Bitcoin Blackout: Proof-of-Work and the Centralization of Mining[†]

Stefan Scharnowski[a,*], Yanghua Shi[a]

[a] *University of Mannheim*
L9,1-2, 68161 Mannheim, Germany

This version: March 30, 2022.

Abstract

Electricity constitutes the main input factor for miners of proof-of-work cryptocurrencies like Bitcoin, so they gravitate towards countries with cheap energy. We analyze risks associated with this geographical centralization of mining by exploiting an exogenous shock to electricity supply in a relatively small region with heavy Bitcoin mining activity. We first document a drop of about 25% in the total computing power of the Bitcoin network during a blackout that lasts several days. Compared to a control group consisting of a proof-of-stake cryptocurrency, we find evidence of blockchain congestion as fees increase substantially while the number and value of transactions decrease. We also document an impact on exchange trading activity. Trading volume and especially exchange rate volatility increase while liquidity deteriorates during the blackout, even though returns are mostly unaffected. Additionally, market integration drops as price differences between exchanges increase considerably.

Keywords: Bitcoin, proof-of-work, proof-of-stake, blackout, mining, centralization
JEL: G1, G2, O30, Q40

[†]We thank Daniel Rabetti (discussant), Erik Theissen, Victoria Treßel (discussant), Stefan Voigt, Christian Westheide, and conference and seminar participants at the 15th RGS Doctoral Conference in Economics, the 4th UWA Blockchain and Cryptocurrency Conference, the Cryptocurrency Research Conference 2021, and the University of Mannheim for helpful comments and suggestions. All remaining errors are our own. We gratefully acknowledge financial support from the German Science Foundation (DFG) under grants TH 724/7-1 and UH 107/5-1.

[*]Corresponding author

Email addresses: `scharnowski@uni-mannheim.de` (Stefan Scharnowski), `yshi@mail.uni-mannheim.de` (Yanghua Shi)

1. Introduction

Cryptocurrencies have seen a striking increase in popularity since their inception only a few years ago. The most prominent one, Bitcoin, was the first to operate without any central authority by relying on a distributed ledger, the blockchain. On it, transactions are recorded and verified by miners through a consensus mechanism called proof-of-work (PoW), which addresses one of the fundamental problems of virtual currencies without trusted authorities, the double-spending problem. To verify the integrity of transactions, miners compete by solving computationally intensive mathematical puzzles. The first to find a solution appends the next block of transactions to the chain and receives newly-issued coins and any fees paid by users. However, the processes is very energy-intensive, so miners tend to gravitate towards regions with cheap electricity. As the cryptocurrency market continues to grow, concerns regarding the resulting limits to decentralization and the ecological impact of mining increase.

We analyze risks associated with this geographical centralization of mining by exploiting an exogenous shock to electricity supply in a relatively small region with heavy Bitcoin mining activity as a quasi-natural experiment. During a blackout lasting several days, we document a drop of about 25% in the computing power of the Bitcoin network. Compared to a control group consisting of a cryptocurrency using a more energy-efficient consensus mechanism, we find that fees paid to miners increase substantially while the number and value of transactions decrease. Exchange trading volume and especially exchange rate volatility increase substantially, while liquidity deteriorates during the blackout. However, returns appear to be mostly unaffected.

The results have important implications regarding the centralization within the Bitcoin network due to its consensus mechanism. While many cryptocurrencies are designed to be decentralized, in practice economic forces might lead to centralization along several dimensions. For example, Böhme et al. (2015) identify cryptocurrency exchanges and wallet services as potential sources of centralization. Mining pools where users combine their resources to obtain a more stable stream of mining rewards are also considered a threat to decentralization, though the model of Cong et al. (2021) expects a decentralized market structure for Bitcoin in the long run even in the presence of centralized mining pools. Focusing on another source of centralization, Arnosti and Weinberg (2021) find that production and ownership of mining hardware leads to a costly arms race and centralization within Bitcoin mining. Similarly, Ferreira et al. (2021) model blockchain governance and show that in a PoW system, so called blockchain conglomerates – large firms that operate in multiple blockchain related business like mining equipment and mining pools – may control blockchain votes and thus governance. Capponi et al. (2021) argue that because miners are capacity constrained, centralization does not necessarily result from increases in hardware efficiency. On the contrary, investments leading to more efficient mining hardware allow new and small miners to enter or expand their operations. Lehar and Parlour (2020) investigate the effect of strategic capacity management by miners and show that mining concentration is related to higher levels of fees for users. In this paper, we add to the literature on the centralization within the Bitcoin network by empirically showing system-wide risks arising from geographically concentrated mining.

By comparing two currencies with different consensus mechanisms, our study also relates to the literature on the relative advantages of PoW and alternative mechanisms. In particular, Arnosti and Weinberg (2021) conjecture that under certain conditions, the proof-of-stake (PoS) consensus mechanism might contribute to cryptocurrency decentralization.[1] This mechanism does not rely on miners to verify transactions, but instead randomly chooses validators where the probability of being drawn increases in the amount of coins deposited as stake. Chosen validators update the blockchain and get rewarded by newly-issued coins. Their stake in the currency incentivizes validators not to compromise the blockchain, which would render the currency worthless. Within the PoS literature, Saleh (2021) provides a first economic analysis of the mechanism and gives equilibrium conditions for consensus. Still, a common criticism of the PoS mechanism is that it could lead to wealth accumulation

[1] The second largest cryptocurrency, Ethereum, is anticipated to transition from PoW to PoS.

and thus centralization because validators with larger stakes have a higher probability of being chosen and thus obtaining the reward, increasing their stake further. Roşu and Saleh (2021) address this concern by showing that without trading, any investor's share in the network follows a martingale and is not expected to change in the long run. Under certain assumptions, this conclusion also holds when investors are allowed to trade.

While according to Irresberger et al. (2020), PoW and PoS are the most common consensus algorithms for cryptocurrencies, we note that other algorithms are sometimes used. Related to PoS is designated proof-of-stake (DPoS), where stakeholders vote from a fixed and limited number of delegates. The voting power is proportional to the stake in the network and the voted delegate then is responsible for producing blocks. This mechanism is e.g. used by the cryptocurrencies Polkadot, Tronix (of the TRON network), and EOS. Leased proof-of-stake (LPoS) is similar to DPoS, but instead of voting, users lease out their tokens and thus the right to produce blocks to generating nodes in exchange for some award. LPoS does not rely on a limited number of nodes and thus tends to be less centralized than DPoS. Waves is the most prominent example of an LPoS cryptocurrency. Some alternative consensus mechanisms rely on storage space. For example, in Burstcoin's proof-of-capacity (PoC), miners compete by providing disk space that is not otherwise used and in Filecoin's proof-of-spacetime consensus mechanism, miners effectively rent out disk space. Other mechanisms include proof-of-importance, proof-of-burn, proof-of-elapsed-time, proof-of-authority, and the more general proof-of-weight. Some cryptocurrencies even use combinations of different consensus algorithms.

An argument favoring non-PoW currencies is that they are generally more energy efficient. This not only contributes to geographical decentralization, but is also particularly important as several studies have voiced concerns that Bitcoin mining could be a substantial factor for climate change, though there is no consensus on the magnitude. (Dittmar and Praktiknjo, 2019; de Vries, 2020). In a related issue, regulators and market participants worry about spillovers from mining activity to the electricity market. For the United States, Benetton et al. (2021) document higher electricity costs for households and small businesses due to regional cryptocurrency mining activity. For China, the authors find a crowding-out effect on the local economy due to mining-induced regional electricity rationing. Karmakar et al. (2021) observe that Bitcoin mining activity is related to increasing volatility levels in the electricity spot market. In a similar vein, Corbet et al. (2021) find a positive relationship between Bitcoin prices and the volatility of returns of certain electricity and utility companies. Closely related to our paper, Akyildirim et al. (2021) investigate coal mining disasters in China. While they do not find substantial effects of mining accidents on a selection of global coal-related financial products, such disasters appear to increase the dynamic correlations with Bitcoin. Since we compare Bitcoin and its energy-intensive consensus mechanism to a more energy-efficient alternative during a shock to the electricity market, our study also relates to this stream within the literature.

The remainder of the paper is structured as follows: Section 2 introduces the event and develops our hypotheses while Section 3 explains the empirical methodology. Section 4 discusses the results for blockchain and trading activity before Section 5 concludes.

2. Background and Hypotheses

2.1. Bitcoin Mining and the Blackout

Cryptocurrency miners tend to be secretive regarding their operations, including their precise geographic location. However, because electricity constitutes the main input factor for miners of PoW currencies, they gravitate towards countries with cheap energy, in particular China (Delgado-Mohatar et al., 2019). While in the wet season from May to October, many miners are located near hydroelectric plants in the provinces of Sichuan and Yunnan, operations migrate to other areas in the dry season, in particular Xinjiang with its cheap coal energy. According to the Cambridge Centre for Alternative Finance (2021), China accounts for about 65% of all Bitcoin mining during our sample. Moreover, Xinjiang alone accounts for about 36% of worldwide activity.

On April 10, 2021, a coal mine flooded in Hutubi County in northern Xinjiang, trapping 21 people. As a consequence, the local government announced extensive safety inspections on April 15, which led to the temporary shutdown of several power plants in the region and resulted in a local electricity shortage (Altxw.com, 2021). Various news articles then document a sharp decrease in the Bitcoin hashrate, i.e., the total computing power of the network, starting April 16 as cryptocurrency mining operations lost electricity (e.g. Fortune.com, 2021; Digiconomist.net, 2021). Power only gradually resumed after about one week, leading to a gradual increase of the hashrate back to its previous level (Theblockcrypto.com, 2021). We hence consider the window from April 16 to April 22 as the blackout period. While we can reasonably precisely timestamp the beginning of the blackout, there is some uncertainty regarding when exactly power was restored. We address this issue in two ways: First, we estimate the implied hashrate and test not only if there is a significant drop during this period, but also if the computing power is restored back to its previous level afterwards. Second, we repeat our regression analysis using different window lengths and find that our results are robust to different specifications.

The blackout provides a unique opportunity to analyze risks associated with the geographical concentration of Bitcoin mining. Firstly, the blackout can be relatively accurately timestamped and immediately affected miners in that region. This is not necessarily the case for other types of events. For example, while government restrictions on cryptocurrencies and mining in particular are highly relevant signals regarding the prospects of cryptocurrencies, they are unlikely to immediately and effectively shut down all local mining operations, making a clear identification difficult (see e.g. Chen and Liu, 2021). Furthermore, the vulnerability of cryptocurrency mining to government restrictions is a consequence of geographical concentration stemming from the PoW consensus mechanism's energy dependence. Investigating the effects of the blackout is thus a more direct test of geographical mining concentration.[2] Secondly, the considered blackout constitutes an exogenous shock to mining,

[2]In July and September 2021, China again banned mining activity and cryptocurrency transactions. While

which might not hold for other events. For instance, the electricity consumption of Bitcoin mining and the resulting stress to the power grid has been blamed for power outages in other regions like Iran (CNBC, 2021). While somewhat unlikely, the causality might be reversed when using those blackouts as shocks to mining. Finally, many alternative shocks only indirectly affect mining, for example through cryptocurrency price changes. In contrast, our event directly impacts not just the profitability, but the possibility of mining in the affected region, which is a direct consequence of the geographical centralization of mining.

2.2. Hypothesis Development

If mining operations are interrupted by the blackout, we expect the total computing power of the network to decrease. We hence first confirm that the hashrate of the Bitcoin network is indeed significantly lower during the blackout.

Hypothesis 1: The hashrate of the Bitcoin network is lower during the blackout.

Keeping the difficulty of mining a block constant, a reduction in the hashrate leads to an increase in the average time between blocks and fewer mined blocks overall. The capacity on the blockchain thus becomes more binding. Consequently, impatient traders compete for the scarce resource of blockchain capacity by bidding up fees, akin to a congestion of the blockchain as in Kim (2020). This reasoning also aligns with Easley et al. (2019). In their model, fees reflect the queuing problem faced by Bitcoin users. As waiting times increase, some users choose to increase their fees. However, others exit and do not submit transactions as the benefit of having the transaction recorded does not outweigh the cost associated with fees and waiting times.

Hypothesis 2: Fees paid to miners increase during the blackout.

---

many miners subsequently left Xinjiang and the rest of China, mining activity mostly migrated to Kazakhstan and the United States, in particular Texas. Both countries now collectively represent more than 50% of worldwide mining capacity (CNBC, 2021). Geographical centralization of mining is hence still a potential problem for the whole network, even though miners may no longer specifically depend on cheap coal energy from Xinjiang.

Reacting to the higher level of fees and the lower overall capacity of the blockchain, patient traders or those with only marginal utility gains from trade omit or postpone their trading, leading to fewer transactions recorded on the blockchain.

Hypothesis 3: The number and value of transactions recorded on the Bitcoin blockchain decreases during the blackout.

So far, we have only considered on-blockchain trading activity. However, we also expect the blackout to impact exchange trading activity. In the model of Zimmerman (2020), limited settlement space and the associated competition between cryptocurrency users and speculators leads to a crowding-out of those who want to use the currency for payments. This in turn decreases the value of the currency as a means of payment while increasing its riskiness in the form of price volatility. Furthermore, Bhambhwani et al. (2019) empirically show that there is a positive relationship between cryptocurrency prices and computing power. They conjecture that computing power is a fundamental pricing factor that proxies for systemic risk.

Hypothesis 4: Bitcoin depreciates during the blackout.

Hypothesis 5: Bitcoin returns become more volatile during the blackout.

The increase in risk and the general uncertainty surrounding the blackout likely leads to a reduction in liquidity as market makers reduce their exposure. Furthermore, increases in settlement times may make it more difficult for market makers to manage their inventories.

Hypothesis 6: Exchange liquidity deteriorates during the blackout.

Finally, higher volatility and lower liquidity make it more difficult for arbitrageurs to exploit arbitrage opportunities across different trading venues. Furthermore, according to the model of Hautsch et al. (2021), settlement latency reduces cross-market trading and makes exploiting potential arbitrage opportunities riskier. This is because arbitrageurs on centralized exchanges face the dilemma of either trusting the exchanges by keeping funds in their accounts or potentially missing out on trading opportunities due to high blockchain latency which reduces the speed of moving funds into and out of exchange accounts used for trading. Since centralized cryptocurrency exchanges have a long history of misplacing customer funds by being hacked or by embezzlement, trust in many exchanges is generally relatively low. Hence, most traders prefer not to keep large amounts of funds with an exchange for longer periods of time. This leads to larger and more volatile cross-venue price differences when settlement latency is high.

Hypothesis 7: Market integration decreases as cross-venue price differences increase.

3. Empirical Approach

3.1. Sample Selection and Data

The sample period includes the blackout period and one week before, though we additionally obtain data for the surrounding weeks to analyze any trends. During this time, we compare Bitcoin to Ada, the internal cryptocurrency of the Cardano platform. Cardano was launched in 2017 and consists of two layers, where the first layer is the settlement layer tracking Ada ownership, similar to the Bitcoin network. The second layer facilitates smart contracts akin to the Ethereum network. Importantly, Cardano uses the PoS consensus mechanism, making Ada the largest PoS and non-PoW cryptocurrency by far, representing more than half of the market capitalization of all PoS currencies (Irresberger et al., 2020). Overall, it is the fifth largest cryptocurrency as of May 2021.

Our data comes from two types of sources: First, we collect hourly data from the currencies' blockchains: the number of new blocks, the average time between two blocks, and the number of transactions contained in all blocks. Furthermore, we compute the value sent within all transactions, the average size of a transaction, and the total fees paid to miners using market prices. Second, we download minutely exchange rate data from Kraken, which is generally considered trustworthy and one of the most liquid exchanges for trading Bitcoin and Ada. We focus on trading cryptocurrencies against the US dollar. For robustness and to study cross-venue market integration, we also consider Binance, where Bitcoin and Ada are traded against the stablecoin Tether, and Bittrex, which is a substantially smaller exchange than either Kraken or Binance.[3]

We aggregate the exchange data to an hourly frequency by calculating logarithmic returns based on hourly closing prices, the standard deviation of minutely logarithmic returns, and the trading volume in USD. Because Scharnowski (2021) indicates that Bitcoin liquidity is related to the hashrate, we follow Brauneis et al. (2021) and consider different measures of liquidity. Firstly, we use the Corwin and Schultz (2012) high-low spread estimator, which according to Brauneis et al. (2021) performs well in capturing the time-series variation of liquidity.

$$\text{Spread}_t = \frac{2\left(\exp\left(\alpha\right) - 1\right)}{1 + \exp\left(\alpha\right)} \quad \text{where} \quad \alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$$

$$\beta = \left[\ln\left(\frac{\text{High}_t}{\text{Low}_t}\right)\right]^2 + \left[\ln\left(\frac{\text{High}_{t+1}}{\text{Low}_{t+1}}\right)\right]^2 \qquad \gamma = \left[\ln\left(\frac{\max\left(\text{High}_t, \text{High}_{t+1}\right)}{\min\left(\text{Low}_t, \text{Low}_{t+1}\right)}\right)\right]^2$$

As commonly done, we set negative spread estimates to zero. Secondly, we compute the Kyle and Obizhaeva (2016) illiquidity index, which performs well in capturing the cross-sectional variation of liquidity. Intuitively, the measure expresses how volatile returns react to a given trading volume. Formally, we use the following specification

$$\text{Illiquidity}_t = \left[\frac{\sigma_t^2}{\text{Volume}_t}\right]^{\frac{1}{3}}$$

[3]While there is a debate on the stability of stablecoins (Hoang and Baur, 2021), differences between USD and Tether are small during our sample period. The maximum and minimum USDT/USD exchange rate at Kraken are 1.0061 and 0.9990, respectively. The choice of quote currency is thus unlikely to meaningfully impact our results. Still, in most analyses we only compare different base currencies while keeping the quote currency fixed.

Finally, the study any changes in market integration, we compute price differences between the trading venues Kraken and Binance based on minutely closing prices.

$$\text{Price Diff}_t = \left| \ln \left(\frac{\text{Close}_{\text{Kraken},t}}{\text{Close}_{\text{Binance},t}} \right) \right|$$

We consider the average, the standard deviation, the 90th percentile, and the maximum absolute price difference during each hourly interval to capture different dimensions of the distribution of cross-venue price differences.

Table 1 provides summary statistics based on two weeks before the blackout. While both currencies are the largest by market capitalization using their respective consensus mechanism, Bitcoin's transaction activity is still much higher. To reduce noise, we hence use data from that week to standardize the variables. In particular, for each currency and for all variables except returns, we subtract this time-series mean and divide by the standard deviation. However, we obtain qualitatively similar results when instead transforming the variables by taking their natural logarithm or not standardizing at all.

3.2. Estimating the Network Hashrate

We first document the extent to which Bitcoin miners were affected by the blackout. While not directly observable, their aggregate computing power can be estimated by the implied hashrate. The hashrate is related to the ratio of the current difficulty within the network and the time between two blocks. The former describes how computationally demanding it is to solve the mathematical puzzle by finding a hash below a certain threshold which would lead to the successful mining of a block. Importantly, while time between blocks is stochastic, the difficulty is adjusted roughly every two weeks to keep the expected time between blocks at ten minutes.[4] It follows that miners' investments change their hashrate, their relative market power, and the total electricity cost of the network due to mining, but

[4] The difficulty stayed constant during the blackout. Several days later there was a sharp drop in difficulty, reflecting the lower average hashrate during the blackout.

Table 1: **Descriptive Statistics**

	Mean	**SD**	**P5**	**P50**	**P95**	**Skew.**	**Kurt.**
Panel A: *Bitcoin*							
$\text{Transactions}_{\text{N}}$	12.24	4.84	5.23	12.00	20.75	0.4	2.8
$\text{Transactions}_{\text{Total Value}}$	3.83	1.99	1.13	3.43	7.66	1.0	4.2
$\text{Transactions}_{\text{Size}}$	0.33	0.17	0.12	0.30	0.61	1.9	11.3
$\text{Transactions}_{\text{Block}}$	2063.74	426.11	1242.33	2083.15	2684.20	−0.3	2.8
Blocktime	11.69	6.39	5.61	10.01	22.12	2.2	9.8
$\text{Fees}_{\text{Total}}$	221.84	85.53	109.27	205.02	380.06	0.6	3.1
$\text{Fees}_{\text{Relative}}$	0.69	0.32	0.34	0.63	1.26	1.4	5.6
Return	−0.71	45.04	−87.36	−3.00	68.89	0.5	4.9
Volatility	6.29	2.67	3.36	5.68	11.52	1.5	5.7
Volume	8.15	6.69	2.07	6.52	20.11	3.0	17.9
Spread	0.50	0.42	0.08	0.36	1.35	1.8	6.7
Illiquidity	1.37	0.32	0.91	1.37	1.94	0.2	2.4
Panel B: *Ada*							
$\text{Transactions}_{\text{N}}$	1.52	1.07	0.94	1.41	2.16	10.5	126.8
$\text{Transactions}_{\text{Total Value}}$	0.20	0.18	0.08	0.16	0.40	5.0	35.4
$\text{Transactions}_{\text{Size}}$	0.14	0.11	0.06	0.11	0.28	4.2	25.6
$\text{Transactions}_{\text{Block}}$	8.86	6.77	5.27	8.11	12.81	10.7	129.2
Blocktime	0.35	0.03	0.31	0.35	0.40	0.5	3.5
$\text{Fees}_{\text{Total}}$	0.40	0.23	0.24	0.37	0.60	8.8	98.9
$\text{Fees}_{\text{Relative}}$	0.03	0.01	0.01	0.02	0.04	2.3	15.6
Return	1.73	92.54	−137.86	4.72	139.98	2.5	22.3
Volatility	11.46	8.04	4.33	9.43	23.87	3.4	20.0
Volume	1.16	1.45	0.29	0.82	2.67	6.2	52.9
Spread	0.78	1.08	0.09	0.53	2.21	6.8	64.3
Illiquidity	6.47	20.06	2.88	4.84	7.52	12.8	164.4

This table shows summary statistics based on hourly data from the week of April 2. $Transactions_N$ is the number of transactions recorded on the blockchain in 1k, $Transactions_{Value}$ their value in USD 1bn, and $Transactions_{Size}$ their average size in USD 1mn. $Transactions_{Block}$ gives the average number of transactions per block and *Blocktime* the average time between two blocks in minutes. $Fees_{Total}$ is the sum of all fees paid by users in USD 1k and $Fees_{Relative}$ the same relative to the value of the transactions in basis points. The remaining variables are based on trading data from Kraken: *Return* is the logarithmic return of hourly closing prices in basis points, *Volatility* the standard deviation of minutely log returns in basis points, *Volume* is the trading volume in USD 1mn, *Spread* is the high-low spread estimate in basis points, and *Illiquidity* is the illiquidity index by Kyle and Obizhaeva (2016) in basis points.

over a longer horizon this arms race does not further impact the Bitcoin network as it simply leads to an increase in difficulty. In particular, the total rewards in the form of newly mined bitcoins stays the same (Alsabah and Capponi, 2020).

Using the observed average time between two blocks during some interval then gives an estimate of the implied network hashrate. Regarding the choice of time interval, there is a trade-off between the stability of the estimate and the frequency with which we can observe the computational power of the network. We use an interval length of three hours, but our results are generally robust to using longer and shorter intervals.

$$\widehat{\text{Hashrate}}_t = 2^{32} \times \frac{\text{Difficulty}_t}{\text{TimeBetweenBlocks}_t}$$

3.3. Regression Analysis

We analyze the impact of the blackout in a difference-in-difference framework by comparing Bitcoin to a non-PoW cryptocurrency that, by design, only trivially depends on electricity and was thus not directly affected by the blackout. Using this approach, we control for unobservable confounding factors that affect both cryptocurrencies, for example through economy-wide or (crypto)market-wide changes, while isolating the effect on Bitcoin with its PoW consensus mechanism.[5]

Specifically, for the period including the blackout and the one week before, we estimate

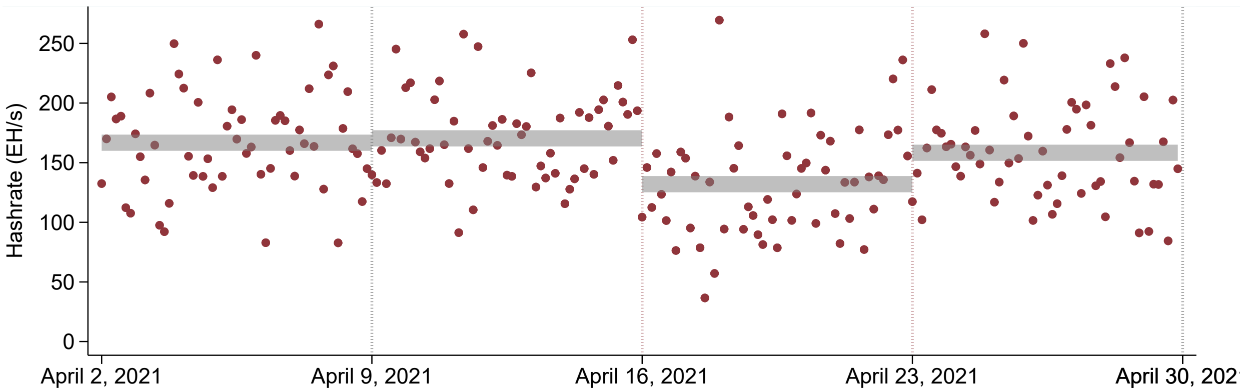
$$\text{Y}_{it} = \alpha + \beta_1 \text{Bitcoin}_i + \beta_2 \text{Blackout}_t + \beta_3 \text{Bitcoin}_i \times \text{Blackout}_t + \varepsilon_t$$

where Y_{it} is a standardized measure of blockchain or trading activity and *Bitcoin* and *Blackout* are binary indicator variables. The constant shows the value of Ada before the blackout, normalized using data from two weeks before. The coefficient for Bitcoin gives the normalized difference between the two currencies before the blackout. The blackout coefficient shows the normalized difference during the blackout, while the interaction term gives its additional effect on Bitcoin.

A concern might be that there are spillover effects from Bitcoin as the leading cryptocurrency to the rest of the market, which then would indirectly affect the control currency.

[5] While in this study we do not consider other PoW currencies, it is ultimately an empirical question whether miners of other PoW cryptocurrencies were located in the same region affected by the blackout. However, using data from etherscan.io, we find that the estimated Ethereum network hashrate was not impacted by the blackout, increasing by about 0.22% during the blackout period compared to the week before.

Figure 1: Computational Power of Bitcoin Network



This graph shows the estimated implied hashrate of the Bitcoin network in exahash per second. Each estimate is based on the current difficulty of the network and the average time between blocks mined within a three hour window. The vertical dashed lines indicate the beginning and end of the blackout and the three surrounding weeks. The horizontal bars show the average hashrate during the respective windows.

However, assuming such spillovers impact the control currency in the same direction, they would actually lead to an underestimation of the additional effect the blackout has on Bitcoin and would instead be captured by the coefficient for the blackout.[6]

4. Results

4.1. Drop in Hashrate

Figure 1 shows the development of the implied hashrate of the Bitcoin network. While volatile, its average during the two weeks before the blackout is virtually identical at about 170 EH/s. During the blackout, the hashrate drops to 130 EH/s, or by about 24%, suggesting that about one quarter of Bitcoin mining operations were affected by the blackout. The drop is highly statistically significant: t-tests for differences between the blackout period and the week before or afterwards give absolute test statistics of 5.19 and 3.37, respectively. Using median instead of average time between two blocks to estimate the hashrate gives similar results, though at an overall higher level. The difference between the implied hashrate during the week before to the week after the blackout is statistically insignificant, supporting the choice of the length of the blackout window.

[6] This underestimation becomes apparent later when we consider abnormal returns to calculate volatility.

The sudden drop in hashrate confirms our first hypothesis and indicates that during the sample period covering the end of the dry season in Southwest China, a significant fraction of global Bitcoin mining was concentrated in a relatively small geographic area in northern Xinjiang and powered mostly by coal. Though Bitcoin is decentralized by design, the power outage shows limits to decentralization of PoW currencies, since miners crucially depend on low electricity prices.

4.2. Blockchain Activity and Transaction Fees

We continue by analyzing the activity on the currencies' blockchains in Table 2. The first two columns indicate that during the blackout, Ada experienced an increase in the number and value of the transactions recorded on its blockchain. The increases of 0.19 and 0.44 of a standard deviation relative to before the blackout are statistically significant, but substantially smaller than the corresponding decrease for Bitcoin. Compared to before the blackout, Bitcoin's transaction activity even decreases by 0.50 and 0.05 standard deviations for the number and value of transactions, respectively, confirming hypothesis 3. The average transaction size and the number of transactions included in each block increase during the blackout, but not especially so for Bitcoin. Reflecting the results for the hashrate, the time between two blocks significantly increases for Bitcoin by 0.675 standard deviations, which translates to roughly four minutes. Given the rule of thumb of waiting for six blocks to consider a transaction confirmed, Bitcoin traders have to wait for about 26 minutes additionally – or 37% longer than usual – to be sure that their transactions are irreversibly recorded on the blockchain. Contrarily, Ada with its PoS consensus mechanism remains unaffected.

The last two columns show how the fees paid for faster settlement increase during the blackout, lending support to hypothesis 2. The descriptive statistics have shown historically high fees in the weeks before the blackout; still, the sum of all fees increases for both currencies, though the effect is much stronger for Bitcoin. Since total fees incorporate both the effects of the average fees and the amount transacted, we additionally consider relative fees.

Table 2: Blockchain Activity

	TX_N	TX_{Value}	TX_{Size}	TX_{Block}	Blocktime	$Fees_{Total}$	$Fees_{Relative}$
Constant	0.057*	0.173*	0.115	0.047	−0.023	0.264***	−0.011
	(1.90)	(1.69)	(0.91)	(1.58)	(−0.27)	(5.54)	(−0.18)
Bitcoin	0.056	0.063	0.146	0.041	0.053	0.376***	0.076
	(0.63)	(0.51)	(0.93)	(0.51)	(0.41)	(2.92)	(0.75)
Blackout	0.193***	0.441***	0.308*	0.155***	−0.158	0.163***	−0.237**
	(4.92)	(2.96)	(1.80)	(4.02)	(−1.43)	(2.67)	(−2.33)
Bitcoin×Blackout	−0.692***	−0.494***	−0.023	0.055	0.833***	3.106***	2.966***
	(−5.83)	(−2.63)	(−0.11)	(0.50)	(4.09)	(11.21)	(11.69)
Observations				667			

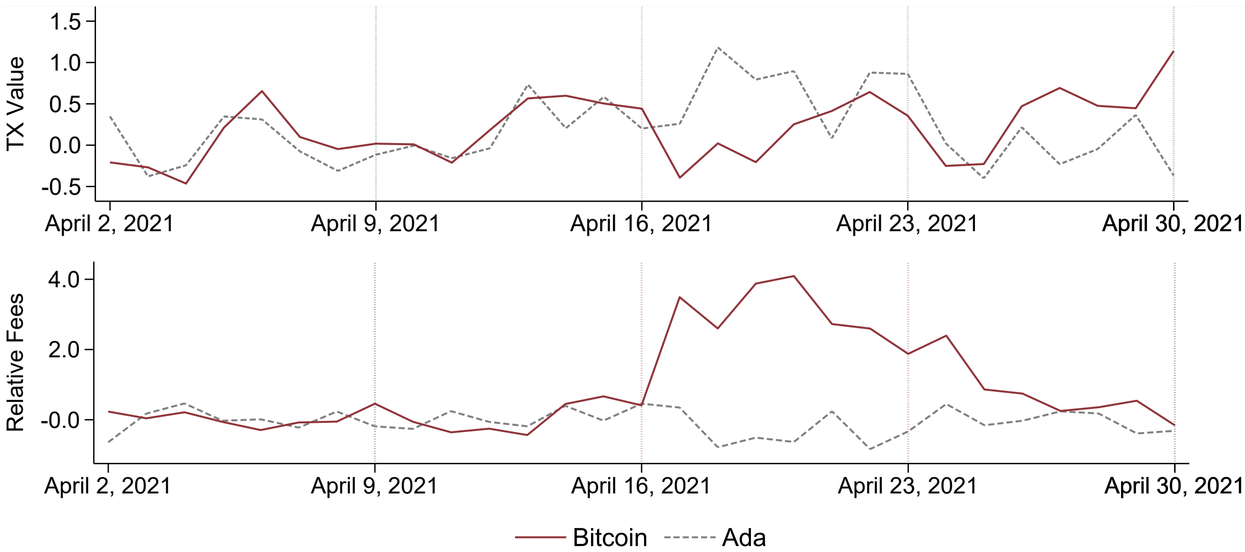
This table shows difference-in-difference regression results for blockchain activity using hourly data. $Transactions_N$ is the total number of transactions recorded on the respective blockchain and $Transactions_{Value}$ the USD value contained in these transactions. *Blocktime* is the average time between two blocks in minutes. $Fees_{Total}$ is total amount of fees paid for the transactions in USD. $Fees_{Relative}$ is the ratio of total fees to total transaction value in basis points. The variables have been standardized for each currency by subtracting their average value and dividing by their standard deviations during the week before the sample period. The treatment period of the blackout from April 16 to April 22, 2021 is compared to the 7 days before the blackout. Robust standard errors are reported in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

We find that relative fees even decrease somewhat for Ada, but soar for Bitcoin by almost three standard deviations. This translates to an economically meaningful increase in relative fees by 0.94 basis points. While still low compared to other financial assets, this constitutes an increase of about 135% relative to before the sample period.

Figure 2 shows the development of transaction value and relative fees, confirming the regression results and illustrating the parallel trends before the event. In the weeks prior to the blackout, both currencies closely co-move. Starting with the blackout, the currencies diverge as Bitcoin's transaction value decreases and relative fees increase substantially. Fees gradually decrease back to previous levels after about ten days. While the reversion is faster for the transaction value, it appears as though for Bitcoin the value actually increases for some time once fees have reverted back to normal levels. This is consistent with the notion that some traders merely postpone their trading.

The results suggest that during the blackout, capacity restrictions on the Bitcoin blockchain became significantly more binding, inducing impatient traders to bid up fees. Our analysis thus also confirms the predictions of Easley et al. (2019), where fees reflect the traders'

Figure 2: Transacted Value and Fees



The top graph shows the total transaction value on the blockchains. The bottom graph shows the fees relative to the value of the transactions. Both variables have been standardized by subtracting the mean and dividing by the standard deviation during the week from April 2 to April 8. The graphs show daily averages of the respective hourly variables.

queuing problem. As waiting times increase, some users choose to increase their fees while others exit. Our findings of an exogenous increase in waiting times due to the blackout and a subsequent increase in fees and a reduction in the number of transactions is thus consistent with their predictions.

4.3. Returns and Liquidity

Finally, we turn to the effect the blackout and resulting shock to mining activity has on cryptocurrency prices and exchange trading activity. The results can be found in Table 3. Prices do not significantly change for either currency as seen in the first column. While several news outlets associated a concurrent decline in prices with the blackout, the observed lower returns during the blackout are well within the usual volatility of the cryptocurrencies and thus insignificant. Conversely, price volatility is generally much higher during the blackout, and especially so for Bitcoin, confirming hypothesis 5. Compared to before the blackout, the volatility of Ada increases by 0.71 while Bitcoin's volatility increases by an additional 1.08 standard deviations, which in both cases is highly statistically and economically significant.

Table 3: Prices and Exchange Trading Activity

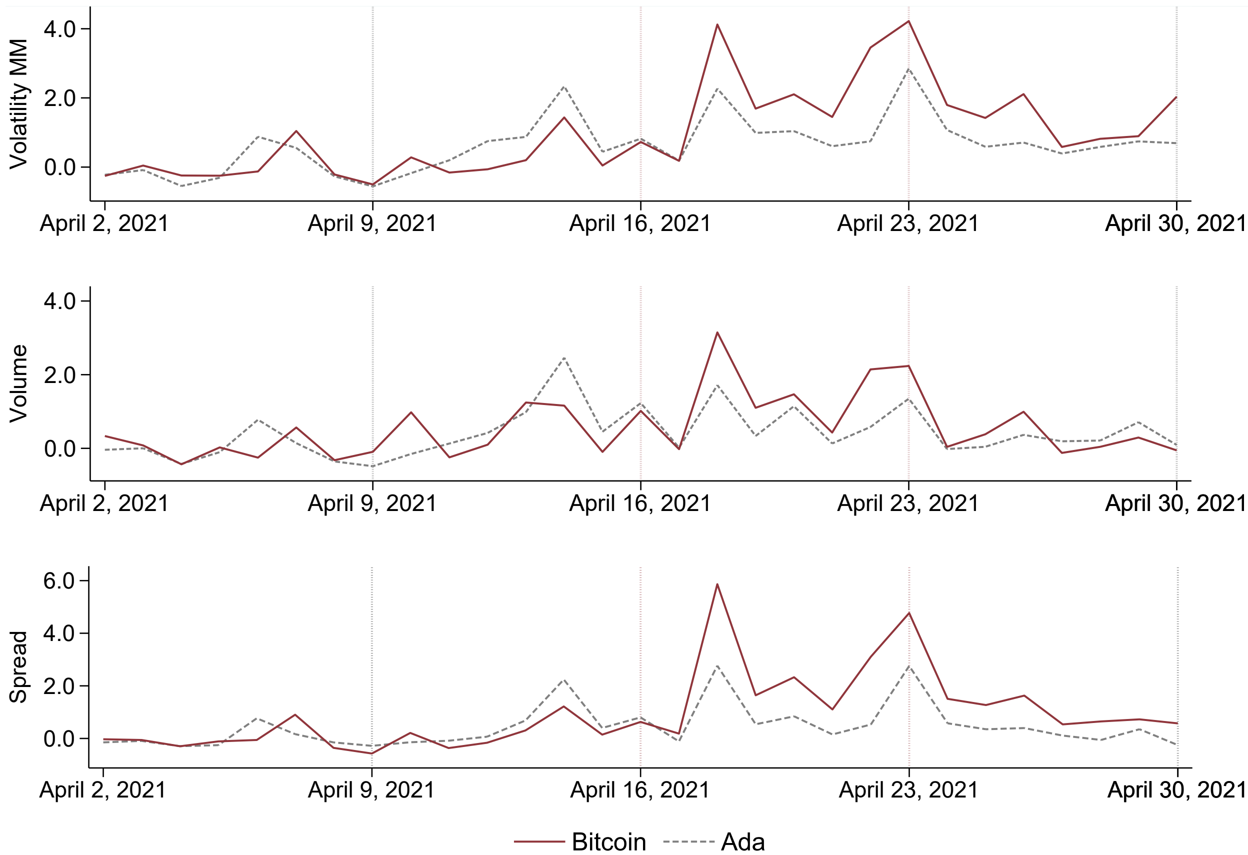
	Return	Volatility	$\text{Return}_{\text{MM}}$	Volatility	Volume	Spread	Illiquidity
Constant	11.516	0.461***	1.480	0.553***	0.544***	0.412***	−0.066***
	(1.21)	(4.83)	(0.17)	(5.69)	(5.29)	(4.75)	(−12.84)
Bitcoin	−6.403	−0.283**	3.633	−0.376***	−0.109	−0.300**	−0.070
	(−0.61)	(−2.18)	(0.38)	(−2.86)	(−0.71)	(−2.43)	(−0.83)
Blackout	−26.926	0.711***	−11.356	0.399***	0.191	0.370*	0.055***
	(−1.61)	(4.74)	(−0.96)	(2.63)	(1.22)	(1.94)	(6.65)
Bitcoin×Blackout	9.634	1.081***	−5.936	1.394***	0.700***	1.633***	0.775***
	(0.51)	(4.16)	(−0.40)	(5.34)	(2.61)	(4.11)	(6.63)
Observations				674			

This table shows difference-in-difference regression results for trading activity on Kraken using hourly data. *Return* is the logarithmic return of hourly closing prices in basis points. *Volatility* is the standard deviation of minutely log returns. For $Return_{MM}$ and $Volatility_{MM}$, the returns of Ada are the residuals of regressing Ada returns on Bitcoin returns. Volume is the total trading volume in USD. *Illiquidity* is the illiquidity index by Kyle and Obizhaeva (2016). The variables except returns have been standardized for each currency by subtracting their average value and dividing by their standard deviations during the week before the sample period. The treatment period of the blackout from April 16 to April 22, 2021 is compared to the 7 days before the blackout. Robust standard errors are reported in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

Since many cryptocurrencies closely co-move with Bitcoin prices, in the third and fourth column we first calculate abnormal returns for Ada by using Bitcoin returns as a single market factor. This way, we control for any expected price changes due to Bitcoin returns. Nevertheless, our findings regarding prices do not change. However, the effect of the blackout on Ada return volatility decreases in magnitude while the effect on Bitcoin increases when using abnormal returns.

Trading volume at Kraken is higher during the blackout, especially and significantly so for Bitcoin. Consistent with the observed increase in volatility, the additional uncertainty surrounding the shock to mining and the drop in hashrate might induce traders to adjust their portfolios. Additionally and according to hypothesis 6, we find that liquidity deteriorates during the blackout as bid-ask spreads widen substantially and the Kyle and Obizhaeva (2016) illiquidity index indicates that trading volume has a larger price impact. Noteworthily, liquidity decreases even though trading volume increases. The reduction in liquidity is potentially due to the increase in volatility and general uncertainty as market makers demand compensation for the additional risk or withdraw due to difficulties in inventory management.

Figure 3: Volatility, Volume, and Spreads



The graphs show the abnormal return volatility, trading volume, and high-low spread estimates. All variables have been standardized by subtracting the mean and dividing by the standard deviation during the week from April 2 to April 8. The graphs show daily averages of the respective hourly variables.

The graphs in Figure 3 show that volatility, volume, and estimated spreads exhibit very similar patterns. Before the blackout, both currencies again closely co-move. Compared to the changes in blockchain activity, the reaction of exchange trading activity occurs with a slightly greater delay of about one day. All measures stay at elevated levels until after about ten days, coinciding with the higher blockchain trading fees.

Our findings regarding exchange trading activity, especially with respect to return volatility and market liquidity, indicate that there are substantial spillover effects from mining to exchange trading activity. Operational risks faced by mining operations, like those arising from geographical mining concentration, thus have potentially severe effects on all market participants.

Table 4: Market Integration

	$\Delta P^{\text{Kraken–Binance}}_{\text{Mean}}$	$\Delta P^{\text{Kraken–Bittrex}}_{\text{Mean}}$	$\Delta P^{\text{Binance–Bittrex}}_{\text{Mean}}$	$\Delta P^{\text{Kraken–Binance}}_{\text{P90}}$	$\Delta P^{\text{Kraken–Binance}}_{\text{Std.Dev.}}$
Constant	0.834***	1.189***	1.347***	0.758***	0.626***
	(7.02)	(4.41)	(6.31)	(7.04)	(6.06)
Bitcoin	0.656***	1.067	0.934**	0.356**	0.009
	(3.27)	(1.60)	(2.44)	(2.03)	(0.06)
Blackout	4.840***	0.725*	2.277***	4.330***	3.048***
	(6.14)	(1.71)	(4.65)	(6.18)	(5.41)
Bitcoin×Blackout	0.028	−0.809	1.824**	−0.806	−1.370
	(0.03)	(−1.00)	(2.45)	(−0.89)	(−1.50)
Observations			670		

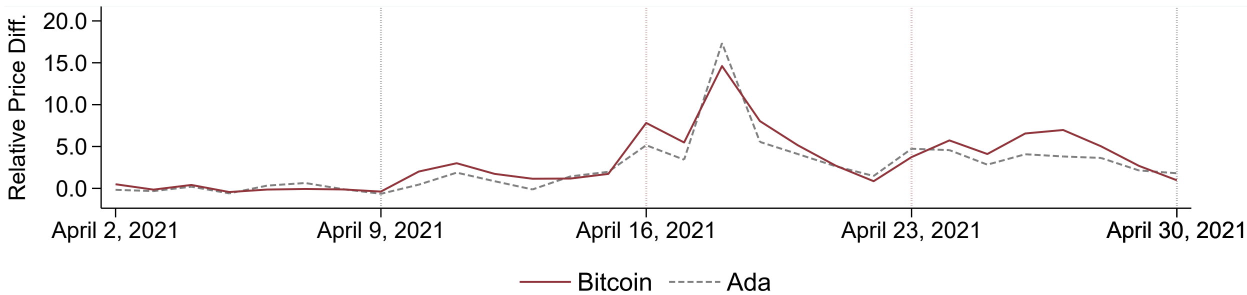
This table shows regression results for market integration. The first four columns show difference-in-difference results for relative absolute price differences between Kraken and Binance. The measures are based on minutely closing prices and aggregated to an hourly frequency by computing the average, standard deviation, 90th percentile, and maximum of differences. The variables have been standardized by subtracting their average value and dividing by their standard deviations during the week before the sample period. The last column shows regression results for the correlation of minutely returns between Bitcoin and Ada during each hourly window. The treatment period of the blackout from April 16 to April 22, 2021 is compared to the 7 days before the blackout. Robust standard errors are reported in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

4.4. Market Integration

Finally, we study market integration by analyzing cross-venue price differences. The results in Table 4 and Figure 4 indicate that generally, price differences increase substantially. For example, price differences between Kraken and Binance increase by almost five standard deviations relative to before for both currencies, though there is no additional effect for Bitcoin. The same holds for more extreme price differences as given by their 90th percentile and for the volatility of price differences. Regarding differences between Kraken and Bittrex, we find an only marginally significant increase for Ada, while Bitcoin does not appear to be impacted at all.

Taken together, these results indicate that exploiting arbitrage opportunities during the blackout period with its higher volatility and lower liquidity becomes more difficult, agreeing with hypothesis 7. This result is mainly driven by price differences to the weakly-regulated exchange Binance where Bitcoin and Cardano trade against Tether. Hence, our findings may also indicate that exploiting arbitrage opportunities between USD- and Tether-denominated exchange rates becomes more difficult. Our results are also in line with Hautsch et al. (2021)

Figure 4: Cross-venue Price Difference



The graph shows the relative price difference between Kraken and Binance. The variable has been standardized by subtracting the mean and dividing by the standard deviation during the week from April 2 to April 8. The graph shows daily averages of the respective hourly variable.

and thus empirically confirm their findings regarding the negative effect of settlement latency on market integration using the exogenous shock of the blackout.

4.5. Robustness

We perform a number of robustness tests. To address concerns regarding our choice of trading venue, we repeat the analysis using data from Binance, where Bitcoin and Ada are quoted against the stablecoin Tether. The results can be seen in Panel A of Table 5. Overall, we obtain very similar results, suggesting that the results are not exchange-specific. The major difference to Kraken is that there is a stronger increase of volatility and trading volume for Bitcoin during the Blackout but an overall weaker reduction in liquidity.

While Ada is the largest non-PoW cryptocurrency and thus an intuitive control group, we additionally verify that our results are not driven by this choice, either. Panels B and C of Table 5 show the same analyses as before, but while using a portfolio of non-PoW cryptocurrencies as the control currency. The equally weighted portfolio additionally contains Waves, Tronix (of the TRON network), and Atom (of the Cosmos network). Reassuringly, our results do not materially change when using the alternative control group. The only meaningful difference is that the relative drop in transaction value of Bitcoin during the blackout is not statistically significant. Overall, this yields further support to the notion that there is a decreases in market quality for Bitcoin during the blackout and that the results are not driven by idiosyncrasies of the control currency. In fact, we obtain very similar

Table 5: Robustness Tests

Panel A: Prices and Exchange Trading Activity using Binance Data							
	Return	Volatility	$\text{Return}_{\text{MM}}$	Volatility	Volume	Spread	Illiquidity
Constant	11.463	0.474***	1.572	0.614***	0.477***	0.551***	0.175***
	(1.17)	(4.89)	(0.18)	(6.26)	(5.35)	(4.84)	(3.28)
Bitcoin	−6.470	−0.340***	3.421	−0.480***	0.023	−0.509***	−0.410***
	(−0.60)	(−2.62)	(0.35)	(−3.67)	(0.16)	(−3.69)	(−4.79)
Blackout	−26.899	0.705***	−11.791	0.219	−0.058	1.179***	1.071***
	(−1.57)	(4.66)	(−0.97)	(1.55)	(−0.55)	(7.21)	(11.92)
Bitcoin×Blackout	9.712	1.107***	−5.396	1.594***	0.867***	0.193	0.441***
	(0.50)	(3.77)	(−0.36)	(5.53)	(4.23)	(0.78)	(2.72)
Panel B: *Blockchain Activity using a non-PoW Portfolio*							
	TX_{N}	TX_{Value}	TX_{Size}	TX_{Block}	Blocktime	$\text{Fees}_{\text{Total}}$	$\text{Fees}_{\text{Relative}}$
Constant	0.049	0.055	0.054	0.003	−0.251***	0.508***	−0.024
	(1.07)	(0.88)	(0.91)	(0.07)	(−6.23)	(8.77)	(−0.70)
Bitcoin	0.064	0.181*	0.207*	0.084	0.281***	0.133	0.089
	(0.66)	(1.92)	(1.87)	(0.96)	(2.65)	(1.00)	(1.00)
Blackout	0.295***	0.161	0.078	0.279***	0.038	−0.074	−0.044
	(4.65)	(1.55)	(0.78)	(4.40)	(0.73)	(−0.98)	(−0.90)
Bitcoin×Blackout	−0.794***	−0.215	0.206	−0.069	0.637***	3.342***	2.773***
	(−6.17)	(−1.39)	(1.26)	(−0.58)	(3.56)	(11.92)	(11.67)
Panel C: *Prices and Exchange Trading Activity using a non-PoW Portfolio*							
	Return	Volatility	$\text{Return}_{\text{MM}}$	Volatility	Volume	Spread	Illiquidity
Constant	13.932*	−0.050	6.478	−0.018	0.689***	0.013	−0.378***
	(1.78)	(−1.02)	(0.94)	(−0.38)	(6.65)	(0.33)	(−15.16)
Bitcoin	−8.819	0.227**	−1.364	0.195*	−0.254*	0.100	0.242***
	(−0.98)	(2.24)	(−0.17)	(1.94)	(−1.65)	(1.04)	(2.77)
Blackout	−32.994*	0.640***	−19.034	0.499***	−0.008	0.241**	0.333***
	(−1.90)	(6.38)	(−1.52)	(5.23)	(−0.05)	(1.97)	(7.28)
Bitcoin×Blackout	15.702	1.152***	1.742	1.293***	0.898***	1.763***	0.496***
	(0.80)	(4.91)	(0.11)	(5.56)	(3.39)	(4.77)	(3.97)

This table shows robustness tests similar to Table 2 and Table 3. In Panel A, exchange data from Binance is used, where Bitcoin and Ada are traded against US Tether. In Panels B and C, an equally weighted portfolio of cryptocurrencies (Ada, Tronix, Atom, and Waves) using consensus protocols other than PoW is used while the exchange data comes from Kraken. Robust standard errors are reported in parentheses. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

results when using each of the control currencies in the portfolio individually.

Our results are also robust to the exact specification of the event window. While we can relatively precisely timestamp the beginning of the blackout, timestamping the end proves more difficult. Though our estimate of the implied hashrate is consistent with a blackout duration of about one week, some of our investigated measures – like fees or volatility – stay at elevated levels longer than one week. While this does not necessarily imply a longer blackout duration, in untabulated results we empirically confirm that changing the window length by moving the end date of the blackout period by several days in either direction does not meaningfully impact our conclusions.

5. Conclusion

Many cryptocurrencies are decentralized by design, though market forces may drive them towards lower degrees of decentralization. While the previous literature has focused on centralization in mining hardware or the effect of centralized mining pools, our results provide evidence that points to another risk associated with mining concentration: When miners crucially depend on low electricity prices and hence accumulate in the same area, local geopolitical and operational risks can adversely affect the whole network. Since we also document strong spillover effects to exchange trading activity, these risks potentially affect a wide range of market participants. Traders and regulator should be aware of these risks associated with proof-of-work cryptocurrencies.

The power outage in one relatively small geographical region thus shows limits to decentralization of PoW currencies. The results also indicate that the Bitcoin network currently not only consumes vast amounts of energy, but also heavily relies on fossil fuels. Currencies based on alternative consensus mechanisms such as proof-of-stake do not necessarily share these same shortcomings stemming from the inherent dependence on electricity as the main input factor.

A noteworthy point about our analysis is that the shock to the network is only temporary. While in our case this is a result of the limited duration of the blackout, the temporary nature of shocks to mining activity is also an inherent feature of the PoW mechanism. The automatic adjustment of mining difficulty ensures that such shocks only temporarily affect the speed of settlement, attenuating the geopolitical and operational risks of centralization in the long term. However, in the short term, mining centralization still potentially leads to higher and more volatile fees and opportunity costs due to slower settlement and missed gains from trade. Future research investigating the welfare implications of centralization within cryptocurrencies and the relative merits of different consensus mechanisms should thus not only consider the costs and environmental externalities associated with mining, but also these indirect costs imposed on users.

References

Akyildirim, E., Corbet, S., Lucey, B.M., 2021. China, Coal, Calamities and Cryptos. Working Paper doi:10.2139/ssrn.3851253.

Alsabah, H., Capponi, A., 2020. Pitfalls of Bitcoin's Proof-of-Work: R&D Arms Race and Mining Centralization. Working Paper doi:10.2139/ssrn.3273982.

Altxw.com, 2021. Xinjiang launches coal mine safety production inspection [accessed 2021-06-02]. URL: http://www.altxw.com/news/system/2021/04/17/030083680.shtml.

Arnosti, N., Weinberg, S.M., 2021. Bitcoin: A Natural Oligopoly. Working Paper arXiv:1811.08572.

Benetton, M., Compiani, G., Morse, A., 2021. When Cryptomining Comes to Town: High Electricity-Use Spillovers to the Local Economy. Working Paper doi:10.2139/ssrn.3779720.

Bhambhwani, S., Delikouras, S., Korniotis, G.M., 2019. Do Fundamentals Drive Cryptocurrency Prices? SSRN Electronic Journal doi:10.2139/ssrn.3342842.

Böhme, R., Christin, N., Edelman, B., Moore, T., 2015. Bitcoin: Economics, Technology, and Governance. Journal of Economic Perspectives 29, 213–238. doi:10.1257/jep.29.2.213.

Brauneis, A., Mestel, R., Riordan, R., Theissen, E., 2021. How to measure the liquidity of cryptocurrency markets? Journal of Banking and Finance 124, 106041. doi:10.1016/j.jbankfin.2020.106041.

Cambridge Centre for Alternative Finance, 2021. Cambridge Bitcoin Electricity Consumption Index [accessed 2021-06-02]. URL: https://cbeci.org/mining_map.

Capponi, A., Olafsson, S., Alsabah, H., 2021. Proof-of-Work Cryptocurrencies: Does Mining Technology Undermine Decentralization? SSRN Electronic Journal URL: https://www.ssrn.com/abstract=3869144, doi:10.2139/ssrn.3869144.

Chen, C., Liu, L., 2021. How effective is China's cryptocurrency trading ban? Finance Research Letters , 102429doi:10.1016/j.frl.2021.102429.

CNBC, 2021. Iran bans bitcoin mining as its cities suffer blackouts and power shortages [accessed 2021-07-27]. URL: https://www.cnbc.com/2021/05/26/iran-bans-bitcoin-mining-as-its-cities-suffer-blackouts.html.

Cong, L.W., He, Z., Li, J., 2021. Decentralized Mining in Centralized Pools. The Review of Financial Studies 34, 1191–1235. doi:10.1093/rfs/hhaa040.

Corbet, S., Lucey, B., Yarovaya, L., 2021. Bitcoin-energy markets interrelationships - New evidence. Resources Policy 70, 101916. doi:10.1016/j.resourpol.2020.101916.

Corwin, S.A., Schultz, P., 2012. A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices. The Journal of Finance 67, 719–760. URL: https://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.2012.01729.x, doi:10.1111/j.1540-6261.2012.01729.x.

Delgado-Mohatar, O., Felis-Rota, M., Fernández-Herraiz, C., 2019. The Bitcoin mining breakdown: Is mining still profitable? Economics Letters 184, 108492. doi:10.1016/j.econlet.2019.05.044.

Digiconomist.net, 2021. Amidst avid greenwashing, Xinjiang blackout exposes the horrid reality of Bitcoin mining [accessed 2021-06-02]. URL: https://digiconomist.net/amidst-avid-greenwashing-xinjiang-blackout-exposes-the-horrid-reality-of-bitcoin-mining/.

Dittmar, L., Praktiknjo, A., 2019. Could Bitcoin emissions push global warming above 2 °C? Nature Climate Change 9, 656–657. doi:10.1038/s41558-019-0534-5.

Easley, D., O'Hara, M., Basu, S., 2019. From mining to markets: The evolution of bitcoin transaction fees. Journal of Financial Economics 134, 91–109. doi:10.1016/j.jfineco.2019.03.004.

Ferreira, D., Li, J., Nikolowa, R., 2021. Corporate Capture of Blockchain Governance. SSRN Electronic Journal URL: https://www.ssrn.com/abstract=3320437, doi:10.2139/ssrn.3320437.

Fortune.com, 2021. How much Bitcoin comes from dirty coal? A flooded mine in China just spotlighted the issue [accessed 2021-06-02]. URL: https://fortune.com/2021/04/20/bitcoin-mining-coal-china-environment-pollution/.

Hautsch, N., Scheuch, C., Voigt, S., 2021. Building Trust Takes Time: Limits to Arbitrage in Blockchain-Based Markets doi:10.2139/ssrn.3302159, arXiv:1812.00595.

Hoang, L.T., Baur, D.G., 2021. How stable are stablecoins? The European Journal of Finance , 1–17doi:10.1080/1351847X.2021.1949369.

Irresberger, F., John, K., Saleh, F., 2020. The Public Blockchain Ecosystem: An Empirical Analysis. SSRN Electronic Journal doi:10.2139/ssrn.3592849.

Karmakar, S., Demirer, R., Gupta, R., 2021. Bitcoin mining activity and volatility dynamics in the power market. Economics Letters , 110111doi:10.1016/j.econlet.2021.110111.

Kim, S.T., 2020. Bitcoin dilemma: Is popularity destroying value? Finance Research Letters 33. doi:10.1016/j.frl.2019.07.001.

Kyle, A.S., Obizhaeva, A.A., 2016. Market Microstructure Invariance: Empirical Hypotheses. Econometrica 84, 1345–1404. doi:10.3982/ecta10486.

Lehar, A., Parlour, C.A., 2020. Miner Collusion and the BitCoin Protocol. Working Paper doi:10.2139/ssrn.3559894.

Roşu, I., Saleh, F., 2021. Evolution of Shares in a Proof-of-Stake Cryptocurrency. Management Science 67, 661–672. doi:10.1287/mnsc.2020.3791.

Saleh, F., 2021. Blockchain without Waste: Proof-of-Stake. The Review of Financial Studies 34, 1156–1190. doi:10.1093/rfs/hhaa075.

Scharnowski, S., 2021. Understanding Bitcoin liquidity. Finance Research Letters 38, 101477. doi:10.1016/j.frl.2020.101477.

Theblockcrypto.com, 2021. Bitcoin's hash rate set to regain loss as Xinjiang miners gradually resume operations [accessed 2021-06-02]. URL: https://www.theblockcrypto.com/post/102603/bitcoin-hash-rate-xinjiang-miner-power.

de Vries, A., 2020. Bitcoin's energy consumption is underestimated: A market dynamics approach. Energy Research and Social Science 70, 101721. doi:10.1016/j.erss.2020.101721.

Zimmerman, P., 2020. Blockchain structure and cryptocurrency prices. Bank of England Staff Working Paper No . 855 , 1–71.