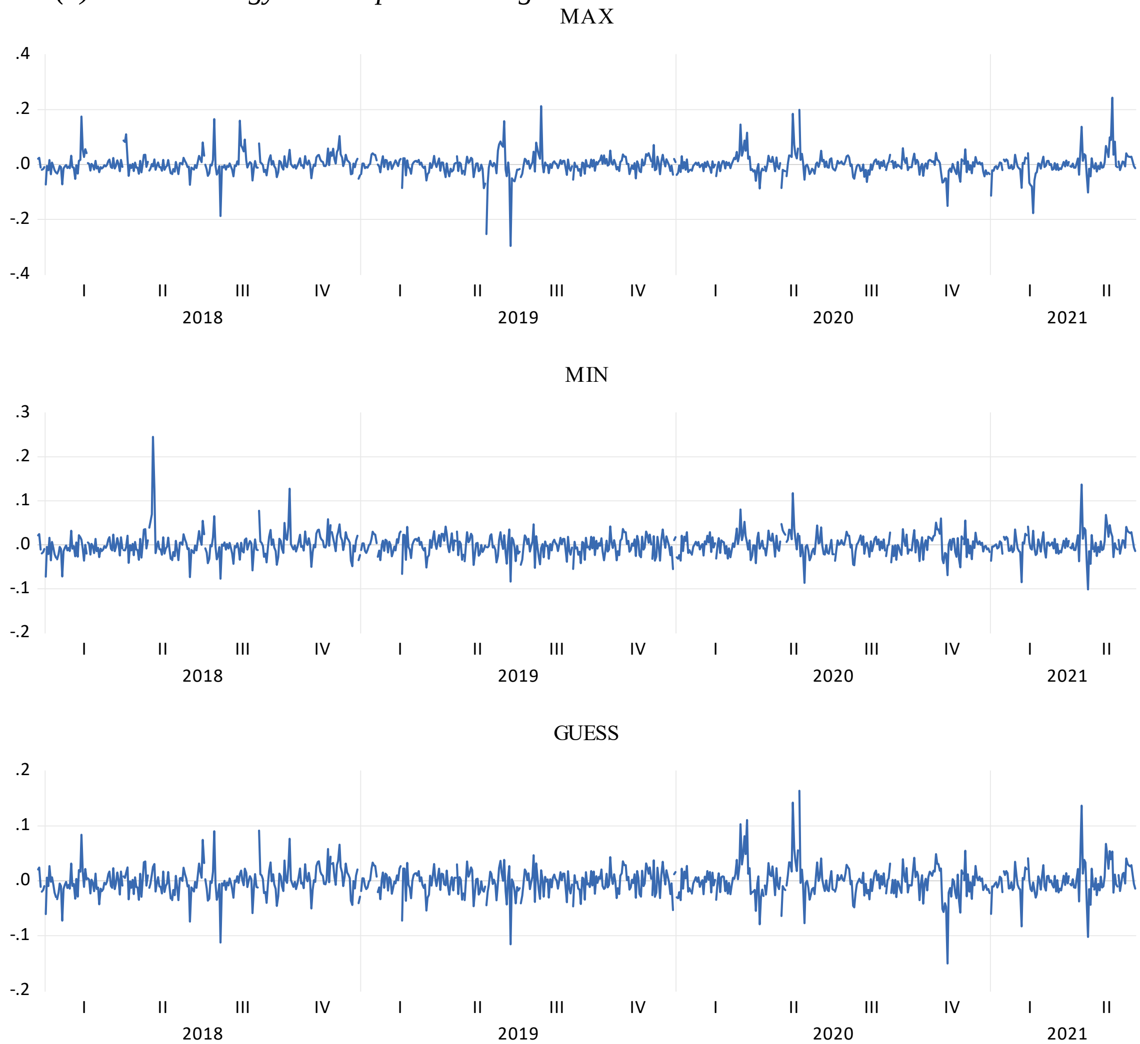
Table A1: Summary statistics.

Statistic	Variable										
	Northern Illinois hub	Western Hub	New England hub	Phelix electricity	French base load	Italian base load	Spanish base load	UK base load	MAX	MIN	GUESS
Mean	0.0002	0.0004	-0.0008	0.0014	0.0007	0.0004	0.0008	0.0008	-0.0006	-0.001	-0.0011
Median	-0.0005	0.0000	-0.0019	-0.0002	0.0000	0.0000	0.0005	0.0000	-0.0015	-0.0012	-0.0014
Maximum	0.2282	0.3626	0.5789	0.3281	0.4342	0.2891	0.3326	0.1984	0.2425	0.2452	0.1638
Minimum	-0.2307	-0.3764	-0.6827	-0.281	-0.4424	-0.2112	-0.3586	-0.1031	-0.297	-0.1021	-0.1504
Std. Dev.	0.0327	0.0398	0.0625	0.04	0.0471	0.0275	0.0365	0.0256	0.0378	0.0254	0.026
Skewness	1.0348	0.706	1.214	2.0911	1.5771	0.9948	0.5384	1.1023	0.1519	1.4294	0.4299
Kurtosis	19.308	32.6536	45.9391	24.1682	33.8685	29.0644	41.8129	10.7138	16.6707	15.9565	9.4893
Jarque-Bera	9683.39***	31581.03***	66279.41***	16683.4***	34500.73***	24485.26***	54022.24***	2306.32***	6700.09***	6308.21***	1535.45***
Observations	860										

Note: *** indicates rejection of the null of normality of the Jarque-Bera test at 1% level of significance.

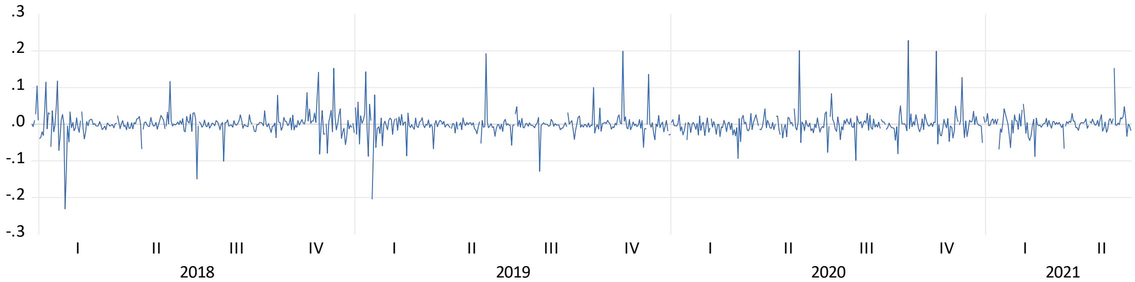
Figure A1: Data plots.

(a) Bitcoin energy consumption index growth

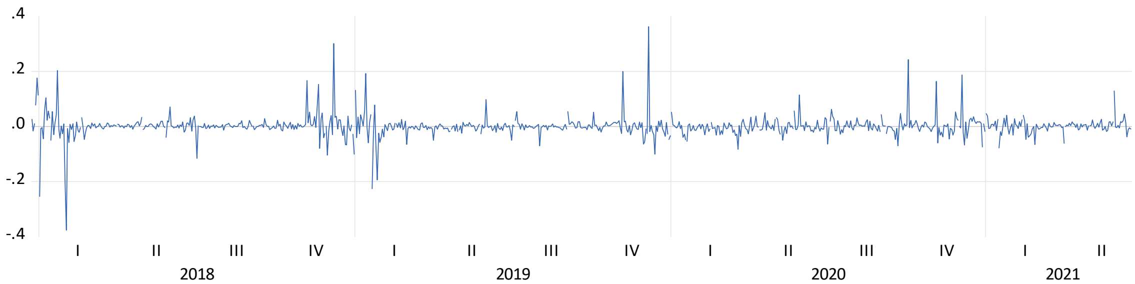


(b) US electricity returns

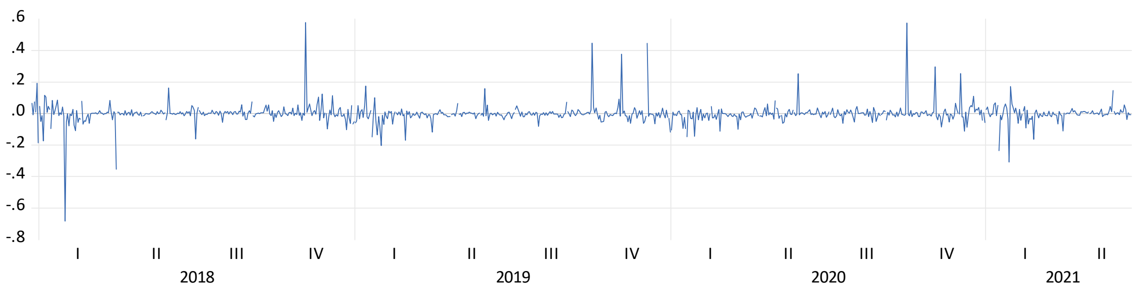
Northern Illinois hub



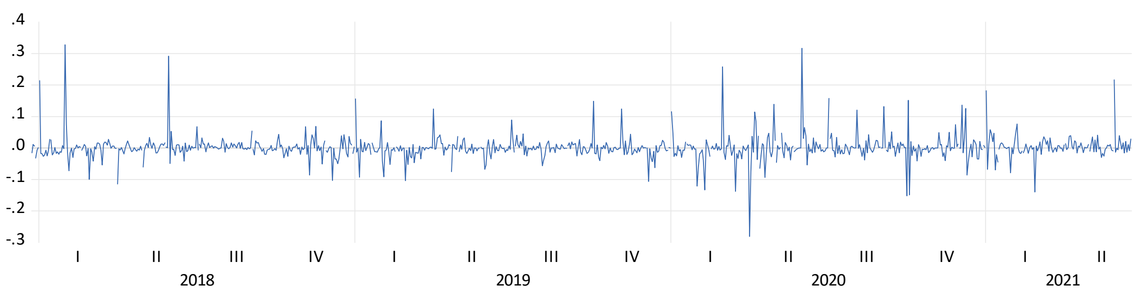
Western Hub



New England hub



Phelix electricity



(c) European electricity returns