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Bitcoin's energy consumption: Is it the Achilles heel to miner's revenue?

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HIGHLIGHTS

- We examine the relationship between Bitcoin's energy consumption and miner's revenue.
- We report a negative association between these variables.
- The negative impact is strongly significant when the miner's revenues are low and volatile.
- Bitcoin's higher energy consumption impedes the miners to break-even.
- Bitcoin mining business is not sustainable unless cheap energy sources and efficient mining hardware are relied upon.

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ABSTRACT

In this paper, we add a new dimension to the cryptocurrency literature by examining the relationship between Bitcoin's energy consumption and miner's revenue. By resorting to quantile and Markov regime switching regression, we report a negative association between these variables. Further, the negative impact is strongly significant when the miner's revenues are low and volatile. Thus, the higher energy consumption in the wake of escalating global energy costs amid bearish market sentiments impedes the miners to break-even. Hence, it would not be viable to sustain the business unless cheap energy sources and efficient mining hardware are relied upon.

1. Introduction

The distinguishable features of Bitcoin to traditional fiat currencies have been a crucial underlying reason for its growing fascination among the investors, regulatory authorities and the academicians alike (Böhme et al., 2015). Nevertheless, severe concerns have also been raised recently by economists over its surging energy consumption in the mining process (De Vries, 2018). Bitcoin is operational on the blockchain technology where the proof-of-work (PoW) algorithm (a kind of cryptographic puzzle) is performed to verify the transactions and generate new Bitcoins. The types of machinery executing the PoW algorithmic-computations are reliant on enormous energy requirements (Symitsi and Chalvatzis, 2018). However, the peaking Bitcoin prices coupled up with the expectations of steady cash flow provide incentivizes to the miners for administering the energy-intensive machines. Consequently, the aggregate energy consumption by the entire Bitcoin network has escalated to epic proportions. By 2018, the annual estimated energy consumption needs of Bitcoin now amount to 52.06 Terawatt–Hours (TwH), which is comparable to the annual energy needs of several largest energy consuming countries in the world.[1] Fig. 1 exhibits Bitcoin's energy consumption relative to several countries (expressed in percentage) by 2018. The statistical trends prominently signify the intensive energy consumption requirement for mining Bitcoin. Nonetheless, it may not concern the miners as long as they are able to generate considerable quantum of profits.

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[1] Digiconomist, "Bitcoin energy consumption index", Bitcoin sustainability, network statistics, available at: https://digiconomist.net/bitcoin-energy-consumption#validation, accessed March 28, 2019, 00:34 h, IST.

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Table 1
Definition of variables.

Variable	Definition	Nomenclature	Source
Bitcoin miner's revenue	Historical data showing (number of bitcoins mined per day + transaction fees) ∗ market price.	*MinRev*	Quandl
Bitcoin energy consumption	Estimated energy consumption for mining Bitcoin daily in Terawatt-Hours (TwH).	*EnCo*	Digiconomist
Bitcoin cost per transaction	Data showing miners revenue divided by the number of transactions.	*TransCost*	Quandl
Bitcoin total transaction fee	Data showing the total BTC value of transaction fees miners earn per day in USD.	*TransFee*	Quandl
Total Bitcoins mined	Data showing the historical total number of bitcoins which have been mined daily.	*TotMin*	Quandl
Bitcoin number of unique Bitcoin address used	Number of unique bitcoin addresses used per day.	*Adress*	Quandl
Bitcoin market price USD	Data showing the USD market price of Bitcoin	*BitRet*	Quandl

Table 2
Descriptive statistics.

Stats	MinRev	EnCo	TransCost	TransFee	TotMin	Adress	BitRet
Mean	0.0016	0.0033	0.0019	−0.0028	0.0112	−0.0003	0.0017
Median	−0.0024	0.0032	0.0063	−0.0099	0.0112	−0.0026	0.0018
St. dev.	0.1312	0.0242	0.1376	0.2647	0.0015	0.1320	0.0434
Max.	0.6393	0.1544	0.4697	2.2358	0.0268	0.4142	0.2466
Min.	−0.5019	−0.1453	−0.5404	−2.4843	0.0000	−0.4786	−0.2257
Skewness	0.2933	0.1544	−0.1950	−0.0011	0.7637	−0.0141	−0.1991
Kurtosis	4.5267	11.2165	3.9261	20.8712	20.8104	3.3163	7.2036
JB	86.16	2177.00	32.52	104.00	140.00	3.25	574.20
Obs.	773	773	773	773	773	773	773
ADF	−42.6390	−26.1900	−33.6560	−32.4110	−19.5950	−34.3710	−27.1890
PP	−48.2300	−26.2860	−46.0160	−38.6600	−20.8930	−60.0610	−27.2320

Notes: The null hypothesis of Jarque–Bera (JB) test is data-series under consideration is normally distributed. The critical values are: 4.61, 5.99 and 9.21 at 1%, 5% and 10% level of significance respectively. The null hypothesis for the unit root tests i.e. Augmented Dickey–Fuller (ADF) and Phillips Perron (PP) is that the time-series under consideration contains a unit root. The critical values are: −3.44, −2.86 and −2.57 at 1%, 5% and 10% level of significance respectively.

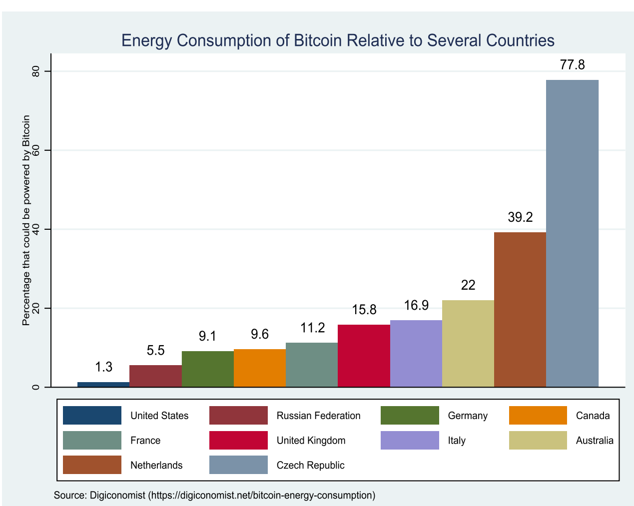

Fig. 1. Bitcoin's annual energy consumption relative to several countries by 2018 (in %).

Of late, the Bitcoin miners are suffering piling losses forcing them to shut mining or switch to other forms of cryptocurrencies.[2] For instance, the Fortress Blockchain, a Canadian Bitcoin miner, reports a net loss of US$ 1.16 million by the third quarter of 2018.[3] The profitability of mining hardware equipment makers such as Bitmain and GMO Internet are also smashed equally.[4] Symitsi and Chalvatzis (2018) argue that as the volume of transactions increases, more miners foray into the business compete over the network. With the heightened competition solving crypto-algorithm becomes effortful which amplifies the difficulty to mine Bitcoins. The difficulty parameter of Bitcoin mining is determined by the extent of intricacy involved in finding a hash below the threshold target specified by the Bitcoin protocol. The hashrate over the Bitcoin's network is an indicator of the pace at which each hash is found by solving the crypto-code by the miners. As the demand for Bitcoin escalates, more miners enter the virtual space in addition to the introduction of advanced mining hardware which in turns raises the hashrate. Recently, Li et al. (2019) find that the mining efficiency (defined as the ratio of hashes per second upon energy consumed) is primarily determined by the hashing algorithm.

Thus, given the enormous energy-intensive algorithmic requirements of Bitcoin in the wake of rising global energy costs amid bearish market sentiments could be a crucial stimulating factor behind the dampening of Bitcoin miner's revenue — which

2 Eric Lam, "Battered Bitcoin miners may start shutting down", Bloomberg, report dated November 26, 2018, available at: https://www.bloomberg.com/news/articles/2018-11-26/battered-bitcoin-miners-seen-shutting-down-as-losses-pile-up, accessed March 26, 2019, 13:51 h, IST.

3 Jeffrey Gogo, "Canadian Bitcoin miner Fortress Blockchain reports $1.16M loss in Q3", News, Bitcoin.com, report dated November 29, 2018, available at: https://news.bitcoin.com/canadian-bitcoin-miner-fortress-blockchain-reports-1-16m-loss-in-q3/, accessed March 21, 2019, 10:16 h, IST.

4 The giant of Bitcoin mining hardware Bitmain witnessed losses of worth US$ 500 million by the third quarter of 2018, report available at: https://www.coindesk.com/mining-giant-bitmain-posts-500-million-loss-in-ipo-financial-filing. Similarly, GMO Internet opted out of Bitcoin mining hardware sector owing to supernormal losses by the fourth quarter of 2018, report available at: https://cointelegraph.com/news/gmo-internet-exits-bitcoin-miner-production-after-recording-extraordinary-loss-in-q4, both links accessed on March 28, 2019, 08:35 h, IST.

Table 3
Correlation matrix.

	MinRev	EnCo	TransCost	TransFee	TotMin	Adress	BitRet
MinRev	1						
EnCo	−0.0237	1					
TransCost	0.4035	0.0038	1				
TransFee	0.1027	−0.0192	−0.3858	1			
TotMin	0.4588	0.2486	0.2838	−0.079	1		
Adress	0.3398	−0.0179	−0.4160	0.4263	0.105	1	
BitRet	0.2897	0.0122	0.2379	−0.0253	0.0469	0.0229	1

we refer as *the Achilles heel*. The past studies concerning the diversified aspects of Bitcoin are largely focussed from the investor's point of view (*see* Katsiampa, 2017; Urquhart, 2016 among others). However, the representation of miner's perspective is limited in the literature. In this article, we add a new dimension to the cryptocurrency literature by examining the relationship between Bitcoin's energy consumption and the miner's revenue. We find a significant negative impact of energy consumption when the revenues are low and volatile.

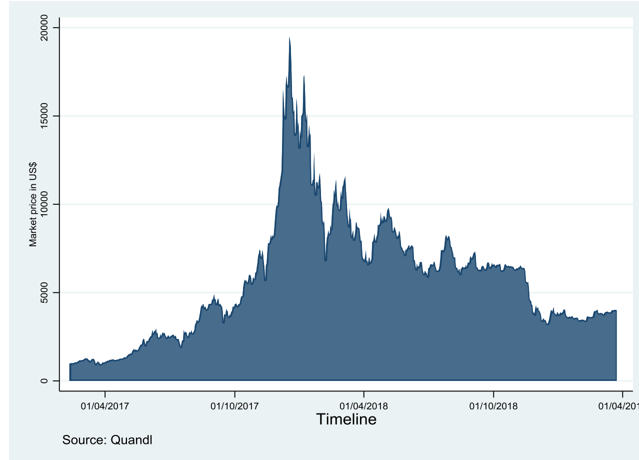

Fig. 2. Bitcoin's price trend during the sample period.

2. Data

To examine the relationship, we consider miner's revenue as the dependent variable. The independent variables are Bitcoin's energy consumption index[5] (which is also our variable of interest) in addition to five control variables related to Bitcoin's market microstructure. The definition of variables and nomenclature used with respective data sources are exhibited in Table 1. The *MinRev* is primarily determined by the interaction of *TotMin*, *TransFee* and *BitRet*, which are considered as the independent variables. Additionally, we consider two more controls *Adress* and *TransCost*. *Adress* is a measure for the volume of daily unique transactions in excess of disproportionate bulk of transactions conducted by the regular and small group of market participants. Since the "network effect" derives the economic value of Bitcoin (Koutmos, 2018), new participants in the system are expected to influence miner's revenue. Whereas, *TransCost* is a measure of contribution to miner's revenue per unit of aggregate transactions. The *EnCo* is estimated as the portion of revenues expended on electricity costs by the miners.

Our sample spans over February 10, 2017 to March 24, 2019 yielding a total of 774 daily observations. The commencing period of our sample is dictated by the availability of energy consumption index. Though the time-span is short, this period has crucial significance in the Bitcoin market. The period has witnessed a steep rise in Bitcoin prices reaching historical highs and again depicting plummeting tendencies as exhibited in Fig. 2. The variables are logarithmically differenced for the purpose of analysis. The variables are exhibited in Fig. 3 and the descriptive statistics are presented in Table 2. The JB tests show that none of the variables follows normal distribution. Besides, the unit root test results of ADF and PP suggests that the data are stationary. The correlations matrix, exhibited in Table 3, indicates that none of the variables are highly correlated.

3. Methodology

We briefly discuss the methodological approach in this section. To explore the likelihood of variations in the relationship between the *EnCo*, control variables and *MinRev* across its conditional distribution, we resort to the quantile regression (QR) approach. By using the QR approach we are able to recognize whether (or not) the impact of independent variables is consistent when the volume of *MinRev* is at higher or lower quantiles. This methodological approach is introduced by Koenker and Bassett (1978) and is widely used to unravel the dependence structure between the financial and economic variables. QR can provide more accurate estimates than the ordinary least square (OLS) since it is less susceptible to the outliers when the underlying time-series depart from the condition of normality. As we show that our dataset under consideration is non-normal and leptokurtic, the choice of QR is supported to discover the relationship at the extreme quantiles of *MinRev*. Let us consider y to be the dependent variable which is linearly dependent on the variable x. In such a case, the τth conditional quantile of y may be expressed as:

$$Q_y\left(\tau|x\right) = \sum_k \beta_k\left(\tau\right)x_k = x'\beta(\tau) \tag{1}$$

where, the dynamic dependence relationship between the τth conditional quantile of y and the vector of x is given by the QR coefficient $\beta(\tau)$. The dependence is held to be conditional if the exogeneous variables are added to x, and unconditional otherwise. The complete dependence structure of y is determined by the values of $\beta(\tau)$ for $\tau \in [0, 1]$. Thus, on the basis of the specific explanatory variable contained in the vector of x, there could be four prime nature of dependence structures: (a) $\beta(\tau)$ decreases (increases) corresponding to the values of τ (i.e. monotonic), (b) $\beta(\tau)$ remains unchanged at different values of τ (i.e. constant), (c) $\beta(\tau)$ is similar at higher and lower quantiles (i.e. symmetric) and (d) $\beta(\tau)$ is dissimilar at higher and lower quantiles (i.e. asymmetric).[6]

In the subsequent step, we estimate the Markov Regime Switching (MRS) regression model to captivate the regime shifts in the *MinRev*-*EnCo* relationship (with controls) using the following specification:

$$\Delta MinRev_{i,t} = \beta_{0,i,\ r_t} + \beta_{1,i,\ r_t}\Delta EnCo_t + \beta_{2,i,\ r_t} + \cdots + \beta_{6,i,\ r_t} + \mu_{i,t} \tag{2}$$

where, the r_t is a discrete regime variable and the regime dependent intercept is noted as $\beta_{0,i,\ r_t}$. The slope coefficient of

[5] The Bitcoin energy consumption index is available at https://digiconomist.net/bitcoin-energy-consumption, the all other time-series of variables are available at https://www.quandl.com/data/BCHAIN-Blockchain.

[6] We test whether the coefficients are monotonic, constant, symmetric or asymmetric by testing the null hypothesis of equality across the quantile using Wald test and results are reported in Table 5.

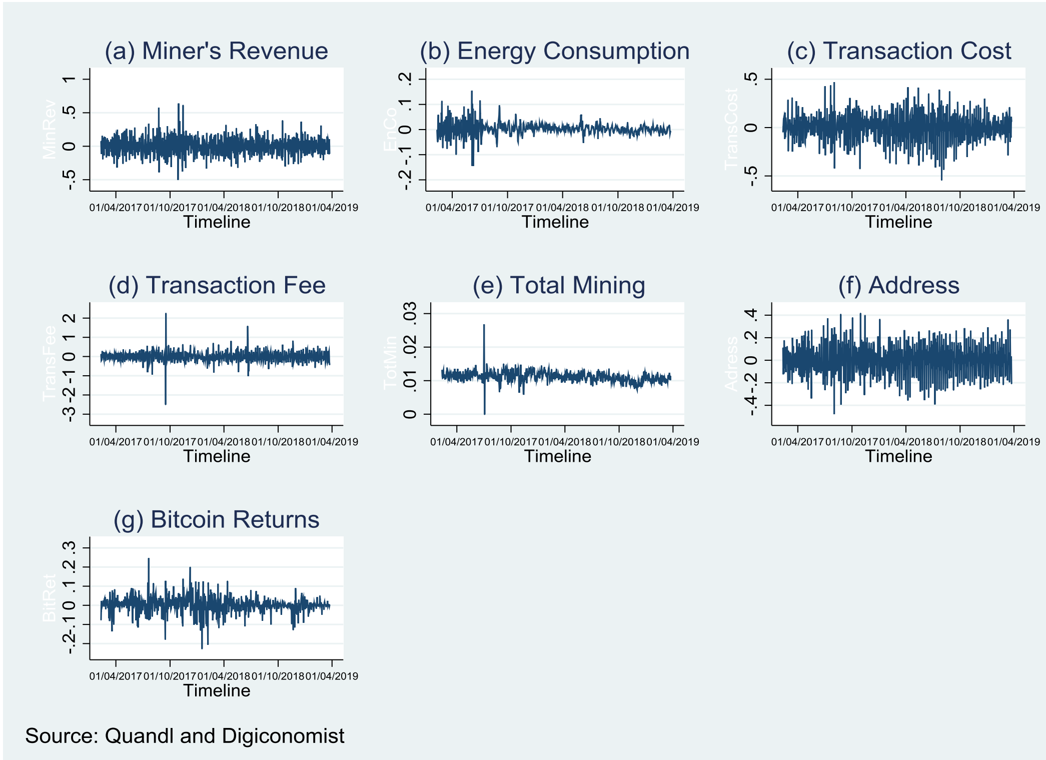

Fig. 3. Plot of variables after logarithmic differencing.

Table 4
OLS and quantile regression results.

	OLS	Quantiles								
		τ 10	τ 20	τ 30	τ 40	τ 50	τ 60	τ 70	τ 80	τ 90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EnCo	−0.272***	−0.293**	−0.239***	−0.188**	−0.130*	−0.110	−0.130	−0.267	−0.233	−0.421
	(0.0933)	(0.116)	(0.0908)	(0.0745)	(0.0679)	(0.0995)	(0.149)	(0.163)	(0.171)	(0.272)
TransCost	0.826***	0.741***	0.802***	0.821***	0.832***	0.866***	0.866***	0.865***	0.865***	0.887***
	(0.0214)	(0.0371)	(0.0388)	(0.0330)	(0.0297)	(0.0282)	(0.0324)	(0.0299)	(0.0339)	(0.0459)
TransFee	0.0274***	0.0171	0.0189	0.0237*	0.0253**	0.0156	0.00937	0.0160	0.0268	0.0256
	(0.00983)	(0.0105)	(0.0204)	(0.0132)	(0.0128)	(0.0177)	(0.0171)	(0.0148)	(0.0205)	(0.0306)
TotMin	12.89***	20.29***	17.61***	15.16***	12.63***	9.646***	8.156***	6.305**	6.961**	7.147
	(1.653)	(4.278)	(3.387)	(2.494)	(2.236)	(2.535)	(2.077)	(3.063)	(3.002)	(4.613)
Adress	0.740***	0.679***	0.745***	0.790***	0.808***	0.849***	0.840***	0.795***	0.773***	0.770***
	(0.0229)	(0.0375)	(0.0403)	(0.0360)	(0.0345)	(0.0412)	(0.0480)	(0.0378)	(0.0499)	(0.0588)
BitRet	0.186***	0.218***	0.207***	0.159***	0.146***	0.0992**	0.0966**	0.132***	0.204***	0.331***
	(0.0526)	(0.0699)	(0.0691)	(0.0612)	(0.0544)	(0.0477)	(0.0430)	(0.0509)	(0.0703)	(0.127)
Constant	−0.143***	−0.292***	−0.240***	−0.196***	−0.154***	−0.110***	−0.0793***	−0.0421	−0.0331	−0.00762
	(0.0185)	(0.0485)	(0.0389)	(0.0282)	(0.0259)	(0.0292)	(0.0233)	(0.0350)	(0.0330)	(0.0508)
Adj. R^2	0.789									
Pseudo R^2		0.545	0.557	0.562	0.565	0.564	0.561	0.559	0.555	0.538
Obs.	773	773	773	773	773	773	773	773	773	773

Notes: The OLS results in column (1) is estimated using the following model specification: $\Delta MinRev = \alpha + \beta_1 \Delta EnCo + \beta_2 \Delta TransCost + \beta_3 \Delta TransFee + \beta_4 \Delta TotMin + \beta_5 \Delta Adress + \beta_6 \Delta BitRet + \varepsilon$. We use the same baseline specification for estimation of the results in QR framework. The 10%, 5% and 1% significance levels are denoted by *, ** and *** respectively.

EnCo and controls are represented as $\beta_{1,i,\ r_t}$ and $\beta_{2,i,\ r_t} \ldots \beta_{6,i,\ r_t}$, respectively and $\mu_{i,t}$ is the random error term. We expect that the impact of *EnCo* on the *MinRev* is likely to be regime dependent. At time period t, the transmission probability from regime 1 to regime m at time period $t+1$ depends upon the regime at time period t entirely.[7] It is also assumed that the stochastic switching process in regime follows ergodic, homogeneous and Markov chain of first order with constant transition probabilities and a finite number of regimes (M).

$$p_{lm} = P\left(r_{t+1} = m | r_{t+1} = l\right), p_{lm} \geq 0, \sum_{m=1}^{M} P_{lm} = 1 \quad (3)$$

In order to derive the regime-dependent coefficients, we estimate Eq. (2) in two regimes.

[7] It must be noted that the Markov switching is conditionally linear within each regime. Additionally, the switching process within the regimes is inherently stochastic. The condition of stochasticity for the switching in regime is based on a transition probability matrix (TPM) which is time-varying. The TPM in our model changes depending upon the values of intercept, the variance, and the independent variables.

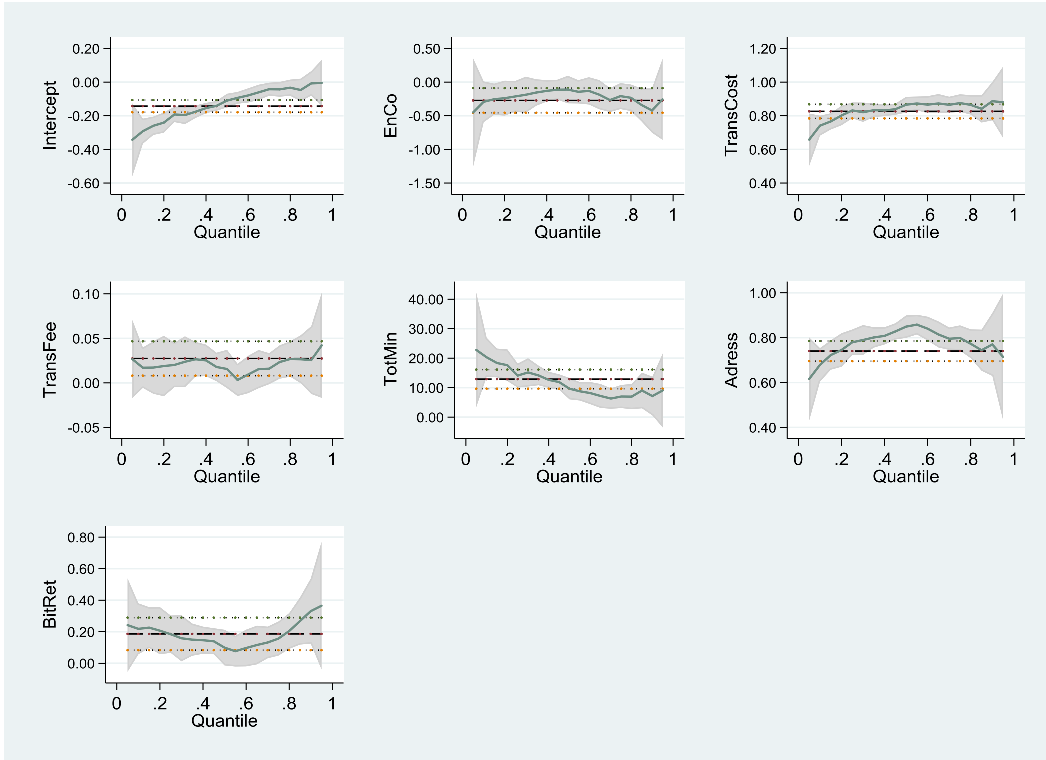

Fig. 4. Coefficient plot of quantile regression estimates. **Notes:** The figure exhibits the estimates of OLS and coefficients of quantile regression. The predictor variables indicated on the vertical axis. The broken black and the dotted horizontal lines represent the coefficient of OLS at its 95% confidence intervals respectively. The shaded areas around the quantile regression coefficient plotline represent the confidence interval at 95%.

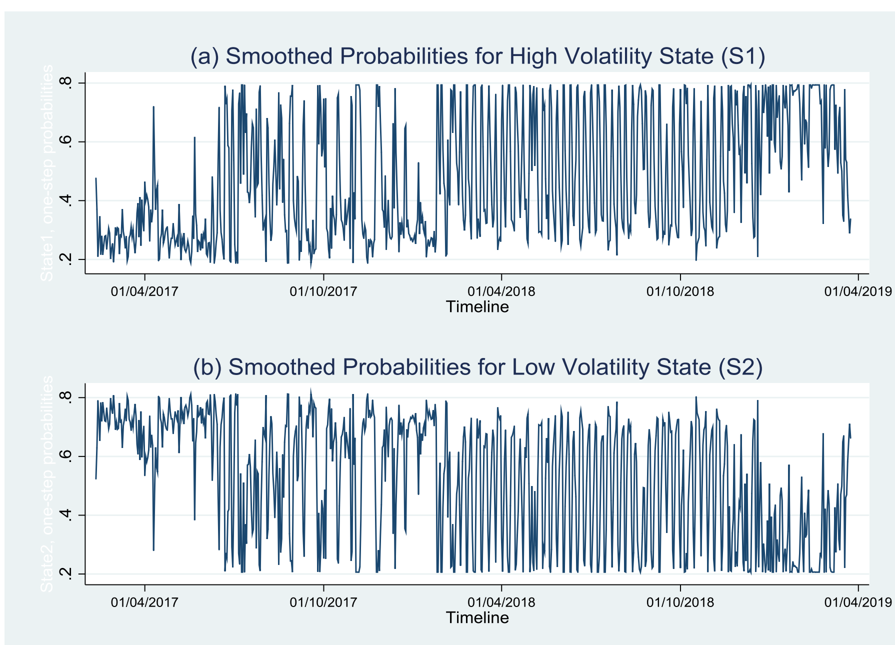

Fig. 5. Smoothed probabilities of high and low volatility states.

4. Empirical results

The OLS and QR results are presented in Table 4 and the graphs of corresponding coefficients are presented in Fig. 4. The column (1) of Table 4 represents the OLS results of the model and shows that the *EnCo* is significantly negative, whereas the other variables are positively associated. The column (2–10) of Table 4 exhibits the QR estimates. If we focus on the coefficients of the variable of interest *EnCo*, an interesting phenomenon could be observed. Though the coefficients are negative throughout the quantiles (τ_s) 10 to 90, they are strongly significant (at 1%) up to quantile 30 and weakly significant at quantile 40. This result indicate that the costs expended for meeting the energy requirements could be detrimental for the miners when the revenues

Table 5
Slope equality test results.

Quant. diff.		EnCo	TransCost	TransFee	TotMin	Adress	BitRet
10–30	Test-statistic	1.61	3.78*	0.41	1.27	18.62***	0.95
	p-value	0.205	0.052	0.523	0.260	0.000	0.329
10–60	Test-statistic	1.41	8.66***	0.47	5.50**	18.37**	3.27*
	p-value	0.236	0.003	0.595	0.019	0.000	0.071
10–90	Test-statistic	0.60	6.83***	0.10	8.05***	1.53	0.76
	p-value	0.440	0.009	0.747	0.004	0.216	0.382

Notes: We test the following hypotheses using the Wald test for three pairs of quantile differences: (a) $H_0: \beta_{10} = \beta_{30} (or \beta_{10} - \beta_{30} = 0)$, (b) $H_0: \beta_{10} = \beta_{60} (or \beta_{10} - \beta_{60} = 0)$ and (c) $H_0: \beta_{10} = \beta_{90} (or \beta_{10} - \beta_{90} = 0)$. The 10%, 5% and 1% significance levels are denoted by *, ** and *** respectively.

are low. Thus, in the absence of energy efficient mining hardware or energy sources, it is difficult for the miners to safeguard the profit margin. Consequently, the miners would be constrained to shut down by virtue of failing to break-even and accumulating losses. We believe that Bitcoin's rising energy requirements and costs coupled with bearish market conditions could be one of the crucial reasons behind the recent fall of the industrial functionaries (miners and hardware manufacturers). We also test the equality of slopes and the results are exhibited in Table 5, we find a somewhat symmetric and monotonic impact of *EnCo* on *MinRev*.

Furthermore, it must also be recognized that the Bitcoin market has witnessed massive price swings during the sample period. Thus, the relationship between the variables could alter in different macroeconomic regimes. Therefore, we use a multi-factor and two-state MRS model, the estimation results are reported in Table 6. The volatility conditions are determined by the values of sigma. State 1 is the high volatility regime in our case. We find the regime-specific coefficient is negative for both the states, however, highly significant in the high volatility regime. This finding is interesting since it shows when the revenues are volatile the *EnCo* could have a greater impact. We also test for equality of coefficients across the states and we observe statistically significant regime-specific dependence of *EnCo*. Besides, the DU stands for the expected duration of a halt in one regime. The general behaviour of the markets shows higher halting duration in low volatility state than otherwise. This result is consistent with the conventional wisdom. Lastly, we also find large constant regime probabilities of P_{11} and P_{22}, which depict high persistence of each regime, exhibited in Fig. 5.

5. Conclusions

This paper examines whether the Bitcoin's rising energy requirements in the wake of escalating global energy costs amid bearish market sentiments are causing the industry participants to exit or not. Thus, we pose a plausible question that: whether the energy consumption is the *Achilles heel* to miner's revenue?

Table 6
Markov regime switching regression results.

	States		Equality across states (χ^2)
	State1	State2	
	(1)	(2)	(3)
Panel A: Estimated coefficients			
EnCo	−1.194***	−0.0568	14.30***
	(0.290)	(0.0560)	
TransCost	0.691***	0.941***	21.47***
	(0.0452)	(0.0194)	
TransFee	0.0600***	0.0239***	2.15
	(0.0222)	(0.00713)	
TotMin	31.54***	2.711**	33.91***
	(4.544)	(1.273)	
Adress	0.387***	1.052***	185.22***
	(0.0484)	(0.0213)	
BitRet	0.294***	0.0492	4.21**
	(0.105)	(0.0401)	
Constant	−0.346***	−0.0312**	
	(0.0494)	(0.0148)	
Sigma	6.281	2.951	70.80***
Obs.	773	773	
Panel B: Transition probabilities and expected durations			
P_{11}	0.794		
P_{12}	0.206		
P_{21}	0.188		
P_{22}	0.812		
DU_1	4.845		
DU_2	5.330		

Notes: The $P_{11} \ldots P_{22}$ are the transition probabilities and reported in the form of P_{ij}. DU is the expected duration in a regime. The 10%, 5% and 1% significance levels are denoted by *, ** and *** respectively.

Our empirical results validate that the energy costs do serve as the *Achilles heel* to miner's revenue when the revenues are low and volatile. Thus, it would not be viable to sustain the business unless cheap energy sources and efficient mining hardware are relied upon. Besides, achieving energy efficient mining would also eliminate the negative externalities (such as carbon emission[8]), which could also make the business environmentally sustainable.

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8 For instance, the Bitcoin mining facilities in China is heavily dependent on coal-based power, which accounts for 47.60% of world's carbon dioxide emission caused by Bitcoin mining. For details, refer the website of Digiconomist (web link provided in footnote 1).