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BLOCKCHAIN MINING POWER AND MARKET QUALITY IN CRYPTOCURRENCY TRADING

KAITAO LIN

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Kaitao Lin[(1)]

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Abstract This paper investigates how the aggregate mining power of blockchain affects the market quality of cryptocurrency trading platforms. Using historical intraday data of three cryptocurrencies traded on three platforms from January to June 2021, we observe that a decrease in the blockchain's aggregate mining power results in wider price discrepancies across platforms and reduced liquidity. We also analyze abnormal hashrate and find consistent results that support our previous findings. The contribution of this study lies in empirically exploring the connection between blockchain mining and the trading environment of the crypto market, highlighting the importance of considering the impact of blockchain validation process when designing fair and efficient markets for crypto assets.

Keywords: Cryptocurrencies, Blockchain, Hashrate, Market quality
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(1) Senior Financial Economist, World Federation of Exchanges. Email: klin@world-exchanges.org. I would like to thank Pedro Gurrola-Perez, Yuxi Chen, and members of the WFE Emerging Markets Working Group for their useful comments. Any errors are mine.

1 Introduction

Cryptocurrencies are a relatively new instrument that has garnered a lot of attention. While their benefits and drawbacks are not well understood by all market participants, it is frequently traded and included in investment strategies. For instance, Corbet et al. (2018) show that cryptocurrencies may offer diversification benefits for investors with short investment horizons. Yet, the trading quality offered by crypto trading platforms is a major concern, as it depends on the operation of the trading venues, the technology embedded in the trading process, and the overall design of the market.

A key feature of blockchain is its reliance on a consensus protocol, which establishes the way validators reach an agreement on the current state of the ledger. As outlined in Nakamoto (2008), the bitcoin blockchain implements the Proof-of-Work consensus protocol, where validators enter into a computationally intensive competition to solve numerical puzzles by continuously guessing the solution of hash functions. This validation process is also generally known as mining and depends on the blockchain's aggregate computing or mining power. More specifically, blockchain's computing power proxies for the cumulative resources expended on mining and relates to blockchains' overall reliability and security.

The validation process plays a crucial role in the settlement of crypto asset trading, as miners need to validate transactions before they can be added to the blockchain. Alterations in the aggregate computing power on the blockchain may result in changes in settlement latency, which can impact the behavior of market participants and overall market quality (Hautsch et al. (2018)).

This paper aims to examine the impact of blockchain computing power on the market quality of cryptocurrency trading. Previous studies in the academic literature have demonstrated that blockchain computing power and the behavior of miners have an influence on cryptocurrency prices (Easley et al. (2019); Bhambhwani et al. (2021); Cong et al. (2021); Pagnotta (2022)). By investigating the connection between the blockchain's setup and the cryptocurrency trading environment, our research contributes to the existing literature and stimulates further discussions on these important issues. To the best of our knowledge, this is the first empirical study that explores the relationship between the aggregate computing power of the blockchain and the market quality offered by crypto trading platforms.

We measure the market efficiency and liquidity by analyzing the historical intraday quote and trading data of three cryptocurrencies (Bitcoin, Ether, and Litecoin) on three different trading platforms (Coinbase, FTX, and Kraken) from January to June 2021. To examine the relationship between market quality and the blockchain's aggregate hashrate, we conduct panel regressions, incorporating fixed effects for each cryptocurrency. The dependent variable in these regressions takes one of the market quality measures, while the independent variable is the normalized aggregate hashrate. We perform panel regressions using contemporaneous hashrate and lagged hashrate as independent variables (both individually and jointly) in order to compare their effects on market quality.

To conduct our analysis, we begin by following the approach outlined by Makarov and Schoar (2020) and calculate a trade-based arbitrage index. This index is derived by comparing the highest traded price to the lowest traded price. Additionally, we examine the bid and ask prices quoted on the trading platforms. In the absence of arbitrage opportunities, the ask price should be higher than the bid price. Any deviation from this condition implies potential arbitrage profits. We compute a quote-based arbitrage index by comparing the highest bid price to the lowest ask price offered by the trading venues on a minute-by-minute basis. We select the higher value between the ratio and one. In our panel regression models, using the arbitrage indexes as the dependent variable, we observe negative and statistically significant estimated coefficients (p-value < 0.1 for the trade-based arbitrage index and p-value < 0.05 for the quote-based index) associated with the blockchain's previous day's hashrate. These findings indicate that a decrease in the blockchain's aggregate mining power leads to wider cross-platform price discrepancies and an increase in arbitrage opportunities.

In addition to examining price discrepancy, we also investigate the liquidity conditions. Although we do not find any statistically significant results for the quoted bid-ask spread and effective spread in the regression analysis, we observe significant findings when analyzing transaction costs in terms of price impact and Kyle (1985)'s Lambda measure. Specifically, we find that these two measures, when lagged by one day, exhibit negative and statistically significant relationships at the 99% and 95% confidence levels, respectively. Furthermore, in addition to the lagged relationship, we discover a negative and significant contemporaneous relationship (p-value <0.05) between Kyle's Lambda and the aggregate computing power of the blockchain. These negative estimated coefficients suggest that a decrease in the blockchain's aggregate computing power results in a deterioration of liquidity in the crypto market.

Moreover, we consider the possibility that unexpected changes in the blockchain's aggregate mining power can have a similar effect on market quality. With this in mind, we calculate the abnormal hashrate to capture unexpected changes. More specifically, we take the difference between the actual daily hashrate and a smoothed hashrate, which is obtained through filtering techniques as outlined by Hamilton (2018). Subsequently, we reevaluate our regression analysis using standardized abnormal hashrate as the independent variable. Confirming our initial findings and intuitive expectations, the results indicate a decline in market quality when there is a decrease in the blockchain's aggregate mining power. Specifically, both the contemporaneous and lagged abnormal hashrate exhibit a negative and statistically significant correlation with the quote-based arbitrage index, effective spread, and Kyle (1985)'s Lambda.

Our paper bridges two strands of existing literature, connecting them in a cohesive manner. The first strand of research focuses on understanding how various characteristics of blockchain, such as mining and network features, influence the pricing of cryptocurrencies. In a theoretical model, Pagnotta and Buraschi (2018) argue that the blockchain's hashrate and the price of Bitcoin are jointly determined since miners receive Bitcoin as a reward for validating transactions. Pagnotta (2022) further links Bitcoin prices to the security level of the blockchain, which is contingent on the aggregate mining power. Additionally, Easley et al. (2019) present a model that emphasizes the relationship between Bitcoin price, mining rewards, transaction fees, and waiting time. On the empirical front, Liu and Tsyvinski (2021) use the price of mining hardware and electricity costs as proxies for mining expenses and find that mining characteristics do not move in tandem with cryptocurrency returns. However, Bhambhwani et al. (2021) demonstrate that blockchain hashrate and cryptocurrency prices are cointegrated with mining capacity. By building upon these studies, our paper extends the analysis to investigate the impact of blockchain's aggregate mining power on the market quality provided by cryptocurrency trading platforms.[1]

The second strand of literature focuses on examining the market quality provided by cryptocurrency trading platforms. In terms of liquidity, Brauneis et al. (2021) analyze trading and quote data of Bitcoin and Ether to compare the accuracy of different low-frequency liquidity measures. Barbon and Ranaldo (2022) compute and compare transaction costs between centralized platforms (e.g., Binance) and decentralized platforms (e.g., Uniswap), finding that transaction costs tend to be lower on centralized platforms. Additionally, several studies investigate arbitrage opportunities and price discrepancies among multiple crypto-trading platforms. Makarov and Schoar (2020) construct an arbitrage index using intraday trading data from a larger sample of 13 crypto trading platforms and aim to explain the drivers of price discrepancies. Meanwhile, Crépellière et al. (2023) observe a decrease in arbitrage opportunities in the crypto market after 2018. Finally, Hautsch et al. (2018) present a theoretical study showing that arbitrage boundaries increase with expected latency and latency uncertainty, a finding that our empirical results confirm.

The implications of our findings carry significant policy implications, particularly with regard to the market design of cryptocurrency trading. We find that market quality provided by crypto trading venues improves with the aggregate blockchain computing power supplied by the miners. However, it is important to note that this aspect is beyond the control of both the trading service providers and the

[1] Several papers (e.g., Cong et al. (2021) and Sockin and Xiong (2023)) focus on the production side of the cryptocurrency and show that the evolution of cryptocurrency prices is linked to the marginal cost of production.

regulators. Instances of decreased hashrate, such as those resulting from escalating electricity costs or power interruptions, pose a threat to the smooth operation of trading venues. In light of these results, it is imperative for stakeholders to consider this distinctive characteristic of blockchain technology when designing an optimal market framework for crypto assets.

The subsequent sections of the paper are structured as follows. Section 2 delves into blockchain mining and provides a detailed explanation of hashrate. Section 3 outlines the data sample used in our analysis and elaborates on the construction of market quality measures. Section 4 presents and discusses the empirical results obtained from our analysis. Finally, Section 5 serves as the conclusion, summarizing the key findings and implications of our study.

2 Proof of Work and hashrate

Blockchain is a decentralized technology that serves as a shared and immutable ledger for recording transactions and tracking assets within a network. It operates as a distributed database, where multiple nodes in a computer network maintain and validate the ledger collectively. Functioning as a database, blockchain stores information electronically in a digital format. Transactions and data are grouped together in blocks, with each block containing a cryptographic hash of the preceding block, a timestamp indicating the block's creation time, and the actual transaction data. When a new block is created, it utilizes a hash function, which is a mathematical algorithm that processes data of any size and generates a fixed-length output known as a hash. This process involves encrypting the previous block's information and combining it with the current block's data and timestamp. The resulting hash serves as a unique identifier for that particular block and ensures the integrity and security of the blockchain.

In a blockchain system like Bitcoin, where there is no central authority to ensure the integrity of the database, validation and control of the information are carried out collectively by the network's nodes. The consensus mechanism used in the Bitcoin blockchain is called Proof-of-Work (PoW). To send a block for validation in the network, a user must first find a valid solution by repeatedly hashing modified data until a specific condition is met. This process, commonly known as "mining," requires computational power and electricity, which act as the user's stake in the network. Once a valid solution is found, the user can submit the block to the network for validation by other users.

Under the Proof-of-Work algorithm, users are incentivized to invest computational power and electricity in the form of mining to earn block rewards. The absence of rewards for unvalidated blocks, combined with the costs associated with electricity consumption, discourages users from engaging in malicious activities within the network. This mechanism helps maintain the security and integrity of the blockchain by ensuring that participants have a vested interest in following the rules and contributing to the network's consensus.

The speed at which new blocks are validated in the blockchain is influenced by two main factors: the difficulty of the computational problem and the overall mining capacity of the network. The difficulty of solving the computational problem is a crucial aspect of the blockchain's protocol. It determines the level of computational effort required to find a valid solution. The difficulty is adjusted dynamically to ensure that the average time to validate a new block remains relatively constant. In the case of Bitcoin, the target is to add one block to the blockchain approximately every ten minutes. If blocks are validated faster than this target rate, indicating an increase in mining capacity, the difficulty is automatically adjusted to become more challenging. On the other hand, if blocks are validated slower than the target rate, indicating a decrease in mining capacity, the difficulty is adjusted to become less challenging. This dynamic adjustment helps maintain a stable rate of block validation over time. The overall mining capacity of the blockchain network also plays a significant role in the validation speed. The more computational power dedicated to mining, the higher the chances of finding a valid solution within a shorter time. Insufficient mining capacity, on the other hand, can result in slower block validation times as there are fewer hash guesses completed by the network within a given period.

Moreover, the aggregate computing power of a blockchain network plays a crucial role in determining its security. A higher mining capacity generally leads to a more secure and robust network. In a healthy and well-functioning blockchain network with a distributed mining capacity, it becomes extremely difficult for any single entity or group to gain majority control. The decentralized nature of blockchain, where mining power is distributed across multiple nodes, helps ensure the security and integrity of the network. The more dispersed the mining capacity is among various nodes, the more resilient the network becomes against malicious attacks. For example, if a single entity or a group of colluding entities amasses a majority of the mining power, they can potentially execute a 51% attack. By controlling the majority of the mining power, they can manipulate the consensus mechanism and undermine the immutability and integrity of the blockchain. This is why a high level of mining capacity and a well-distributed distribution of mining power are crucial to maintain the security of a blockchain network.

Hashrate is a common measure used to quantify the computing power of a blockchain network, specifically in the context of mining. Hashrate represents the number of cryptographic hash calculations that a mining device or network can perform per second. The hashrate of a mining device is dependent on its hardware specifications and capabilities. Different types of hardware, such as CPUs (Central Processing Units), GPUs (Graphics Processing Units), and ASICs (Application-Specific Integrated Circuits), have varying levels of computational power and, consequently, different hashrates. A typical high-performance CPU can achieve a hashrate of around 20,000 hashes per second (H/s). GPUs, which are commonly used for mining, can achieve hashrates in the range of 0.4 Gigahashes per second (GH/s). ASICs, which are specialized mining devices designed specifically for mining cryptocurrencies, can achieve significantly higher hashrates, reaching around eight Terahashes per second (TH/s).

3 Data and variable construction

In our analysis, we utilize data from two primary sources. The first source is Kaiko, a well-established crypto data vendor that specializes in providing comprehensive cryptocurrency market data. Kaiko's data is widely used in empirical studies within the field.[2] We specifically obtain historical intraday order book and trading data for three major cryptocurrencies: Bitcoin, Ether, and Litecoin, all traded against the U.S. dollar. The data covers the period from January to June 2021.

To ensure the reliability and consistency of our data, we specifically focus on three major crypto trading platforms: Coinbase, Kraken, and FTX. These platforms are known for their substantial trading volumes and active user bases. By selecting these platforms, we aim to minimize any potential issues related to false or fabricated trading volumes, which have been a concern in the cryptocurrency market. In fact, according to a report by Hougan et al. (2019), only a limited number of platforms, including the ones in our sample, were identified as having "real volume" and maintaining high standards of trading transparency and integrity.

For the order book data, we get the best bid and ask price at a twice per minute frequency on each platform. For every minute and trading platform, we compute the volume-weighted bid and ask price to form minute-level observations. Moreover, we have the minute-level price and trading information, including last price and trading volume.

We supplement our analysis with data from the second data source, Coin Metrics, which provides us with daily measurements of the Bitcoin blockchain's hashrate. The hashrate serves as an indirect measure of the aggregate computing capacity of the blockchain network. It is estimated based on the number of blocks mined during a given day and the mining difficulty.

[2]For example, see Biais et al. (2023); Makarov and Schoar (2020); Bhambhwani et al. (2021); Barbon and Ranaldo (2022); Crépellière et al. (2023).

3.1 Market quality measures

Our objective is to analyze the relationship between market quality and Bitcoin mining capacity. To achieve this, we collect intraday data on cryptocurrency trading and quote activity. The data we gather is at a minute-level frequency and is used to compute various market efficiency and liquidity measures. However, since the mining hashrate is reported on a daily basis, we aggregate the minute-level data to a daily frequency for each individual crypto platform. This ensures that our data aligns with the frequency of the Bitcoin mining hash rates. Additionally, we calculate the average values across the three crypto platforms, except for the arbitrage indexes, which are computed using data from multiple platforms. This approach allows us to examine the relationship between market quality and mining capacity using consistent daily-level data.

For each crypto platform j and cryptocurrency i, we utilize minute-level data (denoted by subscript τ) to estimate daily market quality measures (denoted by subscript t). The specific methods used for estimation are described below, and we suppress the subscripts i and j in the formulas. To facilitate easier interpretation and comparison with hash rates, we scale certain variables using a multiplier. Finally, the daily market-wide measures for each cryptocurrency are obtained by calculating the average across the three crypto platforms.

- Return (r)
  Return is the natural logarithmic difference between the beginning and closing quote midpoint, which is the average of the best bid and ask prices $price_t^{mid} = (price_t^{ask} + price_t^{bid})/2$

$$r_t = log(price_t^{mid}) - log(price_{t-1}^{mid})$$

- Volatility (σ)
  Return volatility is measured by the realized volatility, which is the squared root of the sum of the intraday squared returns

$$\sigma_t = \sqrt{\sum_{\tau} r_\tau^2}$$

- Quoted spread (QS)
  The percentage quoted spread is the difference between the best ask price ($price^{ask}$) and the best bid price ($price^{bid}$) of each order book snapshot, divided by the quote midpoint ($price^{mid}$). The daily quoted spread is the simple average of the intraday measure. We scale this measure by 1000

$$QS_\tau = \frac{price_\tau^{ask} - price_\tau^{bid}}{price_\tau^{mid}}$$
$$QS_t = \overline{QS_\tau} \times 1000$$

- Effective spread (ES)
  The effective spread is calculated as follow. The daily effective spread is the simple average of the intraday measure. We scale the measure by 1,000

$$ES_\tau = \frac{2 \times |price_\tau^{trade} - price_\tau^{mid}|}{price_\tau^{mid}}$$
$$ES_t = \overline{ES_\tau} \times 1000$$

  where $price_\tau^{trade}$ is the transaction price recorded during the same minute.

- Price impact (PI)
  We first determine the trading indicator (D=+1 for buyer-initiated trades and D=-1 for seller-initiated trades) applying the Lee and Ready (1991) algorithm. Then we compute the percentage

change in the quoted mid price after taking into account the trade direction. The daily price impact is the simple average of the intraday measure. We scale the measure by 1,000

$$PI_\tau = D_\tau \times \frac{Price^{mid}_{\tau+1} - Price^{mid}_\tau}{Price^{mid}_\tau}$$
$$PI_t = \overline{PI_\tau} \times 1000$$

- Kyle's Lambda (λ)
  Kyle (1985)'s Lambda measures the cost, in terms of price movement, of taking liquidity and is an inverse measure of liquidity. To compute the daily Kyle's Lambda, we estimate the OLS coefficient λ using the daily intraday observations. We scale the measure by 10,000

$$r_\tau = c + \lambda D_\tau log(volume_\tau \times price^{trade}_\tau) + \varepsilon_\tau$$
$$\lambda_t = \hat{\lambda} \times 10000$$

In addition to the these market quality measures, we also calculate two arbitrage indexes to evaluate market efficiency. The trade-base arbitrage index quantifies the potential for arbitrage by comparing the highest traded price with the lowest traded price observed across multiple trading venues during each minute. On the other hand, the quote-base arbitrage index assesses arbitrage opportunities by examining the highest bid price and the lowest ask price offered by the trading venues on a minute-to-minute basis. The construction of these two indexes is outlined below.

- Trade-based arbitrage index (Arb^{trade})
  We construct the trading price-based arbitrage index following Makarov and Schoar (2020). For every minute during our sample period, we take the highest price across all platforms and divide it by the minimum price. Then we average the arbitrage index at the daily level.

$$Arb^{trade}_\tau = max(price^{trade}_\tau)/min(price^{trade}_\tau)$$
$$Arb^{trade}_t = \overline{Arb^{trade}_\tau} \times 100$$

- Quote-based arbitrage index (Arb^{quote})
  In addition to the trade-base arbitrage index, we also construct a bid-ask spread-based arbitrage index. In an arbitrage-free market, the ask price should always be greater than the bid price for the same financial instrument across different trading venues. This condition ensures that arbitrageurs cannot exploit price discrepancies and make riskless profits. To capture potential arbitrage opportunities, we calculate an arbitrage index for each minute by dividing the highest bid price by the lowest ask price, but only when the bid price is greater than the ask price. If the bid price is not greater than the ask price, we assign a value of 1 to indicate the absence of arbitrage opportunity. Finally, we take the daily average of the arbitrage index to summarize the overall level of potential arbitrage in the market.

$$Arb^{quote}_\tau = max(max(price^{bid}_\tau)/min(price^{ask}_\tau), 1)$$
$$Arb^{quote}_t = \overline{Arb^{quote}_\tau} \times 100$$

By visualizing the trade-base and quote-base arbitrage indexes for these three cryptocurrencies, Figure 1 provides insights into the presence and variation of arbitrage opportunities within the market. First of all the time dynamic shows that the two indexes are highly correlated. The correlation between the two time series is 0.873 for Bitcoin, 0.808 for Ether, and 0.771 for Litecoin. Additionally, the figure highlights the periods in which arbitrage opportunities tend to rise. Specifically, these periods include January, the end of February to the beginning of March, mid-April, and the second half of May 2021. Both the trade-base and quote-base arbitrage indexes identify these time intervals as periods of increased arbitrage potential across all three cryptocurrencies.The observed similarities in the movement and identification of arbitrage opportunities by both indexes underscore their relevance and effectiveness in capturing market dynamics.

In comparison to the arbitrage index computed by Makarov and Schoar (2020) using a larger sample of 13 crypto trading platforms, our arbitrage indexes (before scaling by 100) exhibit a smaller scale. This difference in scale may arise due to several factors, including the sample size and sample period. It is worth noting that Makarov and Schoar (2020) conducted their analysis during a different time period (2017-2018) which predates our sample period. Furthermore, the study by Crépellière et al. (2023) suggests that the arbitrage opportunities in the crypto market have diminished after 2018. This finding aligns with the notion that the crypto market has undergone significant changes and maturation over time. Therefore, the observed differences in the scale of arbitrage indexes between our study and Makarov and Schoar (2020) may reflect these evolving market dynamics.

Table 1. Summary statistics

This table reports summary statistics of blockchain aggregate hashrate (Panel A) and market quality measures (Panel B). The sample period is January to June 2021. The construction of the measures is described in Section 3.1.

Panel A: Hashrate

	N	mean	std
Hashrate	180	1.5081×10^8	2.1741×10^7

Panel B: Market quality

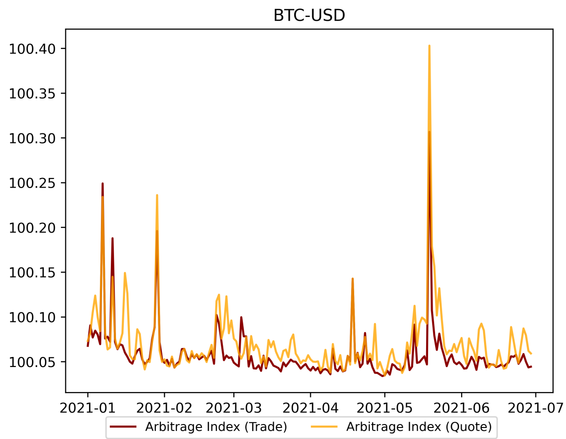
	N	mean	std	N	mean	std
	Return			Volatility		
btc-usd	180	0.0008	0.0493	180	0.0538	0.0255
eth-usd	180	0.0047	0.0681	180	0.0677	0.0385
ltc-usd	180	-0.0003	0.0755	180	0.0794	0.0394
	Arbitrage Index (Trade)			Arbitrage Index (Quote)		
btc-usd	180	100.0582	0.0315	180	100.0708	0.0390
eth-usd	180	100.0740	0.0345	180	100.0768	0.0451
ltc-usd	180	100.1599	0.0811	180	100.0648	0.0625
	Quoted Spread			Effective Spread		
btc-usd	180	0.0811	0.0683	180	1.3995	0.7615
eth-usd	180	0.1748	0.1172	180	1.7556	0.9819
ltc-usd	180	0.7478	0.4349	180	2.0880	1.0287
	Price Impact			Kyle		
btc-usd	180	0.1502	0.1165	180	0.6836	0.3081
eth-usd	180	0.1947	0.1725	180	0.8961	0.4336
ltc-usd	180	0.1324	0.1854	180	1.4184	0.7063

Table 1 presents the summary statistics for the blockchain hashrate and the market quality measures discussed in this section. By examining the sample means of these measures across the three cryptocurrencies, we observe that Bitcoin generally exhibits more favorable market trading conditions compared to Ether and Litecoin.

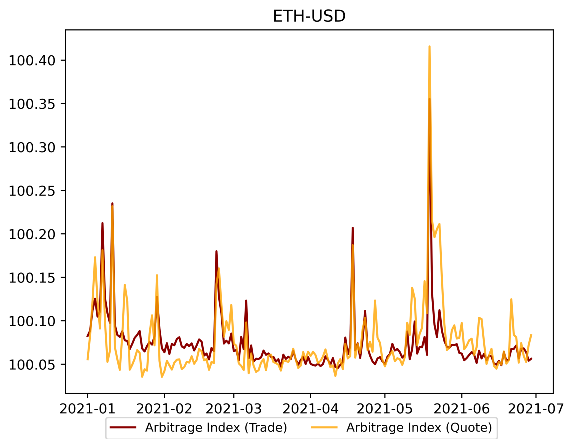
Figure 1. Arbitrage Indexes

This figure plots the trade-base arbitrage index and the quote-base arbitrage index for Bitcoin (Panel A), Ether (Panel B), and Litecoin (Panel C). The sample period is from January to June 2021. The construction of the arbitrage indexes is described in Section 3.1.

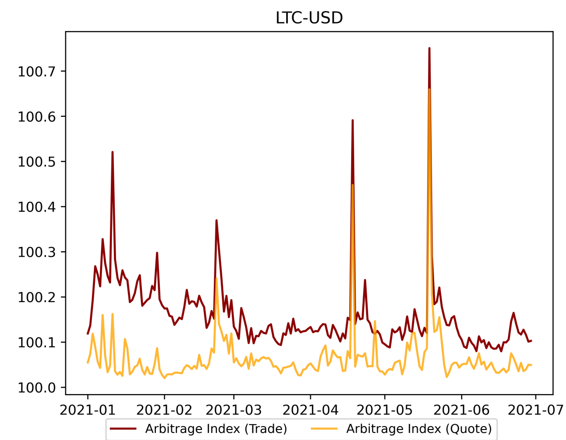
Panel A: Bitcoin



Panel B: Ether



Panel C: Litecoin



4 Hashrate and market quality

To analyze the relationship between blockchain mining capacity and the market quality provided by the crypto trading platforms, we run the following cryptocurrency-day level panel regressions as specified in Equation (1).

$$MarketQuality_{i,t} = \beta_1 norm(HashRate)_t + \alpha_i + \varepsilon_{i,t} \tag{1}$$

$MarketQuality_{i,t}$ represents the market quality measure of interest for cryptocurrency i on day t. $HashRate_t$ denotes the blockchain mining capacity measured by the hashrate on day t. We include cryptocurrency fixed effects as α_i to account for the differences across the instruments.

In addition to the previous panel regression analysis, we also perform a similar regression with one-day lagged hashrate to examine the potential impact of blockchain mining capacity on the market quality of the following day. This allows us to explore whether changes in mining capacity have a delayed effect on market quality. The model specification is as follows:

$$MarketQuality_{i,t} = \beta_1 norm(HashRate)_{t-1} + \alpha_i + \varepsilon_{i,t} \tag{2}$$

In order to account for potential correlation within each cryptocurrency, we cluster the standard errors at the cryptocurrency level in all our regression models. Clustering the standard errors allows us to address any potential heteroscedasticity or correlation within the observations belonging to the same cryptocurrency. By clustering at the cryptocurrency level, we ensure that our standard errors are robust and properly account for the within-cryptocurrency correlation structure in our data.

Table 2 presents the estimated results for the contemporaneous and lagged regressions, where the dependent variables are various market quality measures. Panel A focuses on the price discrepancy measured by the arbitrage indexes. The results indicate that the contemporaneous relationship between the blockchain hashrate and the arbitrage indexes is not statistically significant in Columns (1) and (3). However, the lagged coefficients in Columns (2) and (4) are negative and statistically significant at the 90% and 95% confidence levels, respectively. These findings suggest that a decrease in the blockchain's aggregate computing power is associated with a significant increase in price discrepancy and potential arbitrage opportunities across different crypto-trading platforms in the following day.

The empirical results obtained in our study align with the theoretical implications put forward by Hautsch et al. (2018). Their theoretical model highlights the role of the validation process in the blockchain-based settlement cycle and its impact on the limits to arbitrage across multiple trading platforms. According to their model, latency in the validation process, which is influenced by factors such as hashrate and mining difficulty, translates to settlement latency. This latency and the uncertainty in settlement latency expose traders to potential adverse price movements and hinders their ability to exploit price differences across trading venues through arbitrage. Specifically, Hautsch et al. (2018) find that cryptocurrency price discrepancies increase with the expected settlement latency. As a decrease in mining power slows down the validation process, leading to longer settlement latencies, our empirical findings are consistent with their theoretical predictions.

In Panel B of Table 2, we examine the relationship between the blockchain's aggregate computational power and liquidity measures, specifically the quoted bid-ask spread and effective spread. The results show that the hashrate does not have a statistically significant relationship with these spread-based measures. This implies that changes in mining capacity do not have a direct impact on the level of liquidity as measured by the bid-ask spreads.

Moving to Panel C, we investigate the relationship between the blockchain hashrate and price impact, which measures the extent to which transactions impact asset prices. In the contemporaneous analysis, the coefficient of the hashrate on price impact is negative but not statistically significant. However, when considering the lagged hashrate, we observe a negative and statistically significant relationship, suggesting that a decrease in mining power is associated with larger price movements caused by transactions.

Table 2. Market quality and hashrate

This table reports the panel regression results. The dependent variables are, in Panel A the trade-base arbitrage index and the quote-base arbitrage index, in Panel B the quoted spread and the effective spread, and in Panel C price impact and Kyle (1985)'s Lambda. These measures are computed according to the description in Section 3.1. The independent variable is the actual blockchain hashrate. We also standardize the hashrate. We run the regression for both the contemporaneous hashrate and lagged hashrate separately. Our sample covers three cryptocurrencies (bitcoin, ether, and litecoin) traded on three crypto trading platforms (Coinbase, FTX, and Kraken) from January to June 2021. We include cryptocurrency fixed effects. The standard errors are clustered by cryptocurrency and are reported in parenthesis. *Note:* *p<0.1; **p<0.05; ***p<0.01

Panel A: Arbitrage index

	Arbitrage Index (Trade)		Arbitrage Index (Quote)	
	(1)	(2)	(3)	(4)
$HashRate_t$	0.001		-0.001	
	(0.001)		(0.002)	
$HashRate_{t-1}$		-0.007*		-0.009**
		(0.002)		(0.001)
Crypto FE	Yes	Yes	Yes	Yes
Clustering	Crypto	Crypto	Crypto	Crypto
Observations	540	540	540	540
R^2	0.407	0.411	0.010	0.020

Panel B: Spreads

	Quoted Spread		Effective Spread	
	(1)	(2)	(3)	(4)
$HashRate_t$	0.021		-0.142	
	(0.014)		(0.056)	
$HashRate_{t-1}$		0.011		-0.158
		(0.011)		(0.065)
Crypto FE	Yes	Yes	Yes	Yes
Clustering	Crypto	Crypto	Crypto	Crypto
Observations	540	540	540	540
R^2	0.559	0.558	0.091	0.092

Panel C: Price impact

	Price Impact		Kyle	
	(1)	(2)	(3)	(4)
$HashRate_t$	-0.000		-0.082**	
	(0.004)		(0.014)	
$HashRate_{t-1}$		-0.011***		-0.092**
		(0.000)		(0.011)
Crypto FE	Yes	Yes	Yes	Yes
Clustering	Crypto	Crypto	Crypto	Crypto
Observations	540	540	540	540
R^2	0.026	0.027	0.275	0.276

Furthermore, both the contemporaneous and lagged coefficients for Kyle (1985)'s Lambda are negative and highly significant. Kyle (1985)'s Lambda captures the price impact of trading volume, reflecting the adverse effect of liquidity on transaction costs. These results support the notion that liquidity deteriorates and transactions have a more substantial impact on prices when the blockchain's aggregate computational power decreases.

Overall, based on our analysis, there is a positive association between market quality and blockchain computational power. Specifically, a decrease in the blockchain's aggregate computational power, as measured by the hashrate, is associated with a deterioration in market quality. This is evident from the increased arbitrage opportunities and the worsened liquidity observed in the cryptocurrency market.

4.1 Abnormal mining power

In our analysis, we also examine the unexpected change in blockchain hashrate to better understand its impact on the cryptocurrency trading market. Following Makarov and Schoar (2020)'s measure of buying pressure, which is the difference between the actual bitcoin price and the smoothed bitcoin price, we construct a measure called the abnormal hashrate ($abHashRate$). This measure represents the difference between the realized hashrate and the smoothed hashrate. To estimate the daily smoothed hashrate, we employ the filtering technique proposed by Hamilton (2018).[3] More specifically, we estimate an autoregressive model with four lags for the hashrate, using the previous 90 days' hashrate data.[4] Based on the regression results, we predict the hashrate for the following day (i.e., $t + 1$) as the smoothed hashrate. Finally, the abnormal hashrate is computed as the difference between the actual hashrate and the smoothed hashrate. The estimation is formulated bellow.

$$HashRate_t = c + \sum_{\tau=1}^{4} \beta_\tau HashRate_{t-\tau} + \varepsilon_t \tag{3}$$

$$abHashRate_{t+1} = HashRate_{t+1} - \widehat{HashRate}_{t+1} \tag{4}$$

By focusing on the unexpected changes in hashrate, we aim to capture the unforeseen fluctuations in computational power and assess their effects on various features of the blockchain. This measure allows us to analyze how sudden drops in mining capacity impact the cryptocurrency trading market.

Figure 2 plots the time series of the realized hashrate (blue line) and the smoothed hashrate (orange line) in Panel A. Panel B plots the time series of abnormal hashrate.

We standardize the abnormal hashrate to ensure that the variable is on a comparable scale. We then re-estimate the panel regression models and present the results in Table 3. In Panel A, we examine the estimated coefficients for cryptocurrency return and volatility. Consistent with the findings of Bhambhwani et al. (2021), our results show a positive association between blockchain mining power and cryptocurrency returns. This can be attributed to factors such as the speed of validation, blockchain security, and transaction costs, which are influenced by the mining power. Furthermore, our analysis reveals a statistically significant negative relationship between both the contemporaneous and lagged abnormal hashrate and cryptocurrency return volatility. In other words, a decrease in blockchain mining power is accompanied by an increase in the volatility of cryptocurrency returns.

In Panel B of Table 3, we examine the estimated coefficients for regressing the arbitrage indexes on the abnormal hashrate. While we do not find significant results for the trade price-based arbitrage index, our findings reveal important insights for the bid-ask spread-based arbitrage index.

In the contemporaneous regression using the bid-ask spread-based arbitrage index, we observe a statistically significant negative coefficient of -0.001, indicating that a decrease in the abnormal hashrate

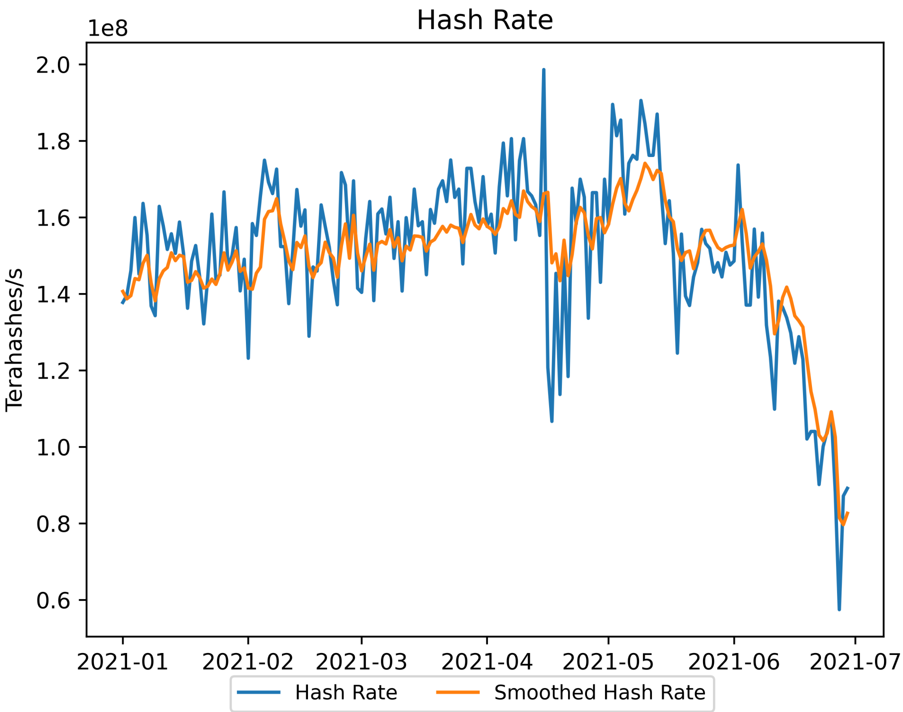
[3] Makarov and Schoar (2020) use the Hodrick-Prescott (Hodrick and Prescott (1997)) filter for unexpected buying pressure, but we use Hamilton (2018) filter to avoid the drawbacks pointed out in this paper.

[4] Results are consistent with a 30-day or 180-day estimation window.

Figure 2. Hashrate and abnormal hashrate

This figure plots the actual blockchain aggregate hashrate and the Hamilton (2018) filtered smoothed hashrate in Panel A. In Panel B, this figures plots the abnormal hashrate, which is the difference between the actual hashrate and smoothed hashrate. The sample period is from January to June 2021.

Panel A



Panel B

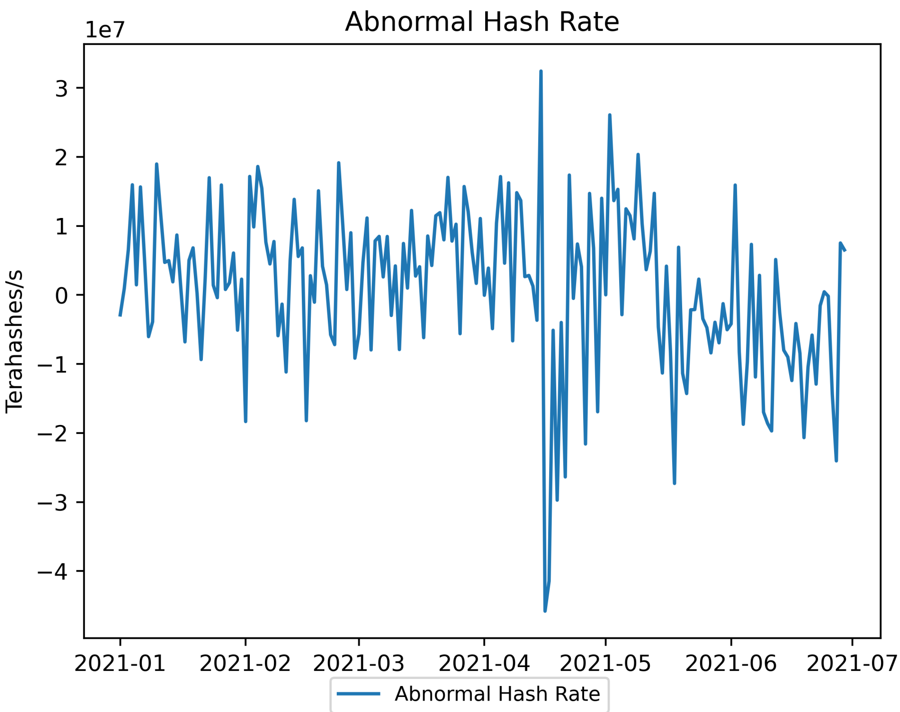


Table 3. Market quality and abnormal hashrate

This table reports the panel regression results. The dependent variables are, in Panel A, cryptocurrency return and return volatility, in Panel B the trade-base arbitrage index and the quote-base arbitrage index, in Panel C in the quoted spread and the effective spread, and in Panel D price impact and Kyle (1985)'s Lambda. These measures are computed according to the description in Section 3.1. The independent variable is the abnormal blockchain hashrate, which is the difference between the actual hashrate and the smoothed hashrate based on Hamilton (2018). We also standardize the abnormal hashrate. We run the regression for both the contemporaneous abnormal hashrate and lagged abnormal hashrate separately. Our sample covers three cryptocurrencies (bitcoin, ether, and litecoin) traded on three crypto trading platforms (Coinbase, FTX, and Kraken) from January to June 2021. We include cryptocurrency fixed effects. The standard errors are clustered by cryptocurrency and are reported in parenthesis. *Note:* *p<0.1; **p<0.05; ***p<0.01

Panel A: Return and volatility

	Return		Volatility	
	(1)	(2)	(3)	(4)
abHashRate_t	0.004*		-0.002**	
	(0.001)		(0.000)	
abHashRate_{t-1}		0.007**		-0.003***
		(0.001)		(0.000)
Crypto FE	Yes	Yes	Yes	Yes
Clustering	Crypto	Crypto	Crypto	Crypto
Observations	540	540	540	540
R^2	0.008	0.022	0.086	0.093

Panel B: Arbitrage index

	Arbitrage Index (Trade)		Arbitrage Index (Quote)	
	(1)	(2)	(3)	(4)
abHashRate_t	0.002		-0.001**	
	(0.001)		(0.000)	
abHashRate_{t-1}		-0.004		-0.007*
		(0.001)		(0.002)
Crypto FE	Yes	Yes	Yes	Yes
Clustering	Crypto	Crypto	Crypto	Crypto
Observations	540	540	540	540
R^2	0.408	0.412	0.010	0.045

Panel C: Spread

	Quoted Spread		Effective Spread	
	(1)	(2)	(3)	(4)
abHashRate_t	0.019		-0.047**	
	(0.010)		(0.008)	
abHashRate_{t-1}		0.015		-0.051***
		(0.010)		(0.003)
Crypto FE	Yes	Yes	Yes	Yes
Clustering	Crypto	Crypto	Crypto	Crypto
Observations	540	540	540	540
R^2	0.562	0.561	0.088	0.089

Panel D: Price impact

	Price Impact		Kyle	
	(1)	(2)	(3)	(4)
abHashRate_t	-0.003		-0.019*	
	(0.003)		(0.005)	
abHashRate_{t-1}		-0.009		-0.021***
		(0.003)		(0.002)
Crypto FE	Yes	Yes	Yes	Yes
Clustering	Crypto	Crypto	Crypto	Crypto
Observations	540	540	540	540
R^2	0.026	0.032	0.271	0.271

is associated with an increase in price discrepancy and potential arbitrage opportunities across crypto-trading platforms. This result aligns with our intuition that a drop in blockchain computing power leads to a greater discrepancy in cryptocurrency prices. Moreover, when we consider the model with the lagged abnormal hashrate, we find a negative and statistically significant coefficient at the 90% confidence level. This further confirms the relationship between unexpected changes in mining power and cryptocurrency price discrepancies.

In Panel C of Table 3, we present the analysis results for the quoted spread and effective spread. Consistent with the findings for the realized hashrate, we do not observe a significant relationship between the abnormal hashrate and the quoted spread. The bid-ask spread, which represents the difference between the best bid and ask prices, does not appear to be affected by changes in blockchain computing power. However, when considering the effective spread, we find a negative and statistically significant association with both the contemporaneous abnormal hashrate (significant with p-value < 0.05) and the lagged abnormal hashrate (significant with p-value < 0.01). This suggests that an unexpected decline in mining power is associated with an increase in the distance between the transaction price and the bid-ask midpoint, indicating higher transaction costs and a deterioration in liquidity.

In Panel D of Table 3, we present the results of the panel regression estimating the price movement after each trade, using price impact as the dependent variable. We find that the contemporaneous abnormal hashrate and lagged abnormal hashrate are both negatively related to price impact, although the coefficients are not statistically significant. However, when we consider the transaction size using Kyle (1985)'s Lambda measure, we observe a significant relationship between the abnormal hashrate and price impact. In Column (3), the estimated coefficient of $abHashRate_t$ is -0.019, marginally significant at the p-value <0.1 level. Similarly, in Column (4), the coefficient of lagged abnormal hashrate is -0.021, significant at the p-value <0.01 level. These results suggest that an unexpected crash in mining power by one standard deviation would increase the price impact by 0.021×10^{-4} in the following day, which is equivalent to a 2.1% increase relative to the sample average.

In summary, the results presented in Table 3 indicate that unexpected changes in the bitcoin blockchain's mining capacity have a significant impact on the market quality of cryptocurrency trading platforms. Specifically, an unexpected decrease in mining capacity leads to higher volatility, increased price discrepancy across platforms, and higher transaction costs. These findings align with the expectation that blockchain mining capacity affects the speed, cost, security, and functionality of transaction validation, which in turn influence the price efficiency and liquidity of cryptocurrency markets. Moreover, our results contribute to the existing literature on blockchain characteristics and their impact on cryptocurrency pricing, supporting the notion that blockchain features play a crucial role in shaping the dynamics of cryptocurrency markets (Easley et al. (2019); Bhambhwani et al. (2021); Datta and Hodor (2022); Pagnotta (2022)).

4.2 Robustness

In addition to conducting separate panel regression models for the contemporaneous and lagged hashrate, as described in Equations (1) and (2), we also explore the combined effects of these measures on market quality. To achieve this, we estimate the following model, utilizing the same variable definitions as before:

$$MarketQuality_{i,t} = \beta_1 norm(HashRate)_t + \beta_2 norm(HashRate)_{t-1} + \alpha_i + \varepsilon_{i,t} \tag{5}$$

By considering both the contemporaneous and lagged hashrate, we aim to gain a comprehensive understanding of how these two factors jointly influence market quality. The coefficient β_1 represents the impact of the current day's hashrate, while β_2 captures the effect of the previous day's hashrate on market quality. Additionally, the variable α_i accounts for the fixed effects specific to each cryptocurrency, ensuring the model captures their unique characteristics. The error term is denoted as $\varepsilon_{i,t}$ and is clustered by cryptocurrency.

Table 4 presents the estimation results, which exhibit minimal changes compared to Table 2. Notably, we observe statistically significant and negative coefficients (β_2) for several market quality measures. Specifically, return volatility, the quote-based arbitrage index, price impact, and Kyle's Lambda exhibit significant negative relationships with the previous day's hashrate (p-value< 0.1 for return volatility, the quote-based arbitrage index, and price impact, p-value < 0.05 for Kyle's Lambda). These findings confirm that a decrease in the previous day's hashrate has an adverse effect on the quality of cryptocurrency trading on the subsequent day.

Table 4. Realized hashrate

This table reports the panel regression results. The dependent variables are, in Panel A, cryptocurrency return, return volatility, the trade-base arbitrage index and the quote-base arbitrage index, in Panel B the quoted spread, the effective spread, price impact, and Kyle (1985)'s Lambda. These measures are computed according to the description in Section 3.1. The independent variable is the actual blockchain hashrate. We also standardize the hashrate. We run the regressions for both the contemporaneous hashrate and lagged hashrate separately. Our sample covers three cryptocurrencies (bitcoin, ether, and litecoin) traded on three crypto trading platforms (Coinbase, FTX, and Kraken) from January to June 2021. We include cryptocurrency fixed effects. The standard errors are clustered by cryptocurrency and are reported in parenthesis. *Note:* *p<0.1; **p<0.05; ***p<0.01

Panel A

	Return	Volatility	Arbitrage Index (Trade)	Arbitrage Index (Quote)
	(1)	(2)	(3)	(4)
HashRate_t	0.002	-0.000	0.011	0.010
	(0.003)	(0.001)	(0.004)	(0.005)
HashRate_{t-1}	0.007	-0.005*	-0.015	-0.016*
	(0.003)	(0.002)	(0.005)	(0.005)
Crypto FE	Yes	Yes	Yes	Yes
Clustering	Crypto	Crypto	Crypto	Crypto
Observations	540	540	540	540
R^2	0.006	0.089	0.415	0.026

Panel B

	Quoted Spread	Effective Spread	Price Impact	Kyle
	(1)	(2)	(3)	(4)
HashRate_t	0.026	-0.068	0.013	-0.039
	(0.012)	(0.041)	(0.007)	(0.019)
HashRate_{t-1}	-0.007	-0.111	-0.020*	-0.065**
	(0.004)	(0.058)	(0.005)	(0.014)
Crypto FE	Yes	Yes	Yes	Yes
Clustering	Crypto	Crypto	Crypto	Crypto
Observations	540	540	540	540
R^2	0.559	0.093	0.029	0.277

Furthermore, the re-estimation of Equation (2) with both the contemporaneous and lagged abnormal hashrate as independent variables confirms the findings reported in Table 3. The estimated coefficients of both the contemporaneous hashrate and the lagged hashrate are consistently negative and statistically significant for return volatility, effective spread, and Kyle's Lambda. This suggests that an unexpected decrease in the same-day's or the previous day's blockchain mining capacity has a significant impact on increasing volatility and trading costs (as measured by effective spread and Kyle's Lambda). Additionally, we observe a significant negative association between the lagged abnormal hashrate and the quote-based arbitrage index, as well as price impact.

Table 5. Abnormal hashrate

This table reports the panel regression results. The dependent variables are, in Panel A, cryptocurrency return, return volatility, the trade-base arbitrage index and the quote-base arbitrage index, in Panel B the quoted spread, the effective spread, price impact, and Kyle (1985)'s Lambda. These measures are computed according to the description in Section 3.1. The independent variable is the abnormal blockchain hashrate, which is the difference between the actual hashrate and the smoothed hashrate based on Hamilton (2018). We also standardize the abnormal hashrate. We run the regressions for both the contemporaneous abnormal hashrate and lagged abnormal hashrate separately. Our sample covers three cryptocurrencies (bitcoin, ether, and litecoin) traded on three crypto trading platforms (Coinbase, FTX, and Kraken) from January to June 2021. We include cryptocurrency fixed effects. The standard errors are clustered by cryptocurrency and are reported in parenthesis. *Note:* *p<0.1; **p<0.05; ***p<0.01

Panel A

	Return	Volatility	Arbitrage Index (Trade)	Arbitrage Index (Quote)
	(1)	(2)	(3)	(4)
abHashRate$_t$	0.003	-0.001**	0.002	0.000
	(0.001)	(0.000)	(0.001)	(0.001)
abHashRate$_{t-1}$	0.006**	-0.003***	-0.004	-0.007*
	(0.001)	(0.000)	(0.002)	(0.002)
Crypto FE	Yes	Yes	Yes	Yes
Clustering	Crypto	Crypto	Crypto	Crypto
Observations	540	540	540	540
R^2	0.025	0.095	0.414	0.045

Panel B

	Quoted Spread	Effective Spread	Price Impact	Kyle
	(1)	(2)	(3)	(4)
abHashRate$_t$	0.017	-0.039*	-0.001	-0.015*
	(0.008)	(0.009)	(0.002)	(0.005)
abHashRate$_{t-1}$	0.012	-0.044**	-0.009*	-0.019**
	(0.008)	(0.005)	(0.003)	(0.002)
Crypto FE	Yes	Yes	Yes	Yes
Clustering	Crypto	Crypto	Crypto	Crypto
Observations	540	540	540	540
R^2	0.564	0.092	0.032	0.272

5 Conclusion

With the surge in popularity of cryptocurrencies as a new financial instrument, concerns regarding the trading quality offered by cryptocurrency trading platforms have surfaced. Regulatory bodies like the U.S. SEC and the U.K. FCA have heightened their scrutiny of cryptocurrency trading, necessitating an investigation into the market quality provided by crypto trading platforms and the factors influencing their proper functioning.

In this study, we explore the relationship between blockchain's aggregate mining power and the market quality offered by crypto trading platforms. Analyzing historical intraday data of three cryptocurrencies traded on three platforms from January to June 2021, we calculate various market quality measures, including price discrepancy and liquidity. Through panel regression analysis, we observe that a decrease in blockchain's aggregate mining power results in wider cross-platform price discrepancies and increased arbitrage opportunities. Furthermore, we find that the liquidity of the crypto market deteriorates when the blockchain's aggregate mining power declines.

Additionally, we compute abnormal hashrate by capturing the difference between the actual daily hashrate and a smoothed hashrate, and repeat the regression analysis using abnormal hashrate as the independent variable. The results validate our previous findings, demonstrating a decline in market quality when the blockchain's aggregate mining power decreases. Specifically, both contemporaneous and one-lag abnormal hashrate exhibit a significant negative correlation with the quote-base arbitrage index, effective spread, and Kyle's Lambda.

Our study makes a valuable contribution to the academic literature as the first empirical examination of the relationship between blockchain mining and the crypto market trading environment. The findings also shed light on the market design of crypto trading, where trading settlement occurs on the blockchain and relies on the validation process beyond the control of trading providers. Nonetheless, we discover that the aggregate mining power can impact the trading quality offered by the platforms. Therefore, regulators and stakeholders should consider this unique feature of blockchain technology when evaluating the design of a fair and well-functioning market for crypto assets.

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