The Effect of DLT Settlement Latency on Market Liquidity

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Abstract

This paper investigates the causal relationship between settlement latency introduced specially by permissionless Distributed Ledger Technology (DLT) and market quality in the cryptocurrency domain. Utilizing the cryptocurrency market as a unique laboratory, we identify blockchain mining power as an instrumental variable for DLT settlement latency. Our analysis reveals that the settlement latency significantly lowers liquidity and increases transaction costs. In addition, through the Huang and Stoll (1997) spread decomposition, we document that such latency reduces the adverse selection costs and increases the inventory management costs faced by liquidity suppliers. Moreover, these effects are more pronounced in smaller trading venues and for the native cryptocurrency of the settlement blockchain. More broadly, this paper contributes novel evidence on the importance of settlement, and highlights the balance between decentralized, near-instantaneous settlement cycles offered by DLT and the potential adverse impacts on market quality.

Keywords: Cryptocurrency, DLT, Settlement, Liquidity

JEL classification: D47, G10, G14

1 Introduction

In the financial markets, settlement processes are fundamental to ensuring the secure and efficient exchange of assets. These processes encompass the physical transfer of securities from sellers to buyers, accompanied by the corresponding transfer of funds, marking the finalization of a transaction.[1] Traditionally overseen by trusted and regulated entities, such as central securities depositories (CSDs) and Central Counterparties (CCPs), the settlement process has generally involved minimal uncertainty and typically spans one to two business days following the trade execution.

However, despite recent endeavors to streamline settlement cycles, emerging technologies, notably Distributed Ledger Technologies (DLT) such as blockchain, present an alternative approach. DLT aims to facilitate near-instantaneous transactions and reduce dependence on intermediaries. Nevertheless, the integration of DLT in settlement processes introduces complexities.[2] The blockchain's inherent features, such as the overall mining capacity of the network, influence block validation speed, thereby affecting settlement latency and introducing uncertainty into the process. Notably, insufficient mining power in the network could empower malicious participants to fork the chain, potentially leading to settlement failures (Chiu and Koeppl (2019)). Consequently, DLT settlement, specially the permissionless blockchains[3], introduces non-negligible uncertainty into the traditionally secure settlement process, and such market frictions can affect the market quality offered by the trading venues.

[1] For instance, the Federal Reserve Bank of New York defines settlement as "*the final step in the transfer of ownership involving the physical exchange of securities or payment*", and the Bank for International Settlements (BIS)'s definition states that settlement is "*the completion of a transaction, wherein the seller transfers securities or financial instruments to the buyer and the buyer transfers money to the seller*."

[2] For example, see the discussion in Benos et al. (2017). For a comprehensive overview of crypto-trading market infrastructure, see Chen et al. (2023).

[3] A permissionless blockchain network is a system consisting of physically distributed computers, each running a copy of a shared ledger and adhering to the same software rules that allow all participants to "read, submit, and validate transactions" (Beck et al. (2018)). In contrast, permissioned blockchains generally do not involve stochastic validation times, as validators are pre-selected by a central authority or a consortium of entities. These validators often follow a predefined schedule or protocol for validating transactions, which can result in more predictable and consistent validation times.

In this paper, we identify the causal relationship between settlement processes and market quality, utilizing the cryptocurrency market as a unique laboratory and delving into the uncertainties linked to DLT settlement. Our investigation lies in analyzing how the confirmation time of the Bitcoin blockchain influences liquidity and trading costs. The primary finding indicates that the uncertainty stemming from DLT settlement latency deters investor participation, leading to a decline in liquidity. Furthermore, for those participants remaining active in cryptocurrency trading, there is a significant increase in transaction costs and larger price impacts.

Identification in such empirical investigations is generally confounded by various endogeneity issues. For example, factors, such as mining rewards and the price of Bitcoin, alongside with transaction fees, can influence the participation of miners and traders. Consequently, both market quality and block validation time are impacted (Easley et al. (2019)), and omitted variable issues arise. Furthermore, the sequencing of trading preceding settlement introduces reverse causality concerns, where the former may affect the latter process. To overcome these identification challenges, we utilize a plausible instrumental variable approach relying on an inherent and exogenous feature of the Bitcoin blockchain, specifically mining power. The blockchain operates on a consensus protocol defining how validators agree on the ledger's current state. In the context of the Bitcoin blockchain's Proof-of-Work (PoW) consensus protocol outlined by Nakamoto (2008), validators engage in a computationally intensive competition, continuously attempting to solve numerical puzzles by guessing hash function solutions. The aggregate computing or mining power of the blockchain plays a pivotal role in determining the time required to validate a new block—higher mining power enables faster computations, thereby shortening validation time. In other words, blockchain mining power plays an important role in DLT settlement latency (inclusion restriction). Importantly, *a priori*, mining power itself is unlikely to have a direct impact on cryptocurrency market quality (exclusion restriction). With these restrictions in place, we employ an instrumental variable (IV) estimation, leveraging the mining power-induced variation in DLT settlement latency. To the best of our knowledge, this is the first paper to empirically identify and test the causal effects of settlement latency on market quality.

For our empirical analysis, we employ a 2-Stage Least Squares (2SLS) approach using data spanning January to June 2021. In the first stage regression, the blockchain daily median confirmation time serves as the dependent variable, while the blockchain's aggregate hash rate acts as the independent variable. Subsequently, in the second stage, we conduct panel regressions using a sample of three cryptocurrencies (Bitcoin, Ether, and Litecoin) traded on three venues (Coinbase, FTX, and Kraken), and we include the fitted value of median confirmation time from the first stage as an independent variable. Our dependent variables encompass various measures of liquidity and trading costs, derived from intraday trading and order book records procured from the crypto data vendor Kaiko. To enhance the robustness of our analysis, we include controls for cryptocurrency return, volatility, and log trading volume. To control for the unobserved and heterogeneous characteristics among the cryptocurrencies and trading venues, we implement various fixed effect (FE) estimations—(1) pooled OLS, (2) cryptocurrency FEs and venue FEs, and (3) cryptocurrency-venue FEs. Further regarding our data, it is worth noting that our measure of settlement latency is the daily median confirmation time, and its standard deviation *underestimates* the actual block-by-block variation in confirmation time. While our sample standard deviation stands at approximately three minutes, Zhang et al. (2021) estimate the block-by-block measure to exceed eight minutes. Consequently, our estimation results are conservative, providing a cautious interpretation of the magnitude of the impacts of DLT settlement latency.

Our analysis first focuses on the impact of DLT settlement latency on cryptocurrency market liquidity. The hypothesis posits that prolonged confirmation times would decrease liquidity, as heightened uncertainty in settlement may dissuade traders from active participation. Utilizing the Kyle and Obizhaeva (2016) illiquidity measure as the dependent variable, a reliable liquidity measure in cryptocurrency markets according to Brauneis et al. (2021), our IV estimation reveals positive and statistically significant coefficients across all fixed-effect estimations. This result substantiates our hypothesis, showing a reduction in liquidity levels due to DLT settlement latency. Specifically, our findings highlight that a one-minute increase in settlement latency corresponds to a 0.009 basis point increase in the Kyle and Obizhaeva (2016) measure. This effect translates to a 2.62% increase relative to the average value, indicating a 7.82% decrease in liquidity for a one-standard deviation increase in settlement time compared to the sample average.

To offer a more comprehensive understanding of the effect of DLT settlement latency, we extend our analysis to additional liquidity dimensions, particularly transaction costs, measure by percentage effective spreads. Our results reveal positive and statistically significant coefficients on confirmation time, signifying a significant impact of DLT settlement latency on transaction costs. We show that a one-minute increase in DLT settlement latency results in an approximately 0.22 basis points upswing in the percentage effective spread. In relation to the average effective spread of 17.48 basis points, this number translates to a 1.26% increase. Alternatively, a one-standard deviation rise in settlement time leads to a 3.76% higher transaction costs.

Considering that a portion of transaction costs is associated with the price impact faced by traders executing large orders, the evidence of DLT settlement latency's adverse impact on liquidity and effective spread implies larger price impacts in cryptocurrency trading as settlement latency lengthens. This expectation is corroborated by the IV estimation results, where Kyle (1985)'s Lambda serves as the dependent variable. Our estimation results indicate that a one-minute increase in settlement time increases Kyle's Lambda by about 0.015 basis points. In comparison to the average value of about 1 basis points, this signifies a 1.5% increase, or alternatively, a one-standard deviation rise in settlement time corresponds to a 4.49% surge in price impact relative to the sample average.

Our findings thus far indicate that the uncertainty associated with DLT settlement latency adversely affects liquidity and elevates transaction costs in cryptocurrency trading. To gain deeper insights into how liquidity supply is impacted, we extend our analysis to the percentage quoted bid-ask spread. The estimated coefficients, characterized by negative values with varying significance interpretation under different fixed effect models. The pooled OLS estimate is significant at the 95% confidence level, crypto FE and venue FE estimation is not statically significant, and the crypto-venue FE estimation is marginally significant at the 90% confidence level. These estimates reveal that DLT settlement latency either reduces the quoted bid-ask spread or has no significant impact. These results on bid-ask spread seemingly disagrees with our earlier findings of reduced liquidity and increased transaction costs.

To further scrutinize the impact of settlement latency on liquidity supply and reconcile our findings, we follow the approach of Huang and Stoll (1997) and decompose the bid-ask spread into three components: adverse selection cost, inventory cost, and fixed costs. Focusing on adverse selection cost, we hypothesize that DLT settlement latency would hinder informed traders' participation, as the latency creates uncertainty in their execution of trading strategies. Indeed, we find that a one-minute increase in DLT settlement latency significantly reduces the weight of adverse selection cost by 1.2 percentage points, indicating that liquidity suppliers face less informed trading and are willing to post narrower bid-ask spreads with increased settlement latency. This aligns with the argument that DLT settlement uncertainty deters market participants, particularly informed traders, as also predicted by Hautsch et al. (2024)'s model. Turning to the second component, we expect an increase in inventory cost due to the deterioration in liquidity associated with longer DLT settlement latency, as liquidity suppliers face higher cost when off-loading their position. Our predictions are confirmed, with a one-minute increase in settlement latency elevating the weight of inventory cost by 1.6 percentage points. Finally, the fixed component of the bid-ask spread shows no significant effect of DLT settlement latency. In agreement with our previous findings, the different impacts of DLT settlement latency on the costs face by liquidity supplier explain it's opposite impact the bid-ask spread and other liquidity measures.

We supplement our main finding by conduction subsample analysis, comparing the different trading venues and cryptocurrencies and exploring their cross-sectional differences. More specifically, we repeat our IV estimation for each trading venue and for each cryptocurrency to see whether the effect of DLT settlement persists. The analysis reveals that DLT settlement latency significantly impacts liquidity and trading costs across different cryptocurrency trading venues and cryptocurrencies. Moreover, comparing the three trading venues, the adverse effects are more pronounced in the smaller platforms (FTX and Kraken) than in the larger Coinbase. Similarly, when comparing cryptocurrencies, the impact is most significant for Bitcoin, the native coin of the settlement blockchain, followed by Litecoin, which shares Bitcoin's codebase, while Ether shows the smallest impact. These findings underscore the nuanced nature of DLT settlement latency's impact, with variations based on the size of the trading venue as well as the link between the cryptocurrency and the settlement blockchain.

Lastly, we conduct IV validation and robustness tests to substantial our results. First, we employ the augmented Durbin–Wu–Hausman test, as suggested by Davidson et al. (1993), to confirm the endogeneity of DLT settlement latency. This test involves including the residual of the first-stage regression, along with the endogenous and not fitted variable in the second-stage regression. A significant coefficient on the first-stage residual indicates that the dependent variable is correlated with unobserved variables influencing settlement latency, supporting the need for an instrument to address potential endogeneity concerns. The reported p-values of the tests across all tables are mostly statistically significant, providing evidence of endogeneity issues without identification strategies and support for our instrumental variable. Second, we iterate the fitted DLT settlement latency in the second stage regression with a dummy variable that indicates the observations with negative returns. The results show no differential impact of DLT settlement latency during negative return days compared to the overall sample period. These symmetric effects reinforce the robustness of our results, suggesting that our findings are not influenced by variations in market conditions, which could be affected by market raises and falls (Zhang et al. (2020)).

The implications of our findings carry significant policy implications, particularly with regard to the market design of cryptocurrency market infrastructure, including the post-trade settlement process. DLT promises to shorten the settlement cycle to minutes in a decentralized manner by removing intermediaries and relying on a network of miners to record transactions. Consequently, it introduces non-negligible uncertainty due to the stochastic nature of settlement time and to the lack of regulated and trusting entities overseeing the settlement cycle. Such market friction leads to significant adverse impacts on market liquidity and trading costs, undermining the overall market quality. Policymakers and market operators should take into account the inherent features of the blockchain technology and the trade-off between near instant settlement and market quality, when evaluating DLT settlement.

Related literature

Notwithstanding the importance of settlement, there is limited study on its effect on market quality, due to the difficulty in identification. In a theoretical model, Hautsch et al. (2024) predict that arbitrage boundaries in cryptocurrency trading increase with expected settlement latency and latency uncertainty, affecting market efficiency and price formation. While our paper doesn't directly test this hypothesis, our findings align with the model's predictions. In a related empirical analysis, Scharnowski and Shi (2021) investigate the reduction in blockchain mining power caused by an electricity blackout, highlighting subsequent deterioration in liquidity. Our paper employs blockchain mining power as an instrument for DLT settlement latency and identifies settlement latency as an explanation for their observed liquidity deterioration.

Our research also bridges and contributes to two strands of existing literature, by connecting the inherent features of blockchain to crypto market quality. The first strand is the broader literature exploring how blockchain characteristics, 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 with cryptocurrency returns. However, Bhambhwani et al. (2021) demonstrate that blockchain hashrate and cryptocurrency prices are cointegrated with mining capacity.

Furthermore, our paper relates to the second strand of literature that investigates 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.

While we focus on settlement latency, the existing literature has provided evidence on other types of latency in the trading process. Hasbrouck and Saar (2013) investigates execution latency, which is the time taken between order submission and execution, highlight its crucial role for high-frequency traders. Holden et al. (2023) takes into account the time need for messages to be sent from exchange to the securities information processor (SIP) in the U.S. market to enhance the matching of trades and quotes.

The subsequent sections of the paper are structured as follows. Section 2 delves into a brief overview of DLT settlement and blockchain mining. Section 3 outlines the data sample used in our analysis and elaborates on the construction of liquidity measures. Section 4 presents our identification strategy and discusses the empirical results. Finally, Section 5 serves as the conclusion, summarizing the key findings and implications of our study.

2 Overview of DLT settlement and blockchain mining

Settlement, the conclusive stage of the trading process, marks the legal exchange of ownership in financial markets. Traditional settlement procedures involve the transfer of securities or financial instruments by sellers to buyers, as well as the transfer of money from buyers to sellers. Typically overseen by central securities depositories (CSDs), this process historically took several business days but has seen recent efforts to reduce settlement cycles. For example, in February 2023, the U.S. Securities and Exchange Commission (SEC) adopted rule amendments to shorten the standard settlement cycle from two business days after the trade date ("T+2") to one business day after the trade date ("T+1") by May 2024.[4] With the trusted and regulated entities guaranteeing the settlement process and with central clearing provides the opportunity for an immediate continuation of trading on a newly acquired position, the settlement process involves close to none uncertainty, and its latency is normally negligible for most market participants.

Distributed ledger technologies (DLT), exemplified by blockchain, present an alternative by offering near-instantaneous settlement and reducing dependence on interme-

[4] For more information, see https://www.sec.gov/investment/settlement-cycle-small-entity-compliance-guide-15c6-1-15c6-2-204-2

diaries. Unlike traditional systems where trusted entities ensure ownership transfer integrity, DLT relies on decentralization and consensus mechanisms. More specifically, DLT leverages blockchain's digital, decentralized ledger to expedite settlements. Transactions are grouped into blocks, linked through cryptographic hashes, and time-stamped. In a blockchain system like Bitcoin, consensus is maintained through Proof-of-Work (PoW), a mechanism where users, or miners, validate transactions by solving computationally intensive problems. Miners invest computational power and electricity, acting as a stake in the network. Once a solution is found, a block is submitted for validation, and the settlement of the transactions recorded in this block is completed.

The speed of DLT settlement is influenced by two main factors: the overall mining capacity of the network and the difficulty of the computational problem. The overall mining capacity of the blockchain network plays a crucial 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. Insufficient mining power in the network could also reduce the security of the blockchain, allowing malicious participants to fork the chain, potentially leading to settlement failures (Chiu and Koeppl (2019)). In addition, the difficulty of solving the computational problem 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.

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 leverage data from three primary sources. The first one is Kaiko, a crypto data vendor providing comprehensive cryptocurrency market data, which is utilized in other empirical studies within the field.[5] Specifically, we acquire historical intraday order book and trading data for three major cryptocurrencies: Bitcoin, Ether, and Litecoin, all of which are traded against the U.S. dollar. The data encompasses the period from January to June 2021. To ensure the reliability and consistency of our data, our focus is specifically directed towards three major cryptocurrency trading venues: Coinbase, Kraken, and FTX. These venues have substantial trading volumes and active user bases. The selection of these platforms aims to mitigate potential issues related to false or fabricated trading volumes, a concern prevalent in the cryptocurrency market. Notably, a report by Hougan et al. (2019) highlights that only a limited number of platforms, including those in our sample, are identified as having "real volume" and maintaining relatively high standards of trading transparency and integrity. In addition to their credibility, these platforms facilitate crypto-fiat transactions, such as trading Bitcoin using U.S. dollars, as opposed to platforms like

[5]See Biais et al. (2023); Makarov and Schoar (2020); Bhambhwani et al. (2021); Barbon and Ranaldo (2022); Crépellière et al. (2023) for examples of studies incorporating Kaiko's data.

Binance, which exclusively permit crypto-crypto or crypto-stablecoin transactions.

For the order book data, we capture the best bid and ask prices at a frequency of two observations per minute on each platform. Subsequently, for every minute and trading platform, we compute the volume-weighted bid and ask prices, forming minute-level observations. Additionally, our dataset includes minute-level information on prices and trading activity, encompassing details such as the last price and trading volume.

We supplement our analysis with data from 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. While the actual hash rate is not directly measured, it is estimated based on the number of blocks mined during a given day and the mining difficulty.

Completing our data collection, we obtain the daily median confirmation time from blockchain.com. Confirmation time denotes the duration required to validate one block on the Bitcoin blockchain. It is worth noting that due to data limitations, there are some missing values in the confirmation time data for January 2021, the initial month of our data sample. To address this issue, we employ interpolation with a quadratic function to complete the data sample. The results remain qualitatively unchanged when using either the interpolated values or dropping the missing days. For the purposes of this paper, we present the results utilizing the interpolated dataset.

3.1 Liquidity measures

Our primary objective is to examine the causal impact of DLT settlement latency on market liquidity. In pursuit of this goal, we assemble intraday data on cryptocurrency trading and quote activity, collected at a minute-level frequency. This dataset serves as the basis for computing diverse liquidity measures. However, considering that blockchain confirmation latency is reported on a daily basis, we adopt an approach of aggregating the minute-level data to a daily frequency for each cryptocurrency and trading venue.

For each trading venue i and cryptocurrency j, we employ minute-level data (denoted by subscript τ) to estimate daily (denoted by subscript t) return characteristics and liquidity measures. The specific methods employed for estimation are described below, with subscripts i and j suppressed in the formulas. Additionally, we scale the variables by a multiplier to enhance interpretability.

Return characteristics

- Return (r)

  Return is the natural logarithmic difference between the beginning and closing quoted midpoint, which is the average of the best bid and ask prices $price_t^{mid} = (price_t^{ask} + price_t^{bid})/2$. We scale the measure by 100.

$$r_t = [log(price_t^{mid}) - log(price_{t-1}^{mid})] \times 100$$

- Volatility (σ)

  Return volatility is measured by the realized volatility, which is the squared root of the sum of the intraday squared returns. We scale the measure by 100.

$$\sigma_t = \sqrt{\sum_\tau r_\tau^2} \times 100$$

Liquidity measures

- Kyle and Obizhaeva (2016) estimator (k)

  Kyle and Obizhaeva (2016) derive an illiquidity index based on the ratio of volatility to dollar volume of an asset within a given interval. We scale the measure by 10,000.

$$k_t = \left[\frac{\overline{\sigma_\tau^2}}{\sum_\tau volume_\tau \times price_\tau}\right]^{1/3} \times 10,000$$

- Percentage effective spread (ES)

The percentage effective spread is calculated as follow. The daily percentage effective spread is the simple average of the intraday measure. We scale the measure by 10,000 to convert the unit to basis points.

$$ES_\tau = \frac{2 \times |price_\tau^{trade} - price_\tau^{mid}|}{price_\tau^{mid}}$$
$$ES_t = \overline{ES_\tau} \times 10,000$$

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

- 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 intraday observations. We scale the measure by 10,000.

$$r_\tau = c + \lambda D_\tau log(volume_\tau \times price_\tau^{trade}) + \varepsilon_\tau$$
$$\lambda_t = \hat{\lambda} \times 10,000$$

where D_τ is the sign of trade backed out the Lee and Ready (1991) algorithm.

- Percentage 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 percentage quoted spread is the simple average of the intraday measure. We scale this measure by 10,000 to convert the unit to basis points.

$$QS_\tau = \frac{price_\tau^{ask} - price_\tau^{bid}}{price_\tau^{mid}}$$
$$QS_t = \overline{QS_\tau} \times 10,000$$

[Table 1 about here.]

Table 1 presents the summary statistics for the blockchain hashrate and the market quality measures discussed in this section. The average blockchain mining power is 1.5×10^8 Terahash/s. The average of the median confirmation time is 11.4 minutes, with a standard deviation close to three minutes. It is important to note that our confirmation time data represents the daily median measure, and thus, our sample standard deviation *underestimates* the block-by-block variation in settlement latency and the economic magnitude of the impact when we discuss the results. According to Zhang et al. (2021), the block-by-block standard deviation estimation of blockchain confirmation time is approximately 8.36 minutes. In our empirical discussion, we provide interpretations based on both standard deviation estimates.

[Table 2 about here.]

Highlighting cross-sectional differences, Table 2 presents summary statistics for each cryptocurrency traded on each trading venue. When comparing the three cryptocurrencies, it is evident that Bitcoin exhibits a more favorable liquidity condition, reflected in lower values for all inverse liquidity measures, including the Kyle and Obizhaeva (2016) measure, effective spread, Kyle's Lambda, and quoted spread. Following this ranking, Ether demonstrates better liquidity conditions compared to Litecoin, which experiences the least favorable liquidity conditions within the group. Turning to the distinctions among the three trading venues, Coinbase emerges as the largest in terms of trading volume, handling a volume surpassing the total of the other two combined. FTX and Kraken demonstrate comparable trading volumes for Bitcoin, while Kraken holds a higher trading volume for Ether and Litecoin compared to FTX. Regarding liquidity conditions, Coinbase generally provides higher liquidity, except for the effective spread measure. The heterogeneity among the cryptocurrency and the trading venue prompts us to include fixed effects estimation, in addition to the basic pooled OLS estimation, in our paper.

4 Effect of settlement latency on liquidity

4.1 Mining power as instrument

Recognizing the challenges posed by endogeneity issues in identifying the impact of the settlement process on the trading process is crucial, as omitted variable may confound the identification, and reverse causality may arise as the trading precedes the settlement process. To mitigate these issues and potential estimation biases, we employ an instrumental variable (IV) approach in our analysis. This method provides a robust framework to disentangle the causal relationship between the DLT settlement process and the trading process.

We identify an instrument for DLT settlement latency by leveraging a distinctive aspect of the Bitcoin blockchain validation process—the aggregate mining power of the blockchain. The time required to validate (i.e., settle) cryptocurrency transactions involves solving a computationally intensive puzzle through continuous guessing and computation of hash functions. Consequently, lower mining power, which could result from factors such as reduced participant numbers, increased electricity costs, or power outages, is anticipated to increase settlement latency, as the validation of transactions takes longer. For instance, with a decrease in mining power, there could be fewer miners actively participating in solving the cryptographic puzzle. This can lead to longer intervals between the creation of new blocks because there are fewer attempts to find a valid hash.

Figure 1 visually represents the daily median confirmation time and aggregate hashrate for the Bitcoin blockchain over time, highlighting a clear negative association between the two blockchain mining features. Furthermore, the correlation coefficient between the two series is -0.586, indicating a substantial and negative correlation.

[Figure 1 about here.]

In our instrumental variable setup, blockchain mining power influences settlement latency as one of the key determinants (inclusion restriction). Also importantly, *a priori*, mining power does not directly impact cryptocurrency market liquidity or trading costs, satisfying the exclusion restriction. Therefore, blockchain mining power emerges as a suitable instrument for DLT settlement latency, enabling us to explore its effects on market liquidity with confidence in the instrument's relevance and exogeneity.

We employ the 2-Stage Least Squares (2SLS) method for our instrumental variable estimation. In the first stage, the daily median confirmation time is regressed on the concurrent blockchain mining hashrate, as depicted in Equation (1). Although the detailed estimation results are not reported here, it is noteworthy that the estimated coefficient of β_0 is negative and statistically significant (p-value < 0.001). Additionally, the first stage model exhibits a F-statistic of 94.65, surpassing the recommended lower bound of 10 and being highly significant (p-value < 0.001). This robust first stage supports the validity and strength of our instrumental variable in capturing the variation in settlement latency.

$$ConfirmationTime_t = c + \beta_0 Hashrate_t + e_t \tag{1}$$

In the second stage, we proceed to regress the market measures on the fitted values of the median confirmation time from the first stage regression, incorporating controls and fixed effects, as expressed in Equation (2). To be specific, for crypto trading venue i, cryptocurrency j, and day t, $Y_{i,j,t}$ represents the market measure detailed in Section 3.1. $\widehat{ConfirmationTime}_t$ denotes the fitted value obtained from the first stage regression. Additionally, we include controls for cryptocurrency return, volatility, and log trading volume.

We conduct the second stage regression using pooled OLS and introduce various fixed effects, such as trading venue fixed effects and cryptocurrency fixed effects, or trading venue-cryptocurrency fixed effects. To address potential correlation within each trading platform and cryptocurrency, we cluster the standard errors at the cryptocurrency-trading venue level.

$$Y_{i,j,t} = \beta_1 \widehat{ConfirmationTime}_t + \Gamma' Controls_{i,j,t} + FEs + \varepsilon_{i,j,t} \tag{2}$$

where

$$Controls_{i,j,t} = \{r_{j,t},\ \sigma_{j,t},\ log(Volume_{i,j,t})\}$$

To reinforce the validity of our instrumental variable approach, we conduct the augmented Durbin–Wu–Hausman test, as recommended by Davidson et al. (1993), demonstrating that DLT settlement latency is indeed endogenous. Specifically, we include the residual of the first stage regression and the endogenous and not fitted $ConfirmationTime$ in the second stage regression. A significant coefficient on the first stage residual indicates that the dependent variable is correlated with some unobserved variables influencing settlement latency. In other words, our instrument is needed to alleviate the concern of endogeneity associated with DLT settlement latency. The p-values of the Durbin–Wu–Hausman tests are reported in all of our tables, and the majority of them are statistically significant.

4.2 Liquidity and trading cost

To assess the direct impact of DLT settlement latency, we first focus on liquidity. Our hypothesis posits that longer confirmation times would reduce liquidity, as increased uncertainty in settlement might discourage traders from participating in the market. Traders may be discouraged to participation, worrying about the possibility that their trades could not be settled on time or worse, settled at all. To test this, we utilize the Kyle and Obizhaeva

(2016) illiquidity measure, where a higher value indicates lower liquidity. Notably, in a comparative study of liquidity measures in the cryptocurrency market, Brauneis et al. (2021) find that this estimator outperforms others and reliably identifies liquidity differences among crypto trading venues.

Table 3 presents the IV estimation results of Equation (2) using the illiquidity measure as the dependent variable. The estimated coefficients of confirmation time are consistently positive and statistically significant across the three estimations with different fixed effects. Under the pooled OLS estimation (Column (1)), the effect is significant at a 90% confidence level. In the models with fixed effects (Columns (2) and (3)), the effect is significant at a 99% confidence level. This finding suggests that DLT settlement latency indeed reduces liquidity levels.

Interpreting the results based on the fixed effect estimations, we find that a one-minute increase in settlement latency increases the Kyle and Obizhaeva (2016) measure by 0.009 basis points. In relation to the average value of 0.344 basis points (as reported in Table 1), this effect represents an increase of about 2.62%. Alternatively, a one-standard deviation increase in settlement time leads to a 7.82% decrease in liquidity relative to the sample average.

[Table 3 about here.]

As previously discussed, our confirmation time data is the daily median measure, causing our sample standard deviation to *underestimate* the block-by-block variation in settlement latency. Drawing on the block-by-block standard deviation estimation of 8.36 minutes by Zhang et al. (2021), a one-standard deviation increase in settlement time results in a substantial 21.87% reduction in liquidity relative to the sample average. This economically significant impact underscores that DLT settlement latency has a non-negligible negative effect on liquidity.

To provide a more comprehensive analysis of the impact of DLT settlement latency, we delve into more aspects of liquidity, including transaction costs. Table 4 presents the IV estimation results, with the percentage effective spread as the dependent variable. Columns (1) to (3) report estimates obtained by including different fixed effects. The results are qualitatively similar across these specifications—the estimated coefficients on confirmation time are consistently positive and statistically significant at the 99% confidence level.

These results suggest that a one-minute increase in settlement time increases the effective spread by approximately 0.22 basis points. Relative to the average effective spread of 17.48 basis points (as reported in Table 1), this effect represents an increase of about 1.26%. Alternatively, a one-standard deviation increase in settlement time leads to a 3.76% increase in effective spread relative to the sample average. When considering the block-by-block confirmation time standard deviation estimate from Zhang et al. (2021), the magnitude is equivalent to a 10.53% increase in trading costs. These findings highlight the adverse impact of DLT settlement latency on transaction costs.

[Table 4 about here.]

Considering that part of the transaction cost is associated with the price impact faced by traders when placing large orders, evidence of the adverse impact of DLT settlement latency on liquidity and trading costs would suggest an expectation of larger price impact in cryptocurrency trading as DLT settlement latency lengthens. The IV estimation results in Table 5, where Kyle's Lambda is the dependent variable, indeed support this expectation. Estimates of confirmation time are consistent across Columns (1) to (3) of the table, all positive and statistically significant with p-values < 0.01. These results imply that a one-minute increase in settlement time increases Kyle's Lambda by about 0.015 basis points. Relative to the average value of 0.999 basis points (as reported in Table 1), this effect represents an increase of about 1.5%. Alternatively, a one-standard deviation increase in settlement time leads to a 4.49% (or 12.54% with Zhang et al. (2021)'s block-by-block standard deviation estimate) increase in price impact relative to the sample average.

[Table 5 about here.]

In summary, the results presented in Tables 3 to 5 consistently demonstrate that a longer DLT settlement latency has adverse effects, reducing liquidity and increasing transaction costs in cryptocurrency trading. The uncertainty associated with DLT settlement discourages investors from participating, resulting in insufficient liquidity in the market. Consequently, those still engaged in cryptocurrency trading face higher transaction costs and experience larger price impacts. These findings underscore the importance of efficient DLT settlement processes for maintaining a well-functioning and liquid cryptocurrency market.

4.3 Liquidity supply and spread decomposition

Our results so far suggest that the uncertainty associated with DLT settlement latency reduces liquidity and increases transaction costs of cryptocurrency trading. To provide a deeper understanding of how liquidity supply is affected, we conduct our IV analysis using the percentage quoted bid-ask spread as the dependent variable and present the results in Table 6. The estimated coefficients exhibit negative values with varying confidence levels—the pooled OLS estimate is significant at the 95% confidence level, the venue and crypto fixed effect estimate is not statistically significant, and the venue-crypto fixed effect estimate is significant at the 90% confidence level. These results suggest that settlement latency either reduces the quoted bid-ask spread or has no significant impact. In terms of magnitude, the impact of a one-standard deviation increase in confirmation time on the reduction in bid-ask spread ranges from 6.61% to 11.26%. The negative impact seems not to align with our previous findings that settlement latency increases transaction costs and reduces liquidity.

[Table 6 about here.]

To further examine the impact of settlement latency on liquidity supply, we follow Huang and Stoll (1997) to decompose the quoted bid-ask spread into three cost components: adverse selection cost, inventory cost, and fixed costs, using intraday quotes and trading data. For each cryptocurrency and each trading venue, we employ a two-stage generalized method of moment (GMM) method to estimate the following model:

$$
\begin{aligned}
Q_\tau &= (1-2\pi)Q_{\tau-1} + \varepsilon_\tau \\
\Delta P_\tau &= \frac{S}{2}Q_\tau + (\alpha+\beta-1)\frac{S}{2}Q_{\tau-1} - \alpha\frac{S}{2}(1-2\pi)Q_{\tau-2} + e_\tau
\end{aligned}
\tag{3}
$$

In the given model, ΔP_τ represents the change in transaction price, and Q_τ denotes the buy-sell indicator determined by the Lee and Ready (1991) algorithm. This buy-sell indicator takes a value of 1 for buy-initiated trades and -1 for sell-initiated trades. The parameters to be estimated are denoted as $\theta = [\pi, \alpha, \beta, S]'$. Specifically, π quantifies the probability of a reversal in trade direction, α captures the proportion of the spread attributed to adverse selection costs, β represents the proportion of the spread attributed to inventory costs, and S quantifies the spread itself. Consequently, the fixed cost component of the spread is calculated as $(1-\alpha-\beta)$.

In Panel A of Table 7, the summary statistics of the spread decomposition results are presented. The findings reveal that, on average, adverse selection cost and inventory cost contribute to 50% and 45% of the spread, respectively. Notably, these weights significantly surpass those observed in equity markets.[6] This disparity suggests that the cryptocurrency market exhibits higher levels of information asymmetry, and managing inventory is comparatively more costly in this market than in the equity market.

[Table 7 about here.]

In Panel B of Table 7, the IV estimation results for the three components of the bid-ask spread are provided. Beginning with the first component of the spread decomposition, adverse selection cost, our expectation is that the uncertainty induced by DLT settlement

[6] For instance, when examining a sample of large stocks in the U.S., Huang and Stoll (1997) estimate that the weights of adverse selection cost and inventory cost are 9.6% and 28.7%, respectively.

latency would impede the participation of informed traders, while uninformed liquidity traders would continue to operate in the market. Consequently, we hypothesize that liquidity suppliers would face lower adverse selection costs. Columns (1)-(3) focus on the adverse selection component and affirm our hypothesis, as the estimated coefficients for confirmation time are negative and statically significant. Interpreting the results, we find that a one-minute increase in DLT settlement latency results in a reduction of the weight of adverse selection cost by 1.2 percentage points. These results demonstrate a negative impact of settlement latency on adverse selection, suggesting that liquidity suppliers encounter less informed trading and are willing to post narrower bid-ask spreads when settlement latency increases. This finding further support our argument that DLT settlement uncertainty deters market participants, particularly informed traders in this context. Our result aligns with the theoretical model of Hautsch et al. (2024), where the authors predict that arbitrageurs find it more challenging to exploit price discrepancies when DLT settlement latency lengthens, resulting in a broader limit-to-arbitrage bound. Thereby, liquidity suppliers face reduced adverse selection risk.

We then move on to the second component of the spread decomposition, inventory cost. These costs emerge when liquidity suppliers need to off-load involuntarily accumulated cryptocurrency positions to mitigate risks. In this case, liquidity suppliers function as liquidity traders and face liquidity deterioration stemming from DLT settlement latency. As a result, we expect higher inventory costs when DLT settlement latency lengthens. Columns (4)-(6) present the IV estimation results for inventory costs, confirming our predictions. The estimated coefficients, consistently at 0.016 with p-values < 0.05 across all three fixed-effect specifications, demonstrate that a one-minute increase in DLT settlement latency elevates the weight of inventory cost by 1.6 percentage points. This adverse impact verifies that DLT settlement latency amplifies inventory costs faced by liquidity suppliers, supporting our previous finding that DLT settlement latency reduces liquidity. An additional channel for this adverse impact could be attributed to the extended holding time of cryptocurrency positions due to settlement latency.

Finally, examining the fixed component of the bid-ask spread, we hypothesize that DLT settlement latency would have no significant impact, as it should not affect the fixed cost of liquidity supplier. Indeed, the estimation results in Columns (7) to (9) confirm this observation, showing non-statistically significant coefficients for confirmation time.

In summary, while DLT settlement latency appears to narrow the quoted bid-ask spread, in seeming disagreement with our main result indicating reduced liquidity, despite their weak statistical significance. Further investigation into the spread components provides an explanation. We observe that DLT settlement latency lowers the adverse selection costs borne by liquidity suppliers, confirming that settlement uncertainty deters investor participation, especially among informed traders. Additionally, we find that settlement latency heightens inventory management costs due to lower liquidity. Finally, we discern no significant effect of DLT settlement latency on the fixed cost component. The opposite effects on the spread components, which in aggregate result in a narrowing of the bid-ask spread when DLT settlement prolongs, align with our main findings and provide further evidences that DLT settlement latency reduces liquidity.

4.4 Comparing trading venues and cryptocurrencies

In this section, we perform subsample analyses to investigate the cross-sectional differences in our dataset. Specifically, we examine the impact of DLT settlement latency on two dimensions: trading venues and cryptocurrencies. To explore these differences, we conduct separate second-stage IV regressions for each dimension as follow.

For each trading venue:

$$Y_{j,t} = \beta_1 \widehat{ConfirmationTime}_t + \Gamma' Controls_{j,t} + FE_j + \varepsilon_{j,t} \tag{4}$$

For each cryptocurrency:

$$Y_{i,t} = \beta_1 \widehat{ConfirmationTime_t} + \Gamma' Controls_{i,t} + FE_i + \varepsilon_{i,t} \tag{5}$$

where FE_j is the cryptocurrency fixed effect, and the standard errors are clustered by cryptocurrency in Equation (4). FE_i is the trading venue fixed effect, and the standard errors are clustered by trading venue in Equation (5). The other variables follow the same setup as in our main IV model in Equation (2).

[Table 8 about here.]

Table 8 presents the IV estimation coefficients of confirmation time, with other test statistics omitted for brevity. In Panel A, the results compare the three trading venues. Firstly, we observe that the estimations for the Kyle and Obizhaeva (2016) measure, effective spread, and Kyle's Lambda are positive and statistically significant across different trading venues. These results are consistent with our main finding. The decline in liquidity and the increase in trading costs due to DLT settlement latency are evident across all cryptocurrency trading platforms. Additionally, when comparing the magnitudes, we find that the effects of DLT settlement latency are more pronounced in smaller venues (FTX and Kraken) than in the larger one (Coinbase). Regarding the quoted bid-ask spread, the estimated coefficients indicate that DLT settlement latency reduces the spread in Coinbase, increases it in FTX, and has no significant impact in Kraken.

Panel B of Table 8 compares the three cryptocurrencies. The estimated coefficients are generally consistent, although some are not statistically significant. Overall, the comparison indicates that the effect of DLT settlement latency is more pronounced for the trading of Bitcoin, which is the native coin of the Bitcoin blockchain used for settlements. Litecoin, sharing a slightly modified Bitcoin codebase and resembling many of Bitcoin's features, also experiences significant impacts. On the other hand, Ether, associated with the Ethereum blockchain created differently with smart contract functionality, shows the smallest impact from the Bitcoin blockchain settlement latency.

In summary, through subsample comparison, we document that the negative effects of DLT settlement latency on liquidity and trading costs are evident across different cryptocurrency trading venues and different cryptocurrencies. Furthermore, we find that such effects are more pronounced for smaller trading venues and for the trading of the settlement blockchain's native cryptocurrency.

4.5 Negative return days

Cryptocurrency market quality may exhibit differences during bull and bear market periods (Zhang et al. (2020)), with liquidity generally lower during market declines. As a robustness test to address concerns about changes in market conditions driving our results, we conduct a comparison between positive return days and negative return days. This is accomplished by introducing an interaction term with a dummy variable $r^{-}_{j,t}$ in our second-stage IV estimation. For cryptocurrency j and day t, $R^{-}_{j,t}$ equals one on negative return days and zero otherwise. In our sample, 47.84% of the observations occur on negative return days. The regression model is formulated as below.

$$
\begin{aligned}
Y_{i,j,t} = {} & \beta_1 \widehat{ConfirmationTime}_t + \beta_2 \widehat{ConfirmationTime}_t \times r^{-}_{j,t} + \beta_3 r^{-}_{j,t} \\
& + \Gamma' Controls_{i,j,t} + FEs + \varepsilon_{i,j,t}
\end{aligned} \tag{6}
$$

where

$$
r^{-}_{j,t} = 1 \; if \; r_{j,t} < 0, \; 0 \, otherwise
$$
$$
Controls_{i,j,t} = \{r_{j,t}, \; \sigma_{j,t}, \; log(Volume_{i,j,t})\}
$$

The coefficient β_2 captures the differential impact of DLT settlement on the dependent variable when the market declines, in addition to the average impact during the entire sample period.

[Table 9 about here.]

Table 9 reports the estimated results. The β_2 coefficients are statistically insignificant for all the liquidity measures we investigate, and the coefficient on confirmation time remains consistent with our main results. These symmetric effects during market declines and market rallies confirm that our results are not driven by market conditions, supporting our identification of the effect of DLT settlement latency.

5 Conclusion

In conclusion, this study delves into the relationship between DLT settlement latency and market quality in the cryptocurrency space. In the financial markets, settlement processes hold a pivotal role in ensuring secure and efficient asset exchange. Traditional settlement involves the physical transfer of securities and funds, overseen by trusted entities like central securities depositories, thereby incurring minimal uncertainty. On the contrary, DLT, particularly blockchain, offers an alternative by aiming for near-instantaneous transactions and reduced reliance on intermediaries. However, the adoption of DLT introduces complexities, primarily associated with settlement latency due to factors like overall mining capacity affecting block validation speed, leading to uncertainty in the settlement process.

This study, employing the cryptocurrency market as a unique laboratory, identifies the causal effects of DLT settlement latency on liquidity. We propose blockchain mining power as a potential instrument for settlement latency and implement a 2-Stage Least Square approach in our IV estimation to address endogeneity concerns. We find that the uncertainty introduced by DLT settlement discourages investor participation, resulting in a deterioration of liquidity and an increase in transaction costs. These effects persist across various liquidity measures and are more pronounced in smaller trading venues and for the native cryptocurrency of the settlement blockchain. Our result stands robust in the face of instrumental variable validation tests and robustness tests.

The policy implications derived from our study are substantial, especially in shaping the market design of cryptocurrency infrastructure. DLT, with its promise of decentralized and swift settlement cycles, comes at the cost of introducing non-negligible uncertainty due to the stochastic nature of settlement time. Policymakers and market operators should carefully consider this trade-off between near-instant settlement and market quality. The findings highlight the need for regulatory adaptation to emerging technologies in the cryptocurrency space, balancing the advantages of DLT with the potential adverse impacts on liquidity and trading costs.

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Figure 1. Blockchain confirmation time and hashrate

This figure plots the daily median confirmation time and aggregate hashrate for the Bitcoin blockchain over time.

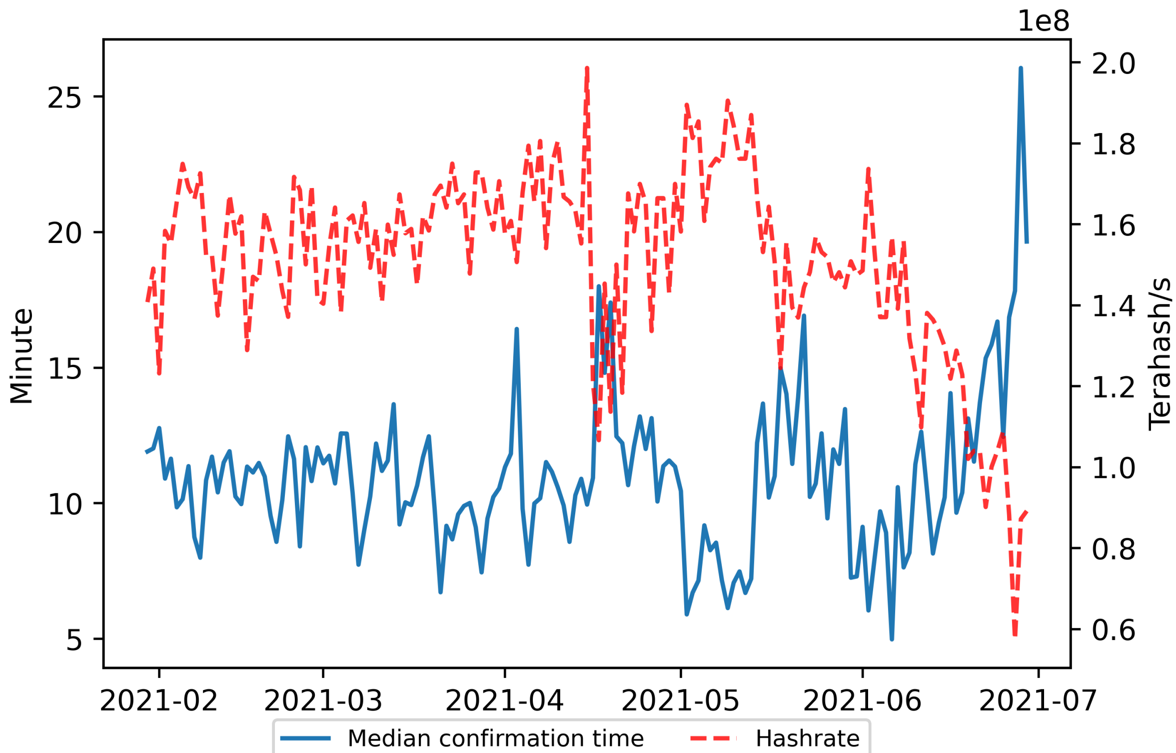

Table 1. Summary statistics

This table reports time series summary statistics (Panel A) and the full sample statistics (Panel B). The sample period is January to June 2021. The construction of the measures is described in Section 3.1.

Panel A: time series

		count	mean	std	25%	50%	75%
Hash rate (Terahash/s)		180	1.508×10^{8}	2.174×10^{7}	1.408×10^{8}	1.540×10^{8}	1.654×10^{8}
Median confirmation time (minute)		180	11.421	2.988	9.835	11.121	12.575
Return (%)	Bitcoin	180	0.079	4.933	-2.340	-0.054	2.729
	Ether	180	0.469	6.815	-3.370	0.627	4.581
	Litecoin	180	-0.029	7.554	-3.254	0.074	4.122
Realized volatility	Bitcoin	180	5.381	2.554	3.788	4.767	6.226
	Ether	180	6.767	3.846	4.521	5.737	7.972
	Litecoin	180	7.943	3.937	5.455	6.902	9.593
Total volume (share)	Bitcoin	180	39,360.221	22,021.419	26,974.716	33,380.525	46,304.832
	Ether	180	593,245.523	384,724.255	327,338.125	467,877.960	740,114.929
	Litecoin	180	724,039.177	428,983.459	382,542.276	654,892.574	948,734.111

Panel B: full sample

	count	mean	std	25%	50%	75%
Return (%)	1620	0.173	6.516	-3.066	0.208	3.766
Realized volatility	1620	6.697	3.776	4.377	5.792	7.902
Volume (share)	1620	150,748.184	240,728.481	14,264.063	54,786.367	179,042.280
Kyle and Obizhaeva (bps)	1620	0.344	0.297	0.162	0.230	0.403
Percentage effective spread (bps)	1620	17.477	10.102	10.878	15.062	21.531
Kyle's Lambda (bps)	1620	0.999	0.659	0.585	0.829	1.177
Percentage quoted spread (bps)	1620	3.346	5.910	0.658	1.466	3.144

Table 2. Summary statistics by cryptocurrency and trading venue

This table reports summary statistics of the variables by cryptocurrency and trading venue. The sample period is January to June 2021. The construction of the measures is described in Section 3.1.

Cryptocurrency	Venue	count	mean	std	25%	50%	75%
			Trading volume (shares)				
Bitcoin	Coinbase	180	24,442.551	15,041.184	15,549.322	19,921.325	28,238.559
	FTX	180	7,586.900	5,137.748	4,028.589	5,609.827	10,848.225
	Kraken	180	7,330.770	4,393.883	4,598.284	6,147.704	8,894.595
Ether	Coinbase	180	379,655.228	252,039.296	210,875.439	292,660.491	484,154.787
	FTX	180	94,958.215	82,303.975	44,312.566	67,567.046	116,491.091
	Kraken	180	118,632.080	76,869.544	64,251.364	94,613.264	150,303.313
Litecoin	Coinbase	180	579,837.910	358,397.710	292,778.512	497,845.967	759,828.940
	FTX	180	39,561.309	32,907.083	15,825.015	32,289.445	53,547.643
	Kraken	180	104,728.689	65,037.913	55,749.452	88,668.921	130,876.554
			Kyle and Obizhaeva (bps)				
Bitcoin	Coinbase	180	0.125	0.024	0.104	0.122	0.142
	FTX	180	0.192	0.057	0.152	0.173	0.229
	Kraken	180	0.182	0.035	0.153	0.181	0.206
Ether	Coinbase	180	0.164	0.030	0.144	0.158	0.183
	FTX	180	0.276	0.085	0.209	0.249	0.336
	Kraken	180	0.241	0.064	0.207	0.231	0.263
Litecoin	Coinbase	180	0.344	0.059	0.304	0.329	0.373
	FTX	180	0.970	0.399	0.696	0.854	1.148
	Kraken	180	0.598	0.118	0.515	0.574	0.657
			Percentage effective spread (bps)				
Bitcoin	Coinbase	180	15.067	8.303	9.413	13.130	17.996
	FTX	180	13.774	7.077	9.399	12.448	16.233
	Kraken	180	13.145	8.138	7.737	11.628	16.414
Ether	Coinbase	180	18.385	10.407	11.560	16.237	22.050
	FTX	180	17.822	9.369	11.642	16.420	21.737
	Kraken	180	16.460	10.301	9.146	14.363	20.425
Litecoin	Coinbase	180	21.012	11.078	13.510	18.244	25.945
	FTX	180	23.505	11.114	15.575	20.262	29.477
	Kraken	180	18.122	9.962	11.743	15.292	20.906
			Kyle's Lambda (bps)				
Bitcoin	Coinbase	180	0.643	0.294	0.447	0.560	0.755
	FTX	180	0.703	0.330	0.496	0.617	0.838
	Kraken	180	0.706	0.319	0.492	0.652	0.859
Ether	Coinbase	180	0.813	0.410	0.543	0.715	0.946
	FTX	180	0.956	0.458	0.654	0.843	1.108
	Kraken	180	0.919	0.458	0.611	0.825	1.065
Litecoin	Coinbase	180	1.130	0.492	0.807	1.018	1.318
	FTX	180	1.793	1.125	1.037	1.455	2.216
	Kraken	180	1.332	0.652	0.871	1.218	1.616
			Percentage quoted spread (bps)				
Bitcoin	Coinbase	180	0.636	0.596	0.256	0.455	0.752
	FTX	180	1.058	0.987	0.373	0.596	1.679
	Kraken	180	0.739	0.797	0.443	0.597	0.820
Ether	Coinbase	180	1.159	0.820	0.689	0.968	1.322
	FTX	180	2.652	2.223	0.916	1.652	4.183
	Kraken	180	1.434	0.981	0.869	1.148	1.721
Litecoin	Coinbase	180	3.434	1.313	2.536	3.063	4.119
	FTX	180	15.787	10.828	9.527	12.484	18.923
	Kraken	180	3.212	2.081	2.079	2.628	3.853

Table 3. Kyle and Obizhaeva

This table presents the results of the second stage of the 2-stage least square (2SLS) estimation. The sample encompasses three cryptocurrencies (Bitcoin, Ether, and Litecoin) traded on three crypto trading platforms (Coinbase, FTX, and Kraken) during the period from January to June 2021. The dependent variable is the Kyle and Obizhaeva (2016) illiquidity measure. $Confirmation\ time$ represents the fitted value obtained from the first stage regression, utilizing blockchain mining rate as the instrument. Control variables include cryptocurrency return, volatility, and log trading volume. We estimate the model using pooled OLS (Column (1)), trading venue fixed effect and cryptocurrency fixed effect (Column (2)), and trading venue-cryptocurrency fixed effect (Column (3)). Standard errors are clustered by trading venue-cryptocurrency and reported in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01

	Kyle and Obizhaeva		
	(1)	(2)	(3)
Confirmation time	0.006^{*}	0.009^{***}	0.009^{***}
	(0.003)	(0.003)	(0.003)
r	0.003	0.003^{***}	0.002^{*}
	(0.003)	(0.001)	(0.001)
σ	0.037^{**}	0.042^{***}	0.037^{***}
	(0.019)	(0.011)	(0.014)
log(volume)	-0.036	-0.234^{***}	-0.193^{**}
	(0.053)	(0.065)	(0.088)
Constant	0.425		
	(0.532)		
Venue FEs	No	Yes	No
Crypto FEs	No	Yes	No
Venue-crypto FEs	No	No	Yes
SE Clustering	Yes	Yes	Yes
Observations	1,620	1,620	1,620
R^2	0.163	0.945	0.952
Adjusted R^2	0.161	0.945	0.952
Durbin–Wu–Hausman (p-value)	0.005	0.545	0.519

Table 4. Percentage Effective Spread

This table presents the results of the second stage of the 2-stage least square (2SLS) estimation. The sample encompasses three cryptocurrencies (Bitcoin, Ether, and Litecoin) traded on three crypto trading platforms (Coinbase, FTX, and Kraken) during the period from January to June 2021. The dependent variable is the percentage effective spread. $Confirmation\,time$ represents the fitted value obtained from the first stage regression, utilizing blockchain mining rate as the instrument. Control variables include cryptocurrency return, volatility, and log trading volume. We estimate the model using pooled OLS (Column (1)), trading venue fixed effect and cryptocurrency fixed effect (Column (2)), and trading venue-cryptocurrency fixed effect (Column (3)). Standard errors are clustered by trading venue-cryptocurrency and reported in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01

	Percentage Effective Spread		
	(1)	(2)	(3)
Confirmation time	0.212***	0.221***	0.215***
	(0.022)	(0.021)	(0.017)
r	0.049	0.051	0.042
	(0.058)	(0.065)	(0.073)
σ	2.159***	2.199***	2.119***
	(0.308)	(0.438)	(0.508)
log(volume)	0.232	−0.400	0.232
	(0.441)	(1.854)	(2.518)
Constant	−1.928		
	(3.979)		
Venue FEs	No	Yes	No
Crypto FEs	No	Yes	No
Venue-crypto FEs	No	No	Yes
SE Clustering	Yes	Yes	Yes
Observations	1,620	1,620	1,620
R^2	0.664	0.919	0.920
Adjusted R^2	0.663	0.918	0.919
Durbin–Wu–Hausman (p-value)	0.000	0.000	0.000

Table 5. Kyle's Lambda

This table presents the results of the second stage of the 2-stage least square (2SLS) estimation. The sample encompasses three cryptocurrencies (Bitcoin, Ether, and Litecoin) traded on three crypto trading platforms (Coinbase, FTX, and Kraken) during the period from January to June 2021. The dependent variable is the Kyle (1985)'s Lambda. $Confirmation\ time$ represents the fitted value obtained from the first stage regression, utilizing blockchain mining rate as the instrument. Control variables include cryptocurrency return, volatility, and log trading volume. We estimate the model using pooled OLS (Column (1)), trading venue fixed effect and cryptocurrency fixed effect (Column (2)), and trading venue-cryptocurrency fixed effect (Column (3)). Standard errors are clustered by trading venue-cryptocurrency and reported in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01

	Kyle's Lambda		
	(1)	(2)	(3)
Confirmation Time	0.012^{***}	0.015^{***}	0.015^{***}
	(0.004)	(0.005)	(0.005)
r	0.006	0.005	0.004
	(0.006)	(0.005)	(0.006)
σ	0.142^{***}	0.149^{***}	0.144^{***}
	(0.036)	(0.037)	(0.044)
log(volume)	-0.039	-0.246^{*}	-0.208
	(0.068)	(0.147)	(0.204)
Constant	0.328		
	(0.586)		
Venue FEs	No	Yes	No
Crypto FEs	No	Yes	No
Venue-crypto FEs	No	No	Yes
SE Clustering	Yes	Yes	Yes
Observations	1,620	1,620	1,620
R^2	0.583	0.918	0.919
Adjusted R^2	0.582	0.917	0.918
Durbin–Wu–Hausman (p-value)	0.000	0.003	0.001

Table 6. Percentage Quoted Spread

This table presents the results of the second stage of the 2-stage least square (2SLS) estimation. The sample encompasses three cryptocurrencies (Bitcoin, Ether, and Litecoin) traded on three crypto trading platforms (Coinbase, FTX, and Kraken) during the period from January to June 2021. The dependent variable is the percentage quoted bid-ask spread. $Confirmation\ time$ represents the fitted value obtained from the first stage regression, utilizing blockchain mining rate as the instrument. Control variables include cryptocurrency return, volatility, and log trading volume. We estimate the model using pooled OLS (Column (1)), trading venue fixed effect and cryptocurrency fixed effect (Column (2)), and trading venue-cryptocurrency fixed effect (Column (3)). Standard errors are clustered by trading venue-cryptocurrency and reported in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01

	Percentage Quoted Spread		
	(1)	(2)	(3)
Confirmation time	-0.126^{**}	-0.074	-0.084^{*}
	(0.054)	(0.066)	(0.049)
r	0.083	0.078^{**}	0.060
	(0.068)	(0.039)	(0.043)
σ	0.793^{*}	0.970^{***}	0.806^{*}
	(0.472)	(0.365)	(0.412)
log(volume)	-0.840	-4.583^{***}	-3.307
	(1.027)	(1.601)	(2.013)
Constant	8.573		
	(10.199)		
Venue FEs	No	Yes	No
Crypto FEs	No	Yes	No
Venue-crypto FEs	No	No	Yes
SE Clustering	Yes	Yes	Yes
Observations	1,620	1,620	1,620
R^2	0.190	0.739	0.785
Adjusted R^2	0.188	0.738	0.784
Durbin–Wu–Hausman (p-value)	0.016	0.000	0.000

Table 7. Bid-ask spread decomposition

This table presents in Panel A the summary statistics (mean, median, and standard deviation) for the three components of the Huang and Stoll (1997) spread decomposition, which are the adverse selection component, inventory cost component, and the fixed cost component. The statistics are reported for the full sample and for each cryptocurrency. Panel B presents the results of the second stage of the 2-stage least square (2SLS) estimation. The sample encompasses three cryptocurrencies (Bitcoin, Ether, and Litecoin) traded on three crypto trading platforms (Coinbase, FTX, and Kraken) during the period from January to June 2021. The dependent variables the three components of the Huang and Stoll (1997) spread decomposition. $Confirmation\, time$ represents the fitted value obtained from the first stage regression, utilizing blockchain mining rate as the instrument. Control variables include cryptocurrency return, volatility, and log trading volume. We estimate the model using pooled OLS, trading venue fixed effect and cryptocurrency fixed effect, and trading venue-cryptocurrency fixed effect. Standard errors are clustered by trading venue-cryptocurrency and reported in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01

Panel A: Summary statistics

	Adverse selection			Inventory			Fixed cost		
	mean	median	std	mean	median	std	mean	median	std
All	0.500	0.477	0.369	0.450	0.510	0.349	0.050	0.018	0.139
Bitcoin	0.545	0.480	0.303	0.460	0531	0.305	-0.005	-0.006	0.064
Ether	0.664	0.817	0.337	0.318	0.144	0.333	0.018	0.010	0.070
Litecoin	0.292	0.049	0.362	0.571	0.631	0.361	0.137	0.073	0.194

Panel B: Instrumental variable estimation

	Adverse selection			Inventory			Fixed cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Confirmation time	-0.010^{*}	-0.012^{**}	-0.012^{**}	0.016^{**}	0.016^{**}	0.016^{**}	-0.005	-0.004	-0.005
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)
r	-0.003^{***}	-0.003^{*}	-0.003	0.002	0.002	0.002	0.002	0.001^{***}	0.001^{***}
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.0003)	(0.0002)
σ	0.008	0.011^{*}	0.011^{*}	-0.009	-0.013^{**}	-0.010	0.001	0.003	-0.001
	(0.008)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.004)	(0.002)	(0.001)
log(volume)	0.006	0.064^{***}	0.062^{**}	-0.002	0.001	-0.025	-0.004	-0.065^{***}	-0.037^{**}
	(0.035)	(0.019)	(0.027)	(0.029)	(0.025)	(0.034)	(0.017)	(0.013)	(0.015)
Constant	0.503			0.350			0.147		
	(0.351)			(0.275)			(0.234)		
Venue FEs	No	Yes	No	No	Yes	No	No	Yes	No
Crypto FEs	No	Yes	No	No	Yes	No	No	Yes	No
Venue-crypto FEs	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1,620	1,620	1,620	1,620	1,620	1,620	1,620	1,620	1,620
R^2	0.018	0.729	0.729	0.019	0.672	0.675	0.011	0.474	0.507
Adjusted R^2	0.015	0.727	0.727	0.017	0.670	0.672	0.008	0.471	0.503
Durbin–Wu–Hausman (p-value)	0.031	0.229	0.253	0.000	0.002	0.001	0.335	0.150	0.246

Table 8. Effect of settlement latency

This table presents the results of the second stage of the 2-stage least square (2SLS) estimation separated by trading venues (Panel A) and by cryptocurrencies (Panel B). The sample encompasses three cryptocurrencies (Bitcoin, Ether, and Litecoin) traded on three crypto trading platforms (Coinbase, FTX, and Kraken) during the period from January to June 2021. The dependent variables are the Kyle and Obizhaeva (2016) measure, percentage effective spread, Kyle's Lambda, and percentage quoted bid-ask spread. We only report the $Confirmationtime$ estimate, which represents the fitted value obtained from the first stage regression, utilizing blockchain mining rate as the instrument. Control variables include cryptocurrency return, volatility, and log trading volume. We include cryptocurrency fixed effect in Panel A and trading venue fixed effect in Panel B. Standard errors, reported in parentheses, are clustered by cryptocurrency in Panel A and by trading venue in Panel B. *Note:* *p<0.1; **p<0.05; ***p<0.01

Panel A: Comparing trading venues

	Coefficient of Confirmation Time		
	Coinbase	FTX	Kraken
	(1)	(2)	(3)
Kyle and Obizhaeva	0.006**	0.020**	0.011**
	(0.003)	(0.008)	(0.005)
Effective spread	0.250***	0.396***	0.389***
	(0.057)	(0.061)	(0.097)
Kyle's Lambda	0.010**	0.041**	0.023***
	(0.005)	(0.019)	(0.005)
Quoted spread	−0.050**	0.105**	−0.019
	(0.022)	(0.045)	(0.019)

Panel B: Comparing cryptocurrencies

	Coefficient of Confirmation Time		
	Bitcoin	Ether	Litecoin
	(1)	(2)	(3)
Kyle and Obizhaeva	0.004***	0.003***	0.011*
	(0.001)	(0.0005)	(0.006)
Effective spread	0.201***	0.162	0.142***
	(0.077)	(0.107)	(0.011)
Kyle's Lambda	0.012***	0.007	0.019
	(0.004)	(0.006)	(0.020)
Quoted spread	−0.029	−0.065***	−0.252***
	(0.030)	(0.014)	(0.034)

Table 9. Negative return days

This table presents the results of the second stage of the 2-stage least square (2SLS) estimation adding the interaction term with dummy variable r^-. r^- equals 1 for observations with negative returns, and 0 otherwise. The sample encompasses three cryptocurrencies (Bitcoin, Ether, and Litecoin) traded on three crypto trading platforms (Coinbase, FTX, and Kraken) during the period from January to June 2021. The dependent variable are the Kyle and Obizhaeva (2016) measure, percentage effective spread, Kyle's Lambda, and percentage quoted bid-ask spread. $Confirmation\ time$ represents the fitted value obtained from the first stage regression, utilizing blockchain mining rate as the instrument. Control variables include cryptocurrency return, volatility, and log trading volume. We include trading venue-cryptocurrency fixed effect. Standard errors are clustered by trading venue-cryptocurrency and reported in parentheses. *Note:* *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:			
	Kyle and Obizhaeva	Effective spread	Kyle's Lambda	Quoted Spread
	(1)	(2)	(3)	(4)
Confirmation time	0.008***	0.161**	0.011**	−0.088*
	(0.002)	(0.065)	(0.005)	(0.048)
Confirmation time × r^-	0.003	0.142	0.009	0.012
	(0.002)	(0.178)	(0.010)	(0.031)
r^-	−0.008	−0.906	−0.069	−0.028
	(0.012)	(1.712)	(0.107)	(0.308)
r	0.003*	0.084	0.007	0.066
	(0.002)	(0.099)	(0.007)	(0.056)
σ	0.037***	2.129***	0.145***	0.807*
	(0.014)	(0.517)	(0.044)	(0.415)
log(volume)	−0.194**	0.198	−0.210	−3.311
	(0.088)	(2.542)	(0.205)	(2.021)
Venue-crypto FEs	Yes	Yes	Yes	Yes
SE Clustering	Yes	Yes	Yes	Yes
Observations	1,620	1,620	1,620	1,620
R^2	0.953	0.920	0.919	0.785
Adjusted R^2	0.952	0.919	0.918	0.783
Durbin–Wu–Hausman (p-value)	0.007	0.000	0.001	0.051