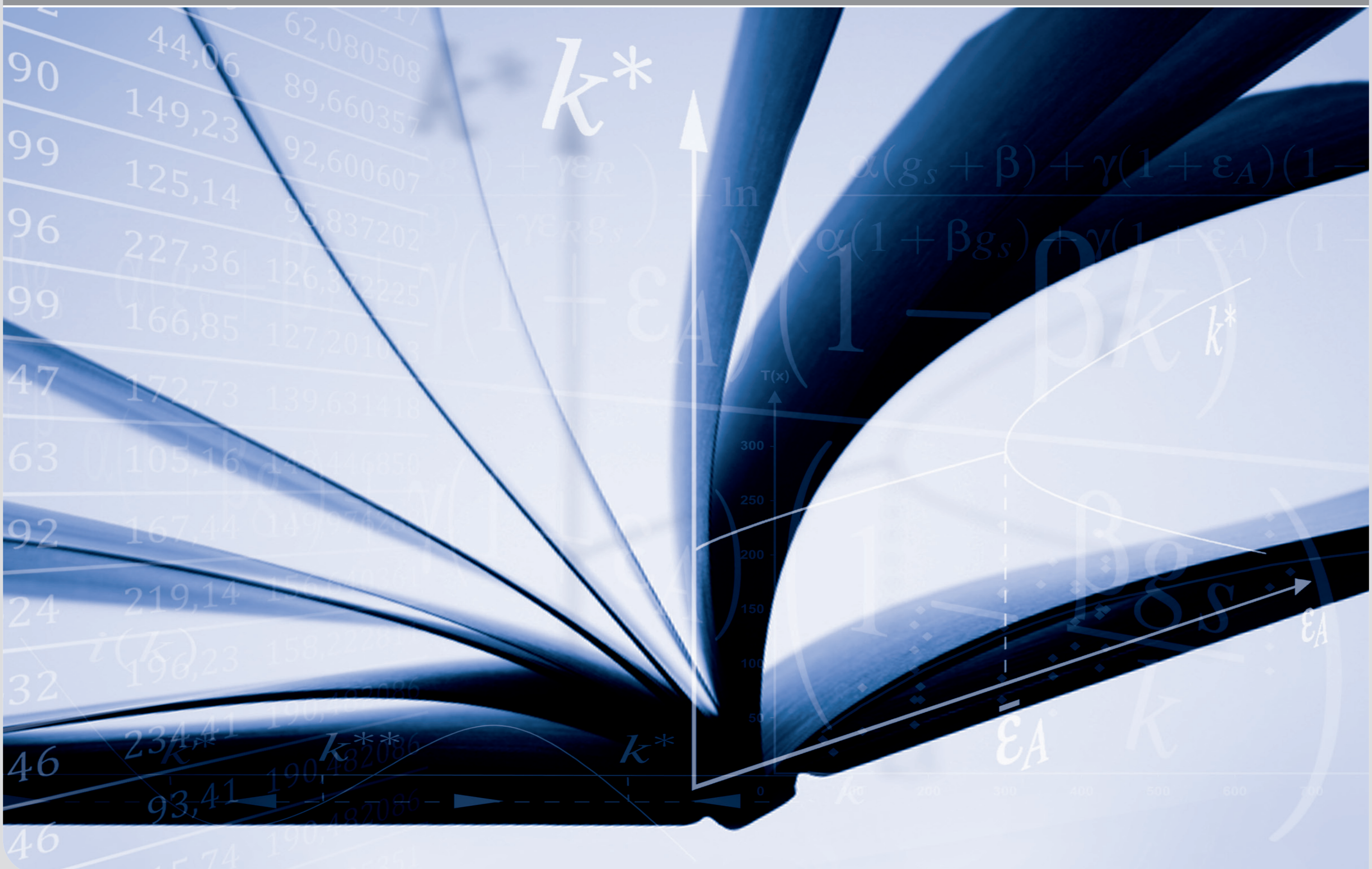
Karlsruher Institut für Technologie

Trading stocks on blocks: The quality of decentralized markets

by Benedikt Notheisen, Vincenzo Marino,
Daniel Englert and Christof Weinhardt

No. 129 | FEBRUARY 2019

WORKING PAPER SERIES IN ECONOMICS



Impressum

Karlsruher Institut für Technologie (KIT)
Fakultät für Wirtschaftswissenschaften
Institut für Volkswirtschaftslehre (ECON)

Kaiserstraße 12
76131 Karlsruhe

KIT – Die Forschungsuniversität in der Helmholtz-Gemeinschaft

Working Paper Series in Economics
No. 129, February 2019

ISSN 2190-9806

econpapers.wiwi.kit.edu

Trading Stocks on Blocks
The Quality of Decentralized Markets*

Benedikt Notheisen[†], Vincenzo Marino, Daniel Englert, and Christof Weinhardt[‡]

January 25, 2019

Abstract

The trust-free nature of blockchain-based systems challenges the role of traditional platform providers and enables the creation of new, intermediary-free markets. Despite the growing number of such markets, the impact of the blockchain's configuration on market outcomes remains unclear. In this study, we utilize order-level data from real-world financial markets to explore the impact of the blockchain parameters block size and block creation time on the quality of decentralized markets. More specifically, we find that increasing the blocks' capacity improves market activity, while higher block frequencies impose a trade-off between higher turnovers and lower trade sizes. In addition, we identify the block creation time and block size as core drivers of daily and intraday liquidity, respectively. In consequence, improving liquidity goes hand in hand with a higher activity. However, the reciprocal relationship between blockchain parameters and the increasing price impact of a block also indicate that faster and bigger blocks are no silver bullet to scale decentralized markets and may facilitate volatility. In total, we contribute an initial, technology-agnostic assessment of the quality of decentralized markets that aims to guide interdisciplinary researchers and innovative practitioners.

JEL classification: D47, G14, L86, N2, O16.

Keywords: Decentralized markets, Blockchain, Market quality, Market design, Market engineering, FinTech.

---

*We want to thank Matthias Burghardt for his helpful advice with respect to data handling and David Dann for his technological support. In addition, we are grateful to Felix Kretzer and Carl Martin for their assistance in preparing this paper. This study has also greatly profited from the comments of the participants of FinteQC 2018, the CCConf 2018, and the IISM doctoral consortia in July and December 2018. All errors are our own. Eventually, financial support of and the provision of data by the Stuttgart Stock Exchange (Boerse Stuttgart) is gratefully acknowledged. Boerse Stuttgart had no role in the study design, the analysis, the decision to publish, or the preparation of this paper.

[†]Karlsruhe Institute of Technology (KIT), Department of Economics and Management, benedikt.notheisen@kit.edu

[‡]Karlsruhe Institute of Technology (KIT), Department of Economics and Management, weinhardt@kit.edu

1. Introduction

As an infrastructure for economic systems, blockchain technology challenges the role of traditional intermediaries and enables the creation of novel market designs that disrupt the traditional value chain of securities trading. Fully and partially decentralized market setups, such as Polymath, IDEX, or Sharevest, claim to utilize this potential to enable users to trade financial and crypto assets and settle their trades without the involvement of intermediaries. In addition, first academic studies such as Malinova and Park (2017) and Notheisen, Gödde, and Weinhardt (2017b) begin to explore trader behavior and market design theoretically. However, while practical approaches promise leaner value chains and cheaper trading, the decentralization's impact on market quality remains unclear.

This study aims to fill this gap by examining the impact of performance-related design parameters – namely the block size (BS) and the block creation time (BCT) – on the quality of decentralized markets. This includes the identification of quality drivers and inhibitors, the assessment of trade-offs between design parameters, and the derivation of design implications to guide market engineers (Weinhardt and Gimpel, 2007). To do so, we replicate 5 years of blockchain-based equity trading with the help of time-stamped order-level data from the Stuttgart stock exchange. This detailed information enables us to conduct a technology-agnostic evaluation of the performance-quality relationship on blockchain-based platforms from a real-world perspective that covers the scope of modern financial markets.

In consequence, our study design comprises a three-step approach: The first step focuses on the data generation process. This includes the development and implementation of a decentralized market mechanism that formalizes and integrates the technological characteristics of blockchain-based infrastructures. To minimize confounding effects, we closely follow the implementation and trading rules of the Stuttgart stock exchange. Then, we utilize the order-level data to replicate market outcomes under 9 parameter combinations that represent different blockchain configurations. To ensure the fit between the input sample and the blockchain parameters, we furthermore set BCTs according to prominent blockchain protocols and previous findings from periodic auctions and calibrate BSs based on the trading data from Stuttgart. To measure the quality of the resulting market outcomes, the second step builds on the market quality framework of Zhang, Wagener, Storkenmaier, and Weinhardt (2011) and adapts activity, liquidity, and information measures from established market quality literature. In addition, we derive an empirical strategy to guide our analyses in following third step. In this third and final step, we use the data panel generated in step 1 to compute the 6 market quality measures defined in step 2 and investigate the quality effects of parameter variations. More specifically, we study the time and size effects that come with different blockchain configurations as well as interactions with activity and quality controls.

In these analyses, we find evidence that decreasing the blocks' capacity increases the daily number of trades but also limits daily trading volume and the average size of a trade. In addition, increasing the block frequency boosts the number of trades and turnover per day but reduces the number of shares included in a trade. As a result, higher BSs offer a means to improve market activity, while lowering BCTs remains ambiguous and imposes a trade-off between rising turnovers and declining trade sizes. With respect to the liquidity of decentralized markets, we furthermore identify the blocks' intervals and size as drivers of daily and intraday liquidity, respectively. As a result, improving liquidity goes hand in hand with increasing throughput, while market engineers can exercise control over daily and intraday liquidity almost separately. Eventually, our analysis on a market's information processing capability indicates that the price impact of a new block is stronger for larger and more frequent blocks. In consequence, blockchain configurations that facilitate activity and liquidity also intensify the price impact of a block, and thus may lead to higher volatility. Moreover, our evidence indicates a reciprocal relationship between blockchain parameters across all quality dimensions.

In total, these findings highlight that increasing the BS and decreasing the BCT is no silver bullet to scale decentralized markets and illustrates the need for a holistic blockchain engineering approach that combines all three quality dimensions with the market's objectives (Notheisen, Hawlitschek, and Weinhardt, 2017c; Hawlitschek, Notheisen, and Teubner, 2018). In consequence, our contribution is threefold: First, we contribute to the growing body of interdisciplinary research on blockchain-based economic systems by providing a first technology-agnostic quantitative analysis of the relationship between performance-related blockchain parameters and market quality. Second, we pave the way for future research that examines decentralized markets by highlighting points of interest, such as changes in investor behavior or the detailed analysis of the liquidity of decentralized markets. Third, we utilize real-world data that resembles to scale and scope of modern financial markets to offer some initial guidance for innovate practitioners to engineer and design new and enhance existing decentralized market platforms.

Finally, the remainder of this paper is structured as follows: Section 2 presents the related literature, identifies a research gap, and formulates our research question. More specifically, we provide an overview of blockchain-based market platforms and illustrate the related blockchain design parameters, introduce the utilized market quality framework, and review recent literature on frequent batch auctions. In Section 3, we describe the data generation process and provide summary statistics. Section 4 introduces the utilized market quality measures and our empirical strategy, while section 5 comprises the empirical results and tests their robustness. Eventually, sections 6 and 7 outline and discuss limitations and conclude this study with opportunities for future research.

2. Related Literature

This paper builds on multiple streams of research and utilizes findings from market quality and market design literature to examine the impact of the underlying blockchain's parameter configuration on the quality of decentralized markets. In order to establish a common understanding for the analysis in section 5, we introduce the concept of blockchain-based markets, outline the current state of research regarding the quality of decentralized markets, and briefly review related literature on market quality and frequent batch auctions in this section. Eventually, we integrate these views to illustrate our study design, identify a research gap, and highlight our contribution.

2.1. The Concept of Blockchain-based Markets

As a peer-to-peer system, blockchain technology enables secure transactions without the necessity of a trusted central authority. From a technical perspective, the blockchain prevents double spending within a network of interacting parties by managing and maintaining an immutable distributed ledger. This ledger is publicly disclosed to all market participants while the cryptographic concatenation of data blocks establishes the timely order of transactions (Donet, Prez-Sol, and Herrera-Joancomart, 2014). When new transactions occur, the network aggregates them into blocks, checks the validity, votes on the correctness, and updates the append only database by the means of a consensus mechanism. In addition, smart contracts enable the implementation of decentralized applications that function reliably despite the absence of intermediaries (Buterin, 2013; Szabo, 1997).

In financial markets, decentralized applications go beyond the conventional tokenization of assets and crypto assets (Peterson, 2018) and include transparent transaction systems (Notheisen, Cholewa, and Shanmugam, 2017a), efficient settlement systems (Mills et al., 2016; Chiu and Koeppl, 2018), and decentralized stock markets (Lee, 2016; Jessel and Marshall, 2016; Notheisen et al., 2017b; Workie and Jain, 2017). As a result, blockchain technology promises improvements in corporate governance, transparency, and liquidity (Yermack, 2017; Malinova and Park, 2017). However, fully decentralizing securities trading is a challenging task, while the actual consequences remain unclear. On one hand, the underlying value chain is rather complex and includes many process steps, such as matching, clearing, and settlement, the blockchain engineer needs to take into account. On the other hand, the blockchain's block-based nature limits the transaction throughput and shifts trading from continuous to discrete time.

In consequence, the first practical decentralization efforts focus on the clearing and settlement processes instead of market mechanisms. In 2016 for instance, Deutsche Bundesbank and Deutsche Börse issued a joint press release, presenting a functional prototype for the blockchain-based settlement of securities. Similarly, the Australian stock exchange ASX aims to settle equity transactions with a blockchain-based system[1]. In recent years however, we observe a growing number of fully decentralized exchange concepts and market platforms that trade a variety of assets. Augur and Gnosis for instance, aim to decentralize prediction markets[2] by building market frameworks based on the Ethereum platform. In addition, there are multiple decentralized market platforms – such as Bancor, Bitsquares, CryptoBridge, OpenLedger DEX, or the Waves platform – that claim to enable investors to trade crypto assets and currencies without the involvement of intermediaries. In the financial sector, start ups – such as BitShares, Polymath, or Sharevest – aim to enable users to trade financial assets in a fully decentralized environment. In addition, there are hybrid approaches that combine decentralized and centralized elements. IDEX, for instance, limits blockchain-based processes to the settlement of transactions and uses a centralized server to update account balances and match orders. Table 10 in appendix B provides a brief overview of selected ventures.

Academic literature, on the other side, has made little progress in developing and evaluating the increasingly popular phenomenon of decentralized markets and exchanges. Patel (2014), for instance, presents a theoretical implementation concept, while Clark, Bonneau, Felten, Kroll, Miller, and Narayanan (2014) derive design principles for matching orders in a decentralized way. In addition, Malinova and Park (2017) study how the increasing transparency that comes with a blockchain-based market affects the trading behavior of different (large/small) investors. In their theoretic model, they show that despite the risk of front-running full transparency improves welfare, because it decreases the costs of finding liquidity. In addition, Notheisen et al. (2017b) implement a proof-of-concept prototype of a blockchain-based exchange and identify the number of transactions processed per block – the block size (BS) – and the periodic creation of new data blocks – the block creation time (BCT) – as obstacles to decentralized trading.

More specifically, these parameters limit transaction throughput of a blockchain-based exchange, and thus affect the way new orders are processed. In the following, we define

[1] More information about the ASX's efforts to replace their current post-trading system CHESS with a blockchain-based alternative is available under https://www.asx.com.au/services/chess-replacement.htm.

[2] For an introduction to the concept of prediction markets, we kindly refer to Kranz (2015).

the BS as the maximum number of trades that fit into one block and the BCT as the fixed time interval between two blocks. The Bitcoin BS, for instance, is currently limited to one megabyte (Kogias, Jovanovic, Gailly, Khoffi, Gasser, and Ford, 2016). In Ethereum, the size of a block is also affected by the gas limit and currently between 20 and 30 kilobytes (Buterin, 2013)[3]. The BCT of an application depends on the applied consensus mechanism and its robustness towards malicious actors. In the case of Bitcoin, a new block is created every 10 minutes, whereas the Ethereum protocol requires approximately 15 seconds to create a block (Kogias et al., 2016). In combination, the BS and the BCT determine the throughput of a blockchain-based system. For the Bitcoin system this leads to 7 transactions per second, while Ethereum reaches up to 15 transactions within the same amount of time. However, in blockchain-based markets, the impact of the underlying blockchain configuration goes beyond scalability but also affects market outcomes.

2.2. Market Quality

To assess the outcomes of decentralized markets, we build on established market quality literature. In consequence, the following paragraphs create a basic understanding of the concept of market quality, outline its dimensions, and briefly describe their measurement. To do so, we utilize the market quality framework introduced by Zhang et al. (2011) and illustrated in figure 1. According to this framework, market quality has three dimensions – activity, liquidity, and information – and depends on the business structure, IT systems, a market's microstructure, and its socio-economic environment. The business structure comprises the business model of market and defines revenue models, target groups, and products and services offered to them. The trading system is borne by the exchange's IT system, which allows traders to connect to the market platform, implements the matching engine, and determines a market's degree of automation. Eventually, the market microstructure formalizes the rules for the exchange of assets (O'Hara, 1998). The resulting trading mechanism transforms latent demand and supply of investors into actual transactions (Madhavan, 1992), while the market model specifies the utilized auction model (Zhang et al., 2011). In combination, the trading mechanism and the market model determine the attributes of a market, such as trading times, matching algorithms, price determination, or order types (Madhavan, 1992). In total, the characteristics of these components affect trading behavior, price formation, transaction costs, and information disclosure (O'Hara, 1998; Pagano and Rell, 1996). In addition, platform characteristics and market outcomes are shaped by external factors, such as regulatory constraints, the current state of technology, and competition.

[3]For up to date information on average BSs we kindly refer to blockchain.com for Bitcoin and etherscan.io for Ethereum.

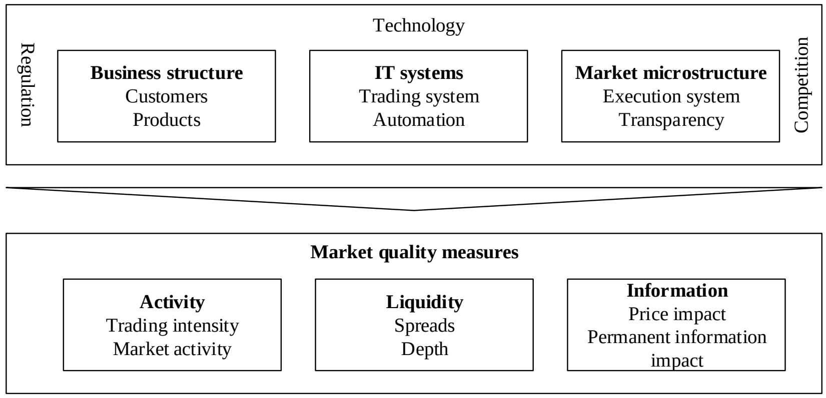


Fig. 1. Market quality framework
This figure illustrates the market quality framework introduced by Zhang et al. (2011) and presents the three dimensions of market quality (activity, liquidity, and information) as well as their determinants (business structure, IT systems, market microstructure, and environmental factors).

The activity dimension captures the trading intensity and can be measured by the number, average size, or the total volume of trades conducted within a specific period of time (e.g., a day). In addition, price-based measures, such as the stock-return volatility and the stock-price momentum shed light on the impact of new information on market activity (Barclay, Hendershott, and McCormick, 2003).

Liquidity refers to a market's ability to execute a trade without affecting the price (Hasbrouck, 1991b) and can be characterized by a immediacy, width, depth, and resiliency (Harris, 2002). Immediacy captures how fast a trade of a given size and cost can be executed. Moreover, wide markets are characterized by the presence of many orders close to the current price, while deep markets are characterized by the presence of large orders close to the current price. Finally, resiliency refers to a market's ability to revert to prior price levels following uninformed order flow. Liquidity is a central element of market quality and a principal criterion for attractiveness and success of securities exchanges (Zhang et al., 2011). However, liquidity is also an elusive concept that comprises multiple aspects, and thus is hard to measure with a single indicator (Amihud, 2002). In consequence, a variety of measures is required to capture the multi-faceted nature of liquidity (Hasbrouck, 1991b). Spread measures for instance use microstructure data such as bid and ask prices to capture the impact of orderflow on prices (Copeland and Galai, 1983). More specifically, spread measures provide ex-ante and ex-post measures of liquidity that enable traders to assess transaction costs (Huang and Stoll, 1996) and (potential) losses due to inferior information (Hasbrouck, 1991a). However, while spread measures are easy to calculate and interpret (Hasbrouck, 1991b), the required order-level data may be hard to obtain (Amihud, 2002). In contrast, volume- or quantity-based measures such as Amihud (2002)'s illiquidity measure or the order book imbalance (Cao, Hansch, and Wang, 2009; Brogaard, Hendershott, and Riordan, 2014) provide a more coarse but robust and readily available means to study market quality developments (Hasbrouck, 1991b).

The third and last dimension of market quality refers to the information content of prices and the way new information is incorporated. Price discovery describes the competitive process by which informed traders drive prices to their efficient value (Hasbrouck, 1991b). Moreover, this process can happen on multiple exchanges simultaneously, while the information share measures the relative contribution of each exchange (Hasbrouck, 1995). Measures to capture the information content of a trade include the price impact and the permanent information impact. The price impact is based on the idea that after a certain period of time only the actual information remains, while inventory effects, other temporary effects, and noise vanish over time (Riordan and Storkenmaier, 2012; Hendershott, Jones, and Menkveld, 2011). The permanent information impact on the other hand, utilizes a vector autoregressive model to analyze the unanticipated component of a trade (Hasbrouck, 1991a). Moreover, the decomposition of the price variance into trade-correlated and trade-uncorrelated components allows a differentiated perspective on the informativeness of a trade (Hasbrouck, 1991c).

To examine the quality of decentralized markets, we consider all three dimensions and include activity, liquidity and information measures in our analysis. A introduction of the applied measures follows in section 4.1.

2.3. Periodic Auctions

In blockchain-based markets, order matching and price determination is tied to the discrete consensus process that limits the addition of new data blocks to periodic time intervals. As a result, the growing body of research on periodic and frequent batch auctions allows a first peak on the impact of discrete market mechanisms on a market's quality.

In contrast to continuous market models, periodic and frequent batch auctions differ in one central aspect: They treat time as a discrete variable (Budish, Cramton, and Shim, 2015). Consequently, orders are not processed serially but in batches. Within each batch, an auction determines a uniform price, which then applies to all orders accumulated and executed in that batch (Budish, Cramton, and Shim, 2014). Similar to continuous limit order markets, orders comprise a limit, a quantity, and a trade direction and can be submitted, modified, and deleted. The list of orders also contains previously submitted orders that could not be executed in preceding auctions. Based on this list, the auction mechanism determines a uniform price that maximizes the executed quantity. To manage excess demand or supply, Budish et al. (2014) suggest pro-rata execution with time priority across but not within batch intervals. Eventually, the resulting price, the traded quantities, and the remaining orders are disclosed.

With respect to market quality, Madhavan (1992) shows that periodic auctions offer greater price efficiency than continuous market models, while the unobservability of order books before a trade increases information costs. In comparison with dealer markets, price and execution risk increases as execution depends on the price limit instead of guaranteed quotes (Pagano and Rell, 1996). In addition, discrete market models may lead to lower commission costs due to easier order handling, are less susceptible to manipulations, and simplify governance by less complex audit trails (Economides and Schwartz, 1995). The theoretic model of Pancs (2012) supports these findings but also indicates that continuous markets offer a higher allocative efficiency, when information asymmetries are low and traders are impatient.

However, if batch intervals are too short, prices may not reach equilibrium as the number of orders within each auction is too low. If on the other hand intervals are too long, prices may not reach equilibrium, because the market equilibrium might have changed in the meantime (Fricke and Gerig, 2018). As a result, it is important to determine the optimal batch interval and Fricke and Gerig (2018) indicate that intervals should be shorter for securities with higher trading intensities, higher volatility, a higher correlation with the market, and more concentrated reservation prices. Based on these factors, they estimate the optimal batch interval for S&P 500 stocks and find that intermediate batch intervals in the range of a few seconds maximize market quality. Budish et al. (2014) aim to support the implementation of frequent batch auctions by providing practical details. More specifically, they highlight the elimination of speed advantages and the shift from speed to price competition as core drivers of liquidity and welfare improvements. Budish et al. (2015) build on this study and propose frequent batch auctions as a countermeasure to prevent mechanical arbitrage by high frequency traders (HFTs) and suggest an optimal time interval from 10 to 100 milliseconds to improve liquidity provision and social welfare. More specifically, the welfare of slow traders increases in frequent call markets, while they seek protection from faster traders (Wah, Hurd, and Wellman, 2016). Farmer and Skouras (2012) also support the negative value of speed from a regulatory perspective and propose to replace continuous markets with frequent call auctions with randomized interval lengths. By setting the average batch interval length to one second while keeping the length of each single interval unpredictable they hope to prevent a last-mover advantage of HFTs. In contrast, Economides and Schwartz (1995) propose to incorporate batch auctions into continuous markets. More precisely, the authors suggest to use three auctions per day: One auction to open the market, one auction during the trading day, and one auction to close the market. One of their key arguments is that opening and closing the trading day this way may facilitate price discovery.

However, a blockchain-based market mechanism is not only restricted by time but also by the number of transactions processed per batch, as each block has a maximum capacity. In consequence, we utilize these findings as a foundation, complement them with a capacity restriction, and formulate our research question in the following paragraph.

2.4. Research Gap & Research Question

After establishing a common understanding of the concept of blockchain-based markets, the dimensions of market quality, and periodic auctions, we highlight the resulting research gap in this section and formulate a research question. While some papers, such as Urquhart (2016) or Wei (2018), analyze the liquidity and efficiency of cryptocurrency markets, other studies, such as Hendershott and Moulton (2011), focus on the impact of technological advancements and automation on market quality. In addition, there is a growing number of studies on the quality effects of periodic auctions that offer some implications for blockchain-based markets. More specifically, these studies indicate that the quality of decentralized markets should be highest for intermediate auction intervals (Budish et al., 2015; Fricke and Gerig, 2018; Farmer and Skouras, 2012). In consequence, improving performance by lowering BCTs may not be a preferable solution from a market quality perspective. However, despite the growing number of decentralized exchanges, none of these streams of literature takes the specific infra- and microstructure features of blockchain-based exchanges into account. In consequence, the current research on the quality of decentralized markets can be summarized as follows: First, blockchain research mainly focuses on theoretical concepts and rarely considers the implementation of securities markets and the resulting implications on an economic level. Second, market quality literature offers a valuable toolbox to examine the quality of decentralized markets but has not been applied to this area, yet. Third, studies on periodic call and frequent batch auctions offer an initial foundation to study the quality of decentralized markets but do not consider the impact of blockchain design features, such as the BS or the relationship between the BS and auction intervals (BCT). Within this study, we take a first step towards filling this research gap by using data from real-world financial markets to empirically investigate the following research question:

Research question. *How do different design parameters that determine the performance of blockchain-based markets impact market quality?*

By answering this research question, we aim to evaluate the potential of intermediary-free market setups, assess their quality characteristics, and identify facilitation and impeding factors and trade-offs between blockchain design parameters (BS, BCT). Based on these findings, we furthermore hope to identify and quantify quality-performance trade-offs that come with different blockchain configurations and derive implications to guide the engineers of decentralized markets. To do so, we replicate five years of equity trading from the Stuttgart stock exchange, while taking different blockchain configurations – i.e., combinations of different BSs and BCTs – into account. Based on the resulting market outcomes, we then assess the impact of blockchain parameter variations on the activity, liquidity, and price formation on decentralized markets.

3. Data

To examine the quality of decentralized markets, we utilize message-level data from the Boerse Stuttgart Research Database to replicate market outcomes in a blockchain-based setup. The Boerse Stuttgart Research Database is jointly managed and maintained by the Stuttgart stock exchange and the Karlsruhe Institute of Technology and provides detailed time-stamped (milliseconds) order and trade data for all instruments traded in Stuttgart. For our analysis, we obtain order data for German blue chips listed in the DAX[4] index from this database. To ensure consistency throughout our observation period, we focus on the 30 stocks included in the DAX as of December 31, 2017. In this section, we describe the data generation process and provide summary statistics to illustrate the data panel used to conduct our empirical analyses in section 5.

3.1. Data Generation Process

The data generation process comprises the following steps: First, we refine the raw data acquired from the Boerse Stuttgart Research Database to create the input sample for the market mechanism. Based on this input sample, we calibrate the size and time parameters of 9 different blockchain configurations and replicate 5 years of equity trading. Eventually, the output data is refined in a last step. The following paragraphs report the pre-processing procedures, illustrate the resulting input sample, outline the calibration of the blockchain parameters, specify the blockchain-based market mechanism, and describe the post-processing procedures.

[4] The index is composed of the 30 most liquid stocks with respect to the free-float market capitalization and the total order book turnover. For further details, we kindly refer to the website of Deutsche Börse.

3.1.1. Pre-processing & Input Sample

The raw data initially acquired from the Stuttgart stock exchange contains 5.63 million transaction messages including order submissions, updates, and cancellations, trade executions, and messages related to the initialization and closing of the trading system. Each message comprises a time stamp, an order and stock identifier, a trade direction, an order quantity and limit, a limit type, the traded quantity, a trade price, and other fields.

At the beginning of the pre-processing, we drop irrelevant fields and delete initialization and closing messages. To reduce computational complexity, we furthermore exclude cancellations from the input sample and condense to remaining orders. More specifically, we remove all messages related to these orders including their initial submission, updates and changes, and eventually their deletion. In addition, we translate stop orders and other event-driven orders into limit or market orders, if the triggering time and all other needed information could be derived from the raw data. If this was not the case, we delete these observations. Jointly with the existing market and limit orders, the translated orders are condensed to the most recent specification. This includes updating each (limit) order to the most recently submitted quantity (and price limit), replacing its time stamp with the time stamp of the update, and deleting all changes. As a result, every order is represented by a single data tupel that comprises a unique order number, the stock's name and identifier, a buy-sell flag, the limit price[5], a trade quantity, and a time stamp. Based on this sample, we finally adjust trade prices, quantities, and limits by stock splits that occurred during the observation period[6]. This way, we ensure that prices remain comparable over time. In this last step, we also remove corrupted data as well as duplicates.

The resulting input sample comprises 1,231 trading days, and covers a period from January 1, 2013 to December 31, 2017[7]. Within this period, 0.79 million market orders and 0.61 million limit orders have been submitted. On a daily level, this corresponds to an average of 1,138 orders per day. From the perspective of the Stuttgart stock exchange, these 1.40 million submissions resulted in 1.32 million trade executions and 1,075 trades per day. On average, each trade comprised a traded quantity of 552 shares. The median of 150 shares per trade is considerably lower. Eventually, the trading volume sums up to EUR 22.57 billion over 5 years, which corresponds to a daily trading volume of EUR 18.34 million.

[5]In case of a market order the limit price is set to zero.

[6]Within our observation period there were two relevant stock splits: The first one was a 10:1 reverse split of the Commerzbank stock (ISIN: DE000CBK1001), which was conducted on March 23, 2013. The second one happened on August 4, 2014 and splitted the Fresenius stock (ISIN: DE0005785604) in a ratio of 1:3. In addition, there was a third split (Merck, DE0006599905, June 30, 2014) that retained a ratio of 1:1, and thus no adjustments were required.

[7]Due to a server problem, the data contains a gap from December 16, 2016 to January 13, 2017.

3.1.2. Parameter Calibration & Blockchain Configurations

To capture the impact of changing blockchain parameters on market quality, we create 9 blockchain configurations that combine a low, medium, and high BS with a low, medium, and high BCT. To take the variations in trading volumes and quantities of the DAX stocks into account and minimize confounding effects that arise from incorporating blockchain parameters in Stuttgart's market model, we fit the BSs and BCTs to the actual trading data from the Stuttgart stock exchange (Budish et al., 2015; Fricke and Gerig, 2018). More specifically, we utilize the trades corresponding to the orders from the input sample to set both blockchain parameters to reach a specific throughput – measured by the number of trades – per day. Moreover, we set the blockchain parameters for each stock i individually.

To do so, we compute the average number of trades per day for each stock between 2013 and 2017. In order to remove outliers, we winsorize the daily number of trades by replacing values below the first percentile by the value of the first percentile and values above the 99^{th} percentile by the value of the 99^{th} percentile. Columns 2 to 4 in table 1 report the number of trading days as well as the resulting average number of trades per day and corresponding standard deviations. In addition, the example of Daimler (129 trades per day) and Beiersdorf (5 trades per day) highlights the need to calibrate the simulation parameters on the stock-level. From a technical perspective, this calibration setup also represents a decentralized exchange with a separate blockchain for each stock.

In the next step, we set the BCT to constant intervals of 10, 60, or 300 minutes for each stock. The minimum and maximum specifications are based on the average BCT of Bitcoin (Nakamoto, 2008) and the study of Economides and Schwartz (1995), who suggest to conduct three auctions per day to maximize market quality. More specifically and consistent with Stuttgart's trading time of 14 hours, we set the BCT to 300 minutes in the maximum scenario. Eventually, we also include a BCT of 60 minutes to create an intermediate scenario[8].

In addition, we set the BS for a stock i to achieve a minimum, medium, and maximum daily throughput at a given BCT. The medium throughput is equal to the average amount of trades per day given in column 3 in table 1. The minimum and maximum configurations also consider shifts by one standard deviation (column 4 in table 1). As a result, we calibrate the minimum, medium, and maximum BS for stock i's market by equation (1), where $\bar{x}_i$

[8]Note that we discarded Ethereum's BCT of 10 to 20 seconds (or other protocols with a BCT below 10 minutes), because of the substantially lower trade frequency in our data.

denotes the average number of trades per day and σ_i the corresponding standard deviation.

$$\begin{aligned}
\text{BS}_i^{min}(\text{BCT}) &= max\left\{\left\lfloor \frac{\bar{x}_i - \sigma_i}{14 \cdot \frac{60}{\text{BCT}}} \right\rfloor, 2\right\}, \\
\text{BS}_i^{med}(\text{BCT}) &= max\left\{\left\lfloor \frac{\bar{x}_i}{14 \cdot \frac{60}{\text{BCT}}} \right\rfloor, 2\right\}, \\
\text{BS}_i^{max}(\text{BCT}) &= max\left\{\left\lfloor \frac{\bar{x}_i + \sigma_i}{14 \cdot \frac{60}{\text{BCT}}} \right\rfloor, 2\right\}.
\end{aligned} \tag{1}$$

In combination with a BCT $\in \{10, 60, 300\}$, this leads to 9 blockchain configurations for each stock. For instance, $\text{BS}^{max}(60)$ for the Daimler stock is computed as follows: Based on a trading time of 14 hours there is a new block every 60 minutes, while $128.65 + 86.63 = 215.28$ trades have to be processed within these 14 blocks (i.e., 15.38 trades per block). However, as a block cannot contain fractions of trades, we set the BS to 15. In some cases – especially in the *min*-configurations – the calibration yields BSs below 2. In these cases, we set the BS to 2, since an execution requires at least one buy and one sell order to be feasible. Columns 5 to 13 in table 1 report the BS of all 9 configurations and 30 stocks.

3.1.3. *Replication of Market Outcomes*

To replicate market outcomes, we extend the market model of the Stuttgart stock exchange with the blockchain parameters BS and BCT, set them according to the calibrated blockchain configurations from subsection 3.1.2, and feed the resulting market mechanism with the input sample from subsection 3.1.1. In consequence, the replication of market outcomes is guided by the following steps:

First, the pre-processed orders from the input sample are submitted to the market, while order books collect the time-stamped buy and sell orders in ascending order (time). Based on this sorted list, the first order of a day triggers the first auction and sets the schedule for the rest of the day. Assuming a BCT of 10 (60, 300) minutes, the auction mechanism then determines a price and executes trades every 10 (60, 300) minutes. Consistent with the trading days at Stuttgart, we furthermore halt trading during the night, on weekends, and on public holidays. To realize these halts, we set the market's clock to the time stamp of the next incoming order, if there is a gap of at least 5 hours between 2 orders and continue trading at this time. To align the market mechanism with our input sample, we utilize the exchange and implementation rules published on the Stuttgart stock exchange's website to implement priority rules, price determination, and the execution algorithm. In consequence, the price determination algorithm scans all orders gathered in the order book, sets a price to

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
				BCT = 10			BCT = 60			BCT = 300		
Stock i	Number of trading days	Daily average ($\bar{x}_i$)	Standard deviation (σ_i)	BS_i^{min}	BS_i^{med}	BS_i^{max}	BS_i^{min}	BS_i^{med}	BS_i^{max}	BS_i^{min}	BS_i^{med}	BS_i^{max}
High Trading Volume												
Daimler AG	1,231	128.65	86.63	2	2	3	3	9	15	15	46	77
BASF SE	1,231	74.79	50.31	2	2	2	2	5	9	9	27	45
Allianz SE	1,231	63.11	40.69	2	2	2	2	5	7	8	23	37
Volkswagen AG	1,231	64.14	67.21	2	2	2	2	5	9	2	23	47
Deutsche Bank AG	1,231	77.00	55.98	2	2	2	2	5	9	8	27	47
Commerzbank AG	1,153	74.59	54.53	2	2	2	2	5	9	7	27	46
Siemens AG	1,231	48.68	34.01	2	2	2	2	3	6	5	17	30
Deutsche Telekom AG	1,231	59.70	41.49	2	2	2	2	4	7	7	21	36
E.ON SE	1,231	56.88	42.25	2	2	2	2	4	7	5	20	35
Munich Re AG	1,231	29.75	19.06	2	2	2	2	2	3	4	11	17
Medium Trading Volume												
Bayer AG	1,231	30.73	18.98	2	2	2	2	2	4	4	11	18
Deutsche Post AG	1,231	36.61	25.07	2	2	2	2	3	4	4	13	22
Deutsche Lufthansa AG	1,230	39.15	29.57	2	2	2	2	3	5	3	14	25
BMW AG	1,231	27.08	17.81	2	2	2	2	2	3	3	10	16
Infineon Technologies AG	1,231	29.58	18.31	2	2	2	2	2	3	4	11	17
SAP SE	1,231	29.51	19.65	2	2	2	2	2	4	4	11	18
RWE AG	1,229	29.03	24.00	2	2	2	2	2	4	2	10	19
Linde AG	1,231	18.76	14.79	2	2	2	2	2	2	2	7	12
Adidas AG	1,229	21.03	17.02	2	2	2	2	2	3	2	8	14
Continental AG	1,227	14.26	9.49	2	2	2	2	2	2	2	5	8
Low Trading Volume												
thyssenkrupp AG	1,231	21.76	16.78	2	2	2	2	2	3	2	8	14
Fresenius SE & Co. KGaA	1,228	15.94	11.80	2	2	2	2	2	2	2	6	10
ProSiebenSat.1 Media SE	1,060	15.11	14.12	2	2	2	2	2	2	2	5	10
HeidelbergCement AG	1,221	9.63	7.08	2	2	2	2	2	2	2	3	6
Fresenius Medical Care AG	1,213	9.85	8.47	2	2	2	2	2	2	2	4	7
Henkel AG & Co. KGaA	1,216	9.18	7.76	2	2	2	2	2	2	2	3	6
Merck KGaA	1,202	8.43	7.13	2	2	2	2	2	2	2	3	6
Deutsche Brse AG	1,187	9.21	7.93	2	2	2	2	2	2	2	3	6
Vonovia SE	961	10.03	8.54	2	2	2	2	2	2	2	4	7
Beiersdorf AG	1,161	5.10	4.33	2	2	2	2	2	2	2	2	3
Average	1,207	35.58	26.03	2.00	2.00	2.03	2.03	2.97	4.53	4.00	12.77	22.03

Table 1: BS calibration

This table illustrates the data basis for the parameter calibration as well as the resulting BS for each configuration. More specifically, column 1 presents the respective stock i and assigns it to the high, medium, or low trading volume tertiary. Columns 2 to 4 comprise the number of trading days, the average number of trades per day, and the daily standard deviation for each stock. Column 5 to 13 report the BS for all 9 blockchain configurations based on equation (1).

maximize turnover, and returns this price as well as the corresponding executable quantities. To take the maximum BS into account, an intermediate step determines the number of ask and bid trades that fit into one block and ensures that the traded bid and ask quantities are the same. Eventually, the execution algorithm finalizes the trades according to the price-time priority principle and outputs the resulting trade data including an uniform clearing price, a traded quantity, an unique trade ID, a time stamp reflecting the time of a block's creation, and a remaining quantity[9]. If two orders have the same price limit, the one with the older time stamp is prioritized. In addition, market orders are prioritized over limit orders. Partially executed orders are updated and stay in the order book for the next auction along

[9] If an order was fully executed, the remaining quantity is equal to 0.

with unexecuted orders, while fully executed orders are removed. Figure 2 summarizes these steps and highlights the integration of the BS and the BCT parameters within the replication of market outcomes.

The following paragraphs will introduce the price determination, the following execution, and the resulting market outcomes in detail. In addition, appendix D.1 illustrates the software structure of the market mechanism in detail.

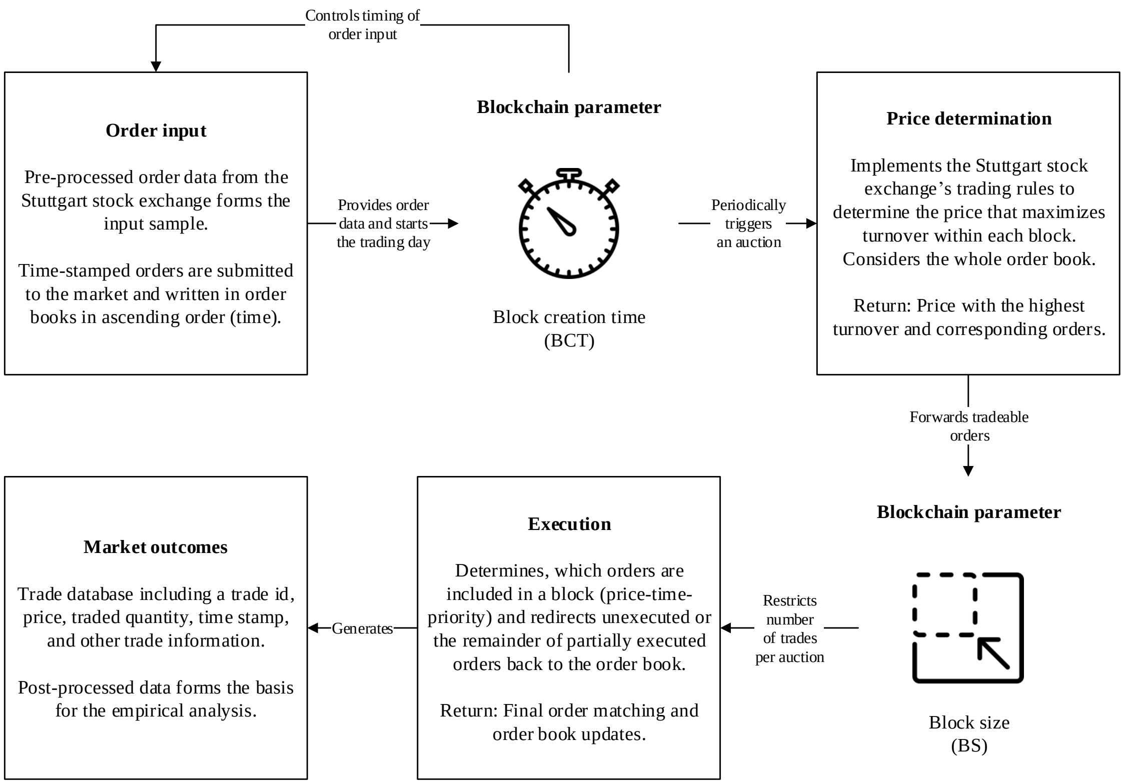


Fig. 2. Process steps to replicate market outcomes

Price Determination. Stuttgart's trading rules state that the price levels "that have the largest turnover within the given framework [...] must be identified". In addition, "if there are several possible price levels, the price level with the lowest surplus must be identified". To minimize frictions that arise from the integration of the blockchain parameters in the market mechanism, we use these and other rules to guide the implementation of the price determination. However, there are also some aspects, where our algorithm differs from Stuttgart's implementation rules. First and foremost, we determine prices independently from any reference price, in order to remain fully decentralized and prevent dependencies on central authorities. Second, at Stuttgart, specialized market makers called 'Quality Liquidity Providers' offer quotes that constitute lower and upper price limits for each instrument. However, the data acquired from the Boerse Stuttgart Research Database is already cleansed and does not contain their orders or trades. In consequence, we neglect them in the replication.

Figure 3 summarizes the resulting price determination algorithm, illustrates potential matching schemes in form of 10 cases, and indicates the resulting market outcomes in each case (price, quantity). In the first attempt, we always try to determine the price with limit orders. However, this is only possible, if either the bid or the ask side crosses the spread and either the highest bid is at least as high as the lowest ask or vice versa. If neither is the case, we extend our scope and include market orders as well. The 10 cases describe the approaches utilized to determine prices given different order book situations. In addition, it is possible that no orders in the book are executable. If this is the case, no price can be determined, no trades occur, and all orders remain in the order book for the next auction in 10, 60, or 300 minutes. Each time a new block is created, the price determination algorithm goes through all cases and returns the determined price along with the tradeable quantity. The BS however, is not considered in this step, yet. Instead, it is incorporated in the execution algorithm, which is introduced in the next paragraph.

Execution. Before orders are executed, we take the BS parameter into account. To do so, we limit the number of trades to the respective BS given in table 1, while the total ask and bid volumes at the uniform clearing price have to be equal. Note that there can be an imbalance between the number of bid and ask orders within a block. In addition, we iterate through all possible combinations of bid and ask orders within a block to find the order matching with the highest turnover[10]. To ensure price-time priority during this process, we fill the blocks with the most recent orders that maximize the price (see 3). Eventually, the execution algorithm returns the bid and ask orders included in a block, determines the corresponding trades, and generates the resulting output data.

Market Outcomes. To illustrate the market outcomes, figure 4 depicts the daily average trade prices and total volumes throughout 2013 in a exemplary manner. Panels (a), (c), and (e) highlight that prices vary substantially across blockchain configurations, while panels (b), (d), and (f) indicate that larger blocks increase turnover at a given BCT.

[10] If we assume a BS of 5 trades for instance, the execution algorithm tries to fill a block with 4 asks and 1 bid order in the first and ask-bid ratios of 3:2, 2:3, and 1:4 in the following iterations. Eventually, the algorithm terminates, after checking all possible combinations or when turnover goes down (because then we are outside of the maximum identified in the price determination).

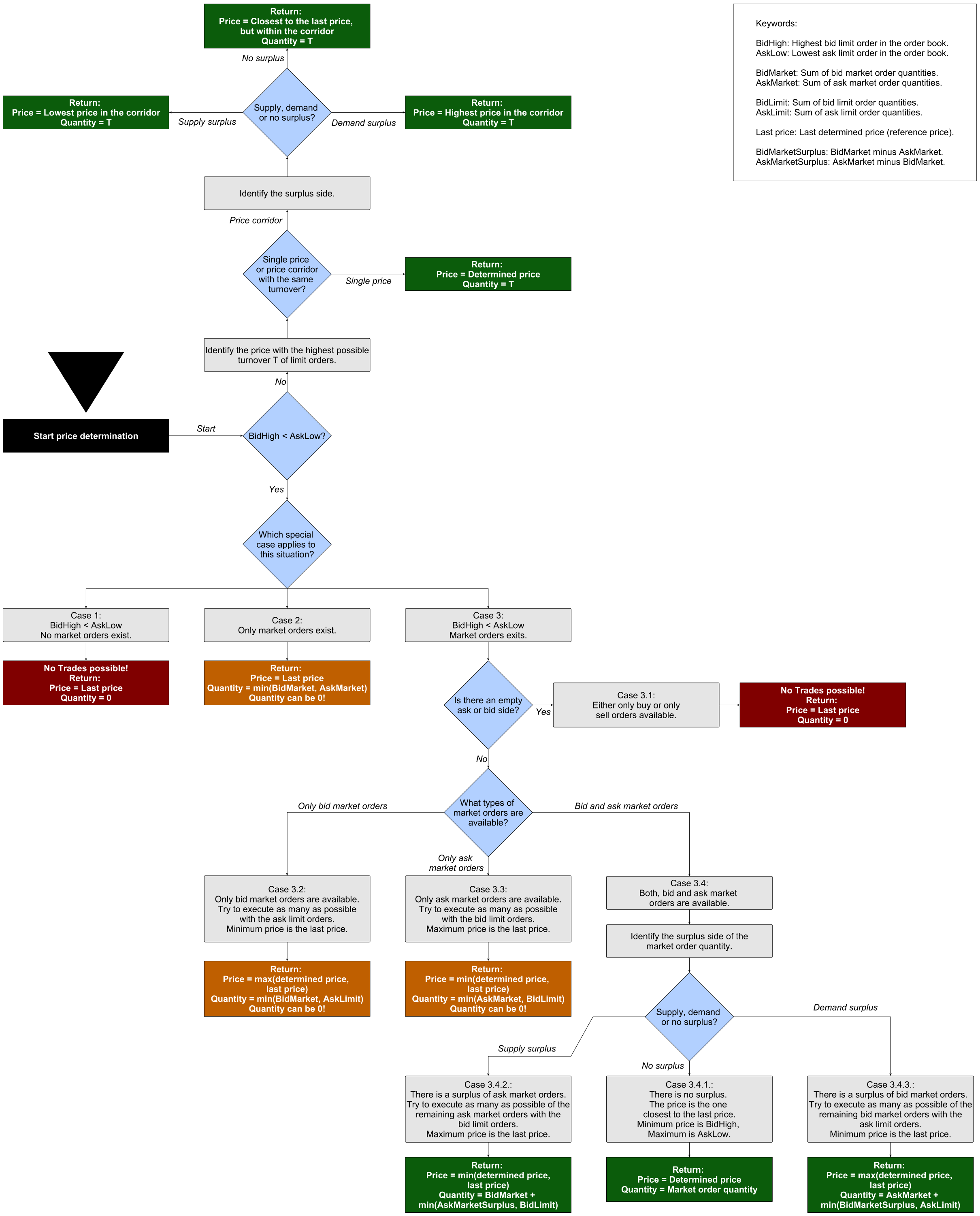


Fig. 3. Price determination algorithm

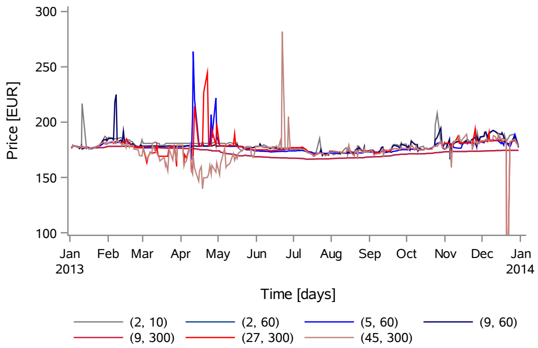
This figure illustrates the price determination algorithm. Blue indicates decisions, grey the results and cases, and green, orange, and red market outcomes. Green implies that a trade is possible, orange that a trade may be possible, and red that no trade is possible. The black box highlights the start of the price determination.

More specifically, a high volatility and the occurrence of extreme prices seem more pronounced in boundary scenarios such as $(Min, 10)$ or $(Max, 300)$. The reason for this can be found in the order books: If there are multiple market orders on one side of the market, one odd limit order (e.g., with a limit of 1 EUR) can disturb prices and lead to abrupt and extreme returns[11]. This effect becomes even more severe for small BSs, because incoming market orders have a higher priority. As a result, the limit order remains in the order book and may trigger a similar price movement in the future. In addition, the chance that an odd order sets the price is higher for scenarios with a high throughput as orders are processed faster and order books become thinner. However, a detailed analysis of the relationship between prices and blockchain parameters will follow in section 5. Furthermore, we can observe a constant price between September and December in Deutsche Börse's $(Min, 10)$ configuration. This effect is caused by a relatively large ask limit order with a quantity of 18,700 (compared to an average of 275) and a limit of 50 EUR, which is partially executed over time. After the first execution, its limit serves as a reference price (i.e., the last determined price), while mostly bid market orders are submitted to the market. As a result, the price determination algorithm (figure 3) stays in case 3.4.3, until the price can be determined by other limit orders again. In total, these issues highlight the need to post-process the replicated data.

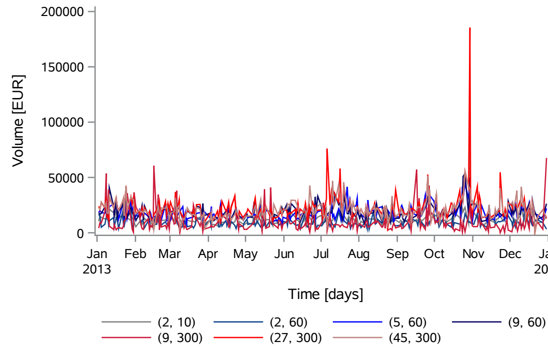
3.1.4. Post-processing

To accommodate for the shortcomings of our market mechanism, such as the lack of reference prices or circuit breakers, we post-process the trade data in several ways: To prevent the most extreme prices from distorting our analysis in section 5, we remove all observations with a price difference of at least four standard deviations compared to the actual stock price observed at Stuttgart. This way, we aim to compensate for the absence of reference prices, replicate the impact of circuit breakers (Subrahmanyam, 1994), while preserving price variations. In addition, if the first order of a day was submitted late in the morning, this could lead to block creations shortly after midnight in 300 minute configurations. To correct these faulty time stamps, we set them to 11.59 p.m. of the previous day.

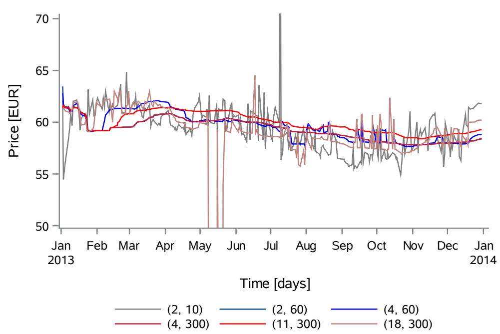
[11] We are aware that exchanges use circuit breakers and reference prices to prevent such effects. However, for the sake of simplicity and computational efficiency of the replication, we deal with these issues outside of the market mechanism by post-processing the market outcomes (see section 3.1.4).



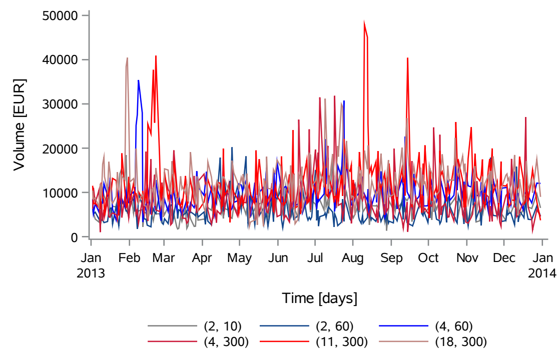
(a) VW AG – Trade prices



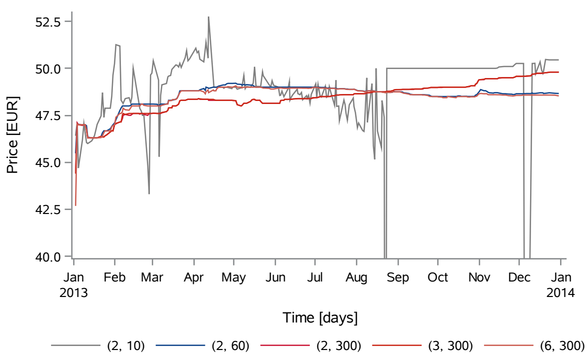
(b) VW AG – Trading volumes



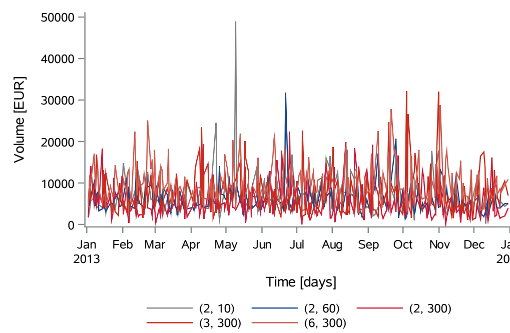
(c) SAP SE – Trade prices



(d) SAP SE – Trading volumes



(e) Deutsche Börse AG – Trade prices



(f) Deutsche Börse AG – Trading volumes

Fig. 4. Market outcomes

This figure illustrates the replicated average trade prices and volumes for BASF (high volume tertiary), SAP (intermediate volume tertiary), and Deutsche Börse (low volume tertiary) in 2013 (253 trading days). Prices are computed as daily averages and volumes as daily totals. The line color indicates the respective blockchain configuration (BS, BCT). In the case of redundant configurations, only the first configuration is included.

3.2. *Summary Statistics*

Eventually, the data generation process described in the previous subsection (3.1) spans the data panel for the empirical analysis over a cross-section of 9 blockchain configurations and 30 DAX stocks. It is based on 5 years of actual trading activity at Stuttgart and covers a period from January 1, 2013 to December 31, 2017, while 12.5 million real-world submissions result in 12 million replicated executions (trades) with a turnover of EUR 122 billion. Eventually, the final data panel comprises 302,493 stock-day-configurations[12] and 4,546,605 blocks. Within each trading day, 9,818 trades lead to a turnover of EUR 100 million on average. Within each block, a mean of 4.67 trades generates a turnover of EUR 59,121 per block. In addition, each trade comprises an average amount of 340 stocks. Note that the variation of the blockchain parameters across different configuration results in a substantial variation of the number of shares per trade (SD 857.32) and the turnover per block (SD EUR 80,528). Table 2 presents summary statistics on the replication's input sample from Stuttgart (column 2), all 9 blockchain configurations (columns 2 to 11), and the aggregated data panel (columns 12 to 14). Another noteworthy aspect is that none of the 9 blockchain configurations reaches the actual trading volume observed at Stuttgart[13]. However, this effect may be due to the winsorization and rounding procedures within the calibration and the removal of simulation outliers in the post-processing. In addition, (min, min)-configurations restrict the maximum turnover by design.

In total, these summary statistics provide some initial insights into the impact of different blockchain configurations on market activity. A comparison between the different scenarios indicates that increasing the BS is beneficial for total trading volume, the total number of executions, and the average trade size. In addition, the impact of a lower BCT seems more pronounced in scenarios with a smaller BS. On the block-level, the turnover per block increases with a larger BS, while a longer BCT also has a positive effect. In addition, the number of executions per block increases in larger blocks. Surprisingly, we can also see that in the scenario with the longest BCT (column 11), the BS is not a limiting factor. More specifically, the average number of executions per block (12.61) is substantially smaller than the calibrated average BS of 22.03 (table 1, column 13).

[12] Note that this is below 332,370 ($= 1,231$ days $*$ 30 DAX stocks $*$ 9 configurations) days, since some shares are not traded daily. Column 2 of table 1 provides the number of trading days for each stock in detail.

[13] The most productive scenario $(Max, 10)$ creates a turnover of EUR 17.92, which is substantially below the actual turnover of EUR 22.57 billion at Stuttgart.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Input sample	**Market outcomes (BS, BCT)**									**Data panel**		
	Stuttgart	$(Min, 10)$	$(Med, 10)$	$(Max, 10)$	$(Min, 60)$	$(Med, 60)$	$(Max, 60)$	$(Min, 300)$	$(Med, 300)$	$(Max, 300)$	Total	Mean	Median
Total Submissions	1,400,444	1,400,444	1,400,444	1,400,444	1,400,444	1,400,444	1,400,444	1,400,444	1,400,444	1,400,444	12,603,996	1,400,444	1,400,444
Total Executions	1,323,857	2,100,934	2,100,934	2,109,755	803,027	1,139,912	1,365,068	371,944	979,934	1,114,968	12,086,476	1,342,942	1,139,912
Total Trading Volume [EUR]	22,574,487,089	17,329,482,335	17,329,482,335	17,924,368,004	5,768,869,557	11,849,980,042	16,549,085,490	3,933,958,256	14,456,286,388	16,901,262,445	122,042,774,852	13,560,308,317	16,549,085,490
Trading Days	1,231	1,231	1,231	1,231	1,231	1,231	1,231	1,231	1,231	1,231	11,079	1,231	1,231
Executions per Day													
Mean	1,075.43	1,706.69	1,706.69	1,713.85	652.34	926.00	1,108.91	302.15	796.05	905.74	9,818.42	1,090.94	926.00
Median	997.00	1,742.00	1,742.00	1,755.00	689.00	984.00	1,160.00	318.00	843.00	921.00	10,154.00	1,128.22	984.00
Standard Deviation	487.57	645.14	645.14	661.69	180.79	268.04	365.44	76.29	249.38	349.64	3,441.55	382.39	349.64
Trading Volume per Day													
Mean [EUR]	18,338,332	14,077,565	14,077,565	14,560,819	4,686,328	9,626,304	13,443,611	3,195,742	11,743,531	13,729,701	99,141,166	11,015,685	13,443,611
Median [EUR]	16,925,251	14,327,298	14,327,298	14,722,189	4,915,441	10,082,046	13,813,772	3,259,503	12,153,912	13,893,371	101,494,830	11,277,203	13,813,772
Standard Deviation [EUR]	8,241,854	5,232,808	5,232,808	5,562,499	1,353,566	2,980,153	4,687,971	895,737	3,828,617	5,500,881	35,275,040	3,919,449	4,687,971
Shares per Trade													
Mean	551.91	277.94	277.94	280.71	198.13	319.20	402.27	317.85	483.08	505.29		340.27	317.85
Median	150.00	100.00	100.00	100.00	79.00	100.00	110.00	100.00	135.00	150.00		108.22	100.00
Standard Deviation	1,761.46	674.79	674.79	674.40	462.90	755.59	988.90	756.33	1,318.39	1,409.80		857.32	755.59
Executions per Block													
Mean		2.00	2.00	2.05	2.04	2.93	3.81	3.98	10.65	12.61		4.67	2.93
Median		2.00	2.00	2.00	2.00	2.00	3.00	3.00	8.00	9.00		3.67	2.00
Standard Deviation		0.00	0.00	0.22	0.19	1.48	2.42	2.88	8.58	11.52		3.03	1.48
Trading Volume per Block													
Mean [EUR]		16,497	16,497	17,407	14,639	30,411	46,184	42,074	157,178	191,202		59,121	30,411
Median [EUR]		8,324	8,324	8,791	7,738	13,889	21,904	18,840	88,992	107,083		31,543	13,889
Standard Deviation [EUR]		26,599	26,599	27,944	22,390	48,358	69,102	63,523	194,991	245,246		80,528	48,358

Table 2: Summary Statistics

This table summarizes key figures on the trade data from Stuttgart (column 2), the replicated market outcomes (columns 3 to 11), and the resulting aggregated data panel (column 12 to 14). The parameters of the blockchain configurations are reported in parentheses (BS, BCT). Column 1 specifies the respective measures and indicates whether a measure was computed on a daily or block-level (intraday). To provide a benchmark, column 2 reports statistics on submissions, executions, trading volume, and shares per trade of the input sample from Stuttgart. Columns 3 to 5 comprise blockchain configurations with a BCT of 10 minutes, 6 to 8 with 60 minutes, and 9 to 11 with 300 minutes, respectively. The BS varies according to the calibration (table 1). Columns 12 to 14 show the total, mean, and median measures of the final data panel. If a measure was not applicable, the corresponding cells are left empty.

4. Methodology

This section introduces the methodology used to assess the quality of decentralized markets. In consequence, we present the utilized market quality measures in subsection 4.1 and embed them into our empirical strategy in subsection 4.2.

4.1. Market Quality Measures

To perform a holistic analysis of blockchain-based exchanges, we consider all three dimensions of market quality. To do so, we utilize established quality, liquidity, and price measures and adapt them to take the specific characteristics of the input sample, the data generation process, and the resulting data panel into account. However, Stuttgart's hybrid market design and the blockchain's discrete nature complicate the use of traditional depth and spread measures. In consequence, we introduce 6 market quality measures (3 activity, 2 liquidity, 1 information) in the following paragraphs. For a better overview, appendix E also summarizes the main characteristics of these measures.

4.1.1. Activity

To assess market activity, we follow Barclay et al. (2003) and Hendershott et al. (2011) and use the trade count (TC) and the turnover (TO) as well as an adapted version of the average trade size (ATS) as activity measures. For each measure, a high value indicates a high level of activity. In combination, all three measures facilitate an integrated analysis of a market's activity.

Trade count. The TC is defined as the daily number of trades and measures the execution frequency within a market. Equation (2) formalizes this definition, while $n_{i,d,s}$ denotes the number of trades on day d for stock i under configuration s.

$$TC_{i,d,s} = n_{i,d,s}. \tag{2}$$

As a result, a higher TC implies a higher level of market activity. However, the TC's meaningfulness is also limited, because it does not consider prices or traded quantities. In consequence, we need additional measures to take these aspects into account.

Turnover. One of these measures is the TO. It measures the aggregated daily trading volume and is specified as

$$TO_{i,d,s} = \sum_{j=1}^{TC_{i,d,s}} Price_{i,d,s,j} \cdot Quantity^{T}_{i,d,s,j}, \tag{3}$$

where $Price_{i,d,s,j}$ and $Quantity^{T}_{i,d,s,j}$ denote the price and the number of traded (T) stocks of a trade j on day d and in a stock i. In addition, s represents the underlying blockchain configuration. Similar to the TC, a higher value indicates a higher level of market activity. Moreover, it comprises both price and quantity information and therefore improves the activity assessment. However, a drawback of the TO measure is that it may be biased by very large trades. Thus, to avoid a misleading interpretation, one needs to consider both the TO and the TC.

Average trade size. Eventually, the ATS measures the average amount of shares included in a trade. To tailor this measure and to study the activity of blockchain-based markets, we compute the ATS on the block-level. As a result, the ATS is equal to the ratio of the total trade quantity within a specific block b to the amount of trades within that block:

$$ATS_{i,b,s} = \frac{\sum_{j=1}^{TC_{i,b,s}} Quantity^{T}_{i,b,s,j}}{TC_{i,b,s}} \tag{4}$$

Analogous to TC and TO, a higher ATS corresponds to a more active market.

4.1.2. Liquidity

To assess the second market quality dimension, we use the daily Amihud illiquidity measure (DILLIQ) and the remaining quantity proportion (RQP) to approximate liquidity. A high value for either measure, indicates low levels of liquidity. Note that we do not consider spread-based liquidity measures as they may be biased by large market orders that have to be eroded over time. More specifically, the limited BS prevents that large market orders are filled immediately and their remaining quantity stays in the order book, while smaller orders from the other side of the market fill it over time. As a result, spreads are equal to zero, despite the actually illiquid market situation on the other side of the market.

Daily illiquidity. The DILLIQ measure formalizes the notion of liquidity as the ability to trade without affecting prices and quantifies the elasticity of liquidity as the ratio of stock returns to trading volume. In other words, it captures the daily price contribution associated with one monetary unit of trading volume (Næs, Skjeltorp, and Ødegaard, 2011). In consequence, we follow Amihud (2002) and define DILLIQ as

$$DILLIQ_{i,d,s} = \frac{|Return_{i,d,s}|}{TO_{i,d,s}}. \tag{5}$$

The $Return_{i,d,s}$ represents the daily logarithmic return of stock i under configuration s. To compute returns, we furthermore compare the last price of day d with the closing price of the previous day $d-1$. In general, a security with a lower DILLIQ can be interpreted as more liquid, while high values indicate a low liquidity, and thus a high price impact of trades (Næs et al., 2011). The main advantage of the DILLIQ measure is its simplicity and robustness, as well as the fact that daily trade data is sufficient for the calculation. On the other hand, this also implies that short-term microstructure aspects cannot be considered.

Remaining quantity proportion. To facilitate the analysis of shorter time intervals, we utilize the RQP measure. It follows Cao et al. (2009) and Brogaard et al. (2014)[14] and captures the proportion of unexecuted orders on the block-level on a scale from 0 to 1. More specifically, the RQP is defined as the ratio of the total remaining quantity ($Quantity^R_{i,b,s,j}$) within a specific block b to its total submitted quantity ($Quantity^S_{i,b,s,j}$):

$$RQP_{i,b,s} = \frac{\sum_{j=1}^{TC_{i,b,s}} Quantity^R_{i,b,s,j}}{\sum_{j=1}^{TC_{i,b,s}} Quantity^S_{i,b,s,j}}. \tag{6}$$

In equation (6), i denotes the stock, b the block of the trades, and s the underlying blockchain configuration. In addition, j enumerates the orders within a block, while $TC_{i,b,s}$ specifies the number of potentially included orders. The remaining quantity $Quantity^R_{i,b,s,j}$ is equal to the remaining quantity of partially or fully executed orders within a block. The submitted quantity $Quantity^S_{i,b,s,j}$ is equal to the trade quantity specified in the order. If an order is partially executed within a block, we update $Quantity^S_{i,b,s,j}$ accordingly for the following blocks.

Consistent with Cao et al. (2009) and Brogaard et al. (2014), we utilize the "scaled imbalances in quantity between demand and supply" to approximate imbalances in the

[14] Brogaard et al. (2014), for instance, define the limit order book imbalance as $LOBI_{i,t} = \frac{(Size^{Offer}_{i,t} - Size^{Bid}_{i,t})}{(Size^{Offer}_{i,t} + Size^{Bid}_{i,t})}$, where $Size$ is the dollar volume of orders, i the stock, and t the respective period.

order books across different blockchain configurations and over time. More precisely, a RQP of 0 indicates that all orders included in a block are fully executed (i.e., $Quantity^R_{i,b,s,j} = 0$), while a RQP of 1 implies that all submitted orders were neither partially nor fully executed ($Quantity^R_{i,b,s,j} = Quantity^S_{i,b,s,j}$). In consequence, a value closer to 1 indicates a lower liquidity ($Quantity^R_{i,b,s,j} < Quantity^S_{i,b,s,j}$). If no orders were submitted to the order books ($Quantity^S_{i,b,s,j} = 0$), the RQP is not defined and set to 1, because there is no trading and the market is not liquid. This way, we aim to measure a traders ability to trade in a market and within a block. In liquid markets, even large orders can be filled almost immediately, while illiquid markets are characterized by a high fraction of un- or partially executed orders. As a result, the RQP captures the ability to trade a large market order or a competitive limit order, while lower vlaues indicate higher liquidity and vice versa. In addition, figure 5 summarizes the interpretation of the RQP.

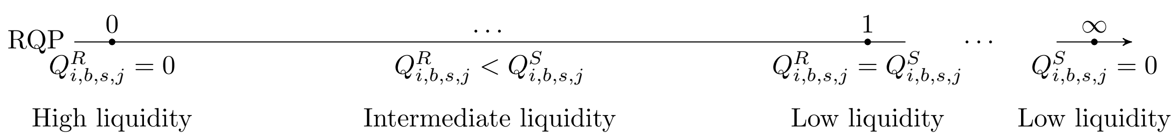


Fig. 5. Interpretation remaining quantity proportion (RQP)
This figure illustrates the interpretation of the RQP. A high value implies low and a low value implies high liquidity. More specifically, if less of the ordered quantity remains after an execution, the ability to trade is higher and vice versa. $Q^R_{i,b,s}$ and $Q^S_{i,b,s}$ denote the total remaining (unexecuted) and submitted order quantities, while i, b, s indicate the stock, block, and configuration.

4.1.3. Information

Block impact. Finally, we build on Hendershott et al. (2011)'s price impact measure to analyze price formation and capture volatility effects on the block-level. The resulting block impact (BI) measures the logarithmic price change that comes with a block b and is equal to

$$BI_{i,b,s} = BD_{i,b,s} \cdot \ln\left(\frac{Price_{i,b,s}}{Price_{i,b-1,s}}\right). \tag{7}$$

$Price_{i,b,s}$ and $Price_{i,b-1,s}$ denote the uniform clearing prices of the current and the previous block of stock i and configuration s. The block direction $BD_{i,b,s}$ furthermore indicates whether buy or sell orders dominate within block b. To determine a block's direction, we apply a heuristic approach that sets $BD_{i,b,s} = -1$, when supply exceeds demand within the current block. If on the other hand, demand exceeds supply $BD_{i,b,s}$ is set to 1. If demand equals supply, we set $BD_{i,b,s} = 0$. In total, this allows us to identify buyer and seller dominated blocks and disentangle the price effects of bullish and bearish markets. In total, the BI represents the price movement between two blocks and a higher value indicates a greater price impact of a block. This way, the BI allows us capture volatility effects that come with different blockchain configurations (see figure 4).

4.2. *Empirical Strategy*

To analyze how different parameter combinations affect market quality, we apply linear OLS regressions with stock and time fixed effects to the data panel generated in section 3.1 and summarized in table 2. Within this panel, the cross-sections of 9 blockchain configurations and 30 DAX stocks enable us to measure the impact of a varying BS and BCT on a market's activity, liquidity, and price formation.

To do so, we evaluate the impact of variations in the BS and BCT on the 6 market quality measures (MQMs) introduced in section 4.1 with the help of multiple regression models. More specifically, TC, TO, and DILLIQ measure market quality on a daily and ATS, RQP, and BI on an intraday block-level. Equation (8) provides the full specification of our empirical model:

$$
\begin{aligned}
MQM_{i,t,s} = \alpha &+ \beta_1 BS_{i,s} + \beta_2 BCT_{i,s} + \beta_3 BS_{i,s} BCT_{i,s} \\
&+ \beta_4 VG_i + \beta_5 VG_i BS_{i,s} + \beta_6 VG_i BCT_{i,s} \\
&+ \beta_7 OQ_{i,t,s} + \beta_8 OQ_{i,t,s} BS_{i,s} + \beta_9 OQ_{i,t,s} BCT_{i,s} \\
&+ \beta_{10} LnReturn_{i,t,s} + \beta_{11} SDPrice_{i,t,s} + \beta_{12} LnSize_i \\
&+ \vec{\gamma} S + \vec{\delta} T + \vec{\omega} D + \varepsilon_{i,t,s}
\end{aligned}
\tag{8}
$$

The dependent variable MQM denotes the market quality measure at hand, while i and s indicate the underlying stock and and blockchain configuration. t represents either a block b or a day d depending on the MQM's frequency. For each measure, we perform 8 regressions (model 1 to 8) that build towards the full specification given in equation (8) (model 6) and relax the included fixed effects (model 7 and 8). In the first stage, we limit our analyses to the blockchain parameters at hand and focus on the effect of the BS (model 1), the BCT (model 2), the combination of both (model 3), and how they affect each other (model 4). The fourth specification furthermore serves as the basis for the second stage, where we sequentially add controls.

The fist group of control variables comprises activity controls and includes the trading volume of a stock and the order quantity within a block or day in model 5. More specifically, the corresponding model specification adds the variables volume group (VG) and order quantity (OQ) as well as interactions with the BS and the BCT. The $\text{VG}_i \in \{1, 2, 3\}$ of stock i is equal to 1 for stocks in the low volume tertiary, equal to 2 for stocks in medium volume tertiary, and equal to 3 for stocks in the high volume tertiary[15]. In addition, we add the OQ of a block b or day d as well as its interaction with BS and BCT. A stock-block's or stock-day's OQ is equal to the total submitted order quantity of completely and partially executed orders.

Adding the second group of control variables incorporates established controls from market quality literature and yields the full specification (model 6). The logarithmic daily return (LnReturn) of day d and stock i is computed as the logarithm of the ratio of a day's closing price to the closing price of the previous day. In addition, we include the daily standard deviation of the uniform price (SDPrice) to control for unobservable volatility patterns. Note that the LnReturn and the SDPrice are always measured on a daily basis and are computed with the replicated trade data. Eventually, we use the total logarithmic market capitalization (LnSize) of stock i to control for firm size[16]. Eventually, model 6 comprises all variables, controls, and fixed effects, and thus is equal to equation (8).

Across models 1 to 6, we control for stock, year, and intraday fixed effects through the terms $\vec{\gamma}S$, $\vec{\delta}T$, $\vec{\omega}D$.[17] By including stock and time fixed effects, we aim to control for unobserved heterogeneity across the DAX 30 stocks and over time. On the stock-level, this may be due to investor preferences in Stuttgart (e.g., a local preference for Daimler), differences in risk, the opinions of analysts, and other stock-specific characteristics. With the help of year fixed effects, we aim to take the development of Stuttgart's market share as well as long-term economic trends into account. Intraday fixed effects absorb heterogeneity due to the extended trading hours at Stuttgart and the time of the day (e.g., lunch breaks, etc.). Note that intraday fixed effects are only included for measures on the block-level. In models 7 and 8, we relax the fixed effects included in the regression and drop time fixed effects (7) and both time and stock fixed effects (8), respectively. Eventually, $\varepsilon_{i,t,s}$ denotes the error term included in each specification.

[15]We classify the 30 DAX stocks into tertiaries based on the actual EUR trading volume observed at the Stuttgart stock exchange during the sample period. Table 11 in appendix C provides details on the resulting classification.

[16]Market capitalization data for all 30 DAX stocks was gathered as of December 31, 2017 from either the annual report or the investor relations website of the corresponding company.

[17]S, T, and D represent identity matrices. While S is a 30×30 matrix accounting for each stock individually, T is a 5×5 matrix considering each year of the sample period. D is a 24×24 matrix, which takes 24 hours of a day into account. Note that we allow for 24 hours, because in some configurations (BCT = 300) the last block creation can happen in the late evening. Also recall that block creations that happen on the early morning of the following day were backdated accordingly (see section 3.1.4). Accordingly, the regression parameters $\vec{\gamma}$, and $\vec{\delta}$, $\vec{\omega}$ are vectors with 30, 5, and 24 dimensions, respectively.

5. Empirical Results

In the following section, we present and interpret the results of our panel regressions. To do so, we apply model 1 to 8 to the MQMs introduced in section 4.1 and analyze each quality dimension in a separate subsection. Hence, subsection 5.1 evaluates market activity (TC, TO, and ATS), subsection 5.2 presents our findings on liquidity (DILLIQ and RQP), and subsection 5.3 investigates price formation (BI). In addition, we ensure the robustness of our findings in subsection 5.4, by aggregating block-based measures to days, considering alternative trading hours, adding additional controls, taking a closer look at trade directions, and disentangling BCT effects.

5.1. Activity

To assess the first dimension of market quality, we examine how different blockchain configurations affect the daily number of trades (TC), daily turnover (TO), and the average trade size on the block-level (ATS). In total, we find that increasing the BS affects market activity in various ways: First, the amount of trades per day is higher for smaller blocks. Second, a larger BS results in an increased trading volume per day. Third, increasing blocks leads to a higher average amount of shares per trade. With respect to the BCT, we identify the following effects: First, the number of trades per day increases with the number of blocks created (lower BCT). Second, increasing the block frequency results in a higher turnover per day. Third, a shorter BCT reduces the average amount of shares per trade. The following subsections introduce and discuss these findings in detail.

5.1.1. Trade Count

First, we take a closer look at the TC regressions and examine how the TC is affected by the BS, BCT, and their interaction. Each regression model is based on 392,493 observations, while the average number of trades per stock-day is equal to 39.96. Table 3 summarizes the regression outputs for models 1 to 8.

Except for models 3 and 8, the BS coefficient is always negative and significant on a 0.1% level. Consequently, a larger BS may lead to a lower amount of trades per day. More specifically, models 6 and 7 imply that increasing the BS by 1 reduces the number of trades per day by 1. However, compared to the average number of trades per day this is equal to a change of 2.5%. In addition, the interaction between BS and VG indicates that the BS effect depends on trading volume and is more pronounced for high volume stocks. This result seems counter-intuitive at first. However, since we calibrate the BS based on actual trading

Dependent Variable: TC (per Day)	Size Effect	Time Effect	Blockchain Configuration	Size-Time Interaction	Robustness Market Activity	Full Specification	Full Specification (no TFE)	Full Specification (no FE)
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	17.22 ***	28.66 ***	29.43 ***	34.98 ***	-9.04 ***	629.50 ***	739.28 ***	-85.59 ***
	(40.09)	(70.34)	(72.35)	(82.78)	(-15.54)	(15.19)	(17.70)	(-38.85)
	0.43	0.41	0.41	0.42	0.58	41.45	41.78	2.20
Blockchain Parameters								
BS	-0.64 ***		0.34 ***	-2.26 ***	-0.91 ***	-0.97 ***	-0.96 ***	1.01 ***
	(-88.43)		(40.77)	(-40.05)	(-12.38)	(-13.31)	(-13.06)	(13.48)
	0.01		0.01	0.06	0.07	0.07	0.07	0.07
BCT		-0.10 ***	-0.12 ***	-0.14 ***	-0.00	0.00	0.00	0.04 ***
		(-221.56)	(-205.21)	(-192.70)	(-0.48)	(0.50)	(0.37)	(28.48)
		0.00	0.00	0.00	0.00	0.00	0.00	0.00
BS·BCT				0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.00 ***
				(46.50)	(65.53)	(65.81)	(64.92)	(17.81)
				0.00	0.00	0.00	0.00	0.00
Activity Controls								
VG					32.62 ***	51.78 ***	55.80 ***	30.18 ***
					(135.14)	(35.75)	(38.23)	(256.40)
					0.24	1.45	1.46	0.12
VG·BS					-0.68 ***	-0.67 ***	-0.67 ***	-0.30 ***
					(-36.26)	(-35.72)	(-35.45)	(-16.28)
					0.02	0.02	0.02	0.02
VG·BCT					-0.08 ***	-0.07 ***	-0.07 ***	-0.09 ***
					(-109.62)	(-108.49)	(-107.36)	(-132.19)
					0.00	0.00	0.00	0.00
OQ					0.00 ***	0.00 ***	0.00 ***	0.00 ***
					(95.49)	(95.51)	(97.05)	(107.12)
					0.00	0.00	0.00	0.00
OQ·BS					0.00 ***	0.00 ***	0.00 ***	0.00 ***
					(71.92)	(72.68)	(71.93)	(58.30)
					0.00	0.00	0.00	0.00
OQ·BCT					-0.00 ***	-0.00 ***	-0.00 ***	-0.00 ***
					(-37.33)	(-38.06)	(-35.61)	(-29.37)
					0.00	0.00	0.00	0.00
Quality Controls								
LnReturn						-1.55 *	-1.67 *	-1.64
						(-2.11)	(-2.25)	(-2.09)
						0.74	0.74	0.79
SDPrice						1.09 ***	1.05 ***	0.64 ***
						(33.06)	(31.55)	(18.45)
						0.03	0.03	0.03
LnSize						-27.74 ***	-32.50 ***	3.01 ***
						(-15.25)	(-17.73)	(32.23)
						1.82	1.83	0.09
Fixed Effects								
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Intraday Fixed Effects	No	No	No	No	No	No	No	No
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Number of observations	392,493	392,493	392,493	392,493	392,493	392,493	392,493	392,493
Average	39.96	39.96	39.96	39.96	39.96	39.96	39.95	39.95
F-statistics	4,918.72 ***	6,756.09 ***	6,646.60 ***	6,568.19 ***	8,441.38 ***	8,092.82 ***	8,607.93 ***	22,191.30 ***
R^2_{adj}	0.3560	0.4316	0.4347	0.4387	0.5336	0.5352	0.5262	0.4684

Table 3: Regression trade count (TC)

This table presents β coefficients of models 1 to 8 (see section 4.2) with TC as dependent variable. The results are based on daily trade data, while the variable BS represents the number of trades that fit into a block and BCT denotes the block frequency. The activity controls comprise a stock's volume group (VG) and the daily order quantity (OQ). VG is either set to 1, 2, or 3, whereas larger values indicate higher trading volumes. Quality controls include the daily mean LnReturn, the corresponding standard deviation SDPrice, and a firm's LnSize as of December 31st, 2017. We report β coefficients, t-statistics (in parentheses), and standard errors for each independent variable and the intercept. ***, **, and * indicate statistical significance at the 0.1%, 1% and 5% level, respectively.

data, partial executions may lead to this effect. More precisely, a small BS – especially in the BS^{min}-configurations – can result in imbalanced matching schemes, where large excess demand or supply leads to partial executions on one side of the market. As a result, the remaining quantities in the order books can increase trading activity in less active trading hours. Blocks with a larger BS, on the other hand, facilitate a more balanced matching, and thus less partial executions. We verify the robustness of this rationale by controlling for the effect of order book imbalances in section 5.4.

For the BCT, models 2 to 4 suggest that a faster block creation has a weak negative effect and leads to less trades per day. However, these findings do not hold after adding activity and quality controls in models 5, 6, and 7. Instead, the interaction term with trading volume (VG) assumes the effect and indicates that a fast block creation is only beneficial for high volume stocks. In total, the negative coefficients for either the BCT or the VG-BCT-interaction imply that a shorter BCT, i.e., a higher trade frequency, leads to more trades per day. In addition, our results are consistent with the findings on periodic auctions (Fricke and Gerig, 2018), and indicate that a shorter BCT and a higher trading intensity go hand in hand.

Eventually, the interaction between BS and BCT is positive and statistically significant for all models implying a weak contrarian effect on the number of trades per day. In contrast, the OQ and corresponding interactions remain economically insignificant for both blockchain parameters. R^2_{adj} increases while adding blockchain parameters and related interactions from models 1 to 6, is above 50% in the full specification (6 and 7), and declines by 7 percentage points after dropping stock fixed effects. Supported by F-statistics at the 0.1% level, this suggests that both BS and BCT have a substantial impact on the number of trades per day, while BCT effects are mediated through a volume channel. In addition, the partly inverting coefficients in model 8 point to towards a distorting influence of unobserved heterogeneity on the stock-level.

5.1.2. Turnover

Second, we consider the TO to capture a blockchain configuration's impact on the daily trading volume of a stock. Models 1 to 8 are based on 392,493 observations with an average TO of EUR 403,456 per stock-day. Similar to the TC (see section 5.1.1), we examine the individual effects of the BS and the BCT first (model 1 and 2) and extend our focus and include interactions to test the robustness of the effects (model 3 to 6). In addition, models 7 and 8 relax the fixed effects gradually.

Across all specifications presented in table 4, the BS has a positive, significant (0.1% level), and economically large effect on the TO of a stock. More precisely, the full specification

Dependent Variable: TO (per Day)	Size Effect	Time Effect	Blockchain Configuration	Size-Time Interaction	Robustness Market Activity	Full Specification	Full Specification (no TFE)	Full Specification (no FE)
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	97,594.95 ***	167,011.27 ***	198,760.92 ***	110,879.64 ***	-383,939.58 ***	1,745,006.19 ***	2,020,571.80 ***	-2,861,970.25 ***
	(19.23)	(32.62)	(39.97)	(21.52)	(-54.59)	(3.48)	(4.02)	(-106.69)
	5,073.93	5,119.96	4,972.66	5,152.54	7,033.43	501,725.74	502,331.17	26,825.55
Blockchain Parameters								
BS	5,792.56 ***		13,853.29 ***	55,056.64 ***	61,365.64 ***	60,828.49 ***	60,826.70 ***	72,471.55 ***
	(68.08)		(137.40)	(79.87)	(69.30)	(68.67)	(68.47)	(79.42)
	85.08		100.82	689.35	885.53	885.83	888.43	912.54
BCT		-418.55 ***	-969.24 ***	-655.65 ***	467.28 ***	478.10 ***	479.09 ***	983.46 ***
		(-71.20)	(-139.05)	(-75.73)	(27.42)	(28.04)	(28.02)	(55.70)
		5.88	6.97	8.66	17.04	17.05	17.10	17.66
BS·BCT				-136.20 ***	-115.58 ***	-115.29 ***	-115.54 ***	-192.60 ***
				(-60.41)	(-55.85)	(-55.71)	(-55.67)	(-89.60)
				2.25	2.07	2.07	2.08	2.15
Activity Controls								
VG					401,392.98 ***	461,821.32 ***	472,806.73 ***	241,742.96 ***
					(137.57)	(26.34)	(26.94)	(168.65)
					2,917.77	17,532.02	17,550.17	1,433.39
VG·BS					-5,561.06 ***	-5,477.14 ***	-5,465.74 ***	842.17 ***
					(-24.60)	-24.22	(-24.10)	(3.77)
					226.09	226.11	226.77	223.14
VG·BCT					-603.10 ***	-596.44 ***	-597.23 ***	-813.61 ***
					(-72.77)	(-71.93)	(-71.82)	(-93.56)
					8.29	8.29	8.32	8.70
OQ					0.48 ***	0.48 ***	0.48 ***	0.47 ***
					(77.13)	(77.04)	(77.82)	(71.23)
					0.01	0.01	0.01	0.01
OQ·BS					0.19 ***	0.19 ***	0.19 ***	0.18 ***
					(74.58)	(75.05)	(74.55)	(66.10)
					0.00	0.00	0.00	0.00
OQ·BCT					0.00 ***	0.00 ***	0.00 ***	-0.00 ***
					(9.68)	(9.20)	(10.53)	(-6.28)
					0.00	0.00	0.00	0.00
Quality Controls								
LnReturn						5,027.18	4,971.67	5,186.04
						(0.56)	(0.56)	(0.54)
						8,897.90	8,923.96	9,572.57
SDPrice						8,744.15 ***	8,601.06 ***	10,278.91 ***
						(22.01)	(21.59)	(24.40)
						397.33	398.37	421.20
LnSize						-92,385.23 ***	-104,947.47	107,478.76 ***
						(-4.20)	(-4.76)	(94.57)
						22,013.04	22,040.71	1,136.44
Fixed Effects								
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Intraday Fixed Effects	No	No	No	No	No	No	No	No
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Number of observations	392,493	392,493	392,493	392,493	392,493	392,493	392,493	392,493
Average	403,456.50	403,456.50	403,456.50	403,456.50	403,456.50	403,456.50	403,507.10	403,507.10
F-statistics	5,684.94 ***	5,705.59 ***	6,427.96 ***	6,426.18 ***	8,567.15 ***	8,181.84 ***	8,922.79 ***	21,902.30 ***
R^2_{adj}	0.3898	0.3907	0.4265	0.4333	0.5373	0.5379	0.5352	0.4651

Table 4: Regression turnover (TO)

This table presents β coefficients of models 1 to 8 (see section 4.2) with TO as dependent variable. The results are based on daily trade data, while the variable BS represents the number of trades that fit into a block and BCT denotes the block frequency. The activity controls comprise a stock's volume group (VG) and its daily order quantity (OQ). VG is either set to 1, 2, or 3, whereas larger values indicate higher trading volumes. Quality controls include the daily mean LnReturn, the corresponding standard deviation SDPrice, and a firm's LnSize as of December 31st, 2017. We report β coefficients, t-statistics (in parentheses), and standard errors for each independent variable and the intercept. ***, **, and * indicate statistical significance at the 0.1%, 1% and 5% level, respectively.

in model 6 suggests that increasing a block's size by 1 raises trading volume by EUR 60,828 or 15%. Despite a varying size, this effect is furthermore robust across all 8 specifications. However, this finding also highlights that a higher TC (that comes with smaller blocks) does not go hand in hand with a higher TO. In addition, a higher VG weakens the positive effect of a larger BS on TO.

With respect to the BCT, we observe a similar direction but more inconsistent effect patterns, as coefficients are negative and statistically significant for models 2 to 4. This indicates that a shorter BCT enhances daily TOs by EUR 655 per minute (model 4). However, similar to the TC this effect turns positive, after adding activity controls in model 5, while the VG-BCT-interaction assumes the negative impact from the BCT coefficient. This indicates that the negative impact of enhanced BCTs is more pronounced for high- than for low-volume stocks. However, this finding may be driven by the calibration process, where we set low-volume stock's BS to 2 in most BCT^{min} and BCT^{med} configurations (although the input sample suggested lower values). As a result, throughput in these scenarios is not restricted and increasing the BCT has no negative effect on TO. Unfortunately, the interaction between OQ and BCT also remains economically small, and thus struggles to support this reasoning.

In aggregate, we furthermore find that a shorter BCT supports the positive effect a larger BS has on daily TOs. More specifically, we find a negative, statistically significant, and robust interaction effect between BS and BCT. In consequence, reducing the time between the creation of two blocks by 1 minute raises TO by EUR 115 (model 6 and 7). Eventually, R^2_{adj} is equal to 0.3898 and 0.3907 in models 1 and 2 and increases to 0.53 after including activity controls and interactions. Adding quality controls from literature and dropping time fixed effects has no effect, while dropping stock fixed effects diminishes the R^2_{adj} to 0.4651. Similar to the TC regressions in table 3, this highlights the presence of unobserved heterogeneity on the stock-level. However, in combination with significant F-statistics (0.1%) across all models, the R^2_{adj} supports the relevance of the blockchain configuration for TOs.

5.1.3. Average Trade Size

The third and last activity measure is the ATS. The ATS is computed on the block-level, measures the number of shares included in a trade, and is equal to 279.31 shares per trade on average. Table 5 summarizes the results of the regressions (model 1 to 8) and highlights the impact of BS and BCT on ATS.

The BS parameter is statistically (0.1%) and economically significant across all model specifications. Models 5 to 7 for instance suggest that including 1 additional trade in a block adds about 25 shares to a trade (i.e., an increase of 9% on average). Consistent with our

Dependent Variable: ATS (per Block)	Size Effect	Time Effect	Blockchain Configuration	Size-Time Interaction	Robustness Market Activity	Full Specification	Full Specification (no TFE)	Full Specification (no FE)
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	232.29 ***	210.42 ***	214.64 ***	187.74 ***	170.75 ***	9293.66 ***	8,999.86 ***	3,528.77 ***
	(41.90)	(37.20)	(37.98)	(33.17)	(28.47)	(36.04)	(35.00)	(368.61)
	5.54	5.66	5.65	5.66	6.00	257.88	257.16	9.57
Blockchain Parameters								
BS	7.39 ***		6.63 ***	25.44 ***	24.64 ***	24.83 ***	25.00 ***	35.98 ***
	(123.42)		(87.49)	(96.09)	(39.23)	(39.48)	(39.74)	(57.55)
	0.06		0.08	0.26	0.63	0.63	0.63	0.63
BCT		0.38 ***	0.09 ***	0.24 ***	0.05 **	0.04 **	0.06 ***	-0.20 ***
		(88.47)	(16.12)	(41.16)	(3.26)	(2.90)	(4.43)	(-14.52)
		0.00	0.01	0.01	0.01	0.01	0.01	0.01
BS·BCT				-0.07 ***	-0.05 ***	-0.05 ***	-0.05 ***	-0.04 ***
				(-74.13)	(-59.04)	(-59.03)	(-59.72)	(-53.21)
				0.00	0.00	0.00	0.00	0.00
Activity Controls								
VG					-35.66 ***	249.00 ***	239.85 ***	107.20 ***
					(-26.08)	(27.25)	(26.32)	(191.43)
					1.37	9.14	9.11	0.56
VG·BS					-2.73 ***	-2.76 ***	-2.77 ***	-6.78 ***
					(-13.83)	(-13.98)	(-14.03)	(-34.70)
					0.20	0.20	0.20	0.20
VG·BCT					-0.03 ***	-0.03 ***	-0.03 ***	-0.00
					(-4.04)	(-4.36)	(-4.11)	(-0.18)
					0.01	0.01	0.01	0.01
OQ					0.04 ***	0.04 ***	0.04 ***	0.04 ***
					(784.35)	(783.76)	(784.35)	(878.63)
					0.00	0.00	0.00	0.00
OQ·BS					-0.00 ***	-0.00 ***	-0.00 ***	-0.00 ***
					(-87.05)	(-87.31)	(-87.41)	(-103.03)
					0.00	0.00	0.00	0.00
OQ·BCT					0.00 ***	0.00 ***	0.00 ***	0.00 ***
					(31.81)	(32.20)	(32.17)	(42.87)
					0.00	0.00	0.00	0.00
Quality Controls								
LnReturn						9.08 **	10.18 **	13.90 ***
						(2.82)	(3.16)	(4.24)
						3.22	3.22	3.28
SDPrice						-1.64 ***	-1.62 ***	-9.57 ***
						(-12.23)	(-12.04)	(-72.04)
						0.13	0.13	0.13
LnSize						-396.49 ***	-385.63 ***	-148.87 ***
						(-34.99)	(-34.12)	(-369.13)
						11.33	11.30	0.40
Fixed Effects								
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Intraday Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Number of observations	4,546,605	4,546,605	4,546,605	4,546,605	4,546,605	4,546,605	4,541,841	4,541,841
Average	279.31	279.31	279.31	279.31	279.31	279.31	279.40	279.40
F-statistics	14,385.70 ***	14,223.10 ***	14,125.00 ***	13,984.80 ***	27,638.60 ***	26,721.50 ***	42,401.80 ***	118,680.00 ***
R^2_{adj}	0.1436	0.1422	0.1437	0.1447	0.2673	0.2673	0.2669	0.2387

Table 5: Regression average trade size (ATS)

This table presents β coefficients of models 1 to 8 (see section 4.2) with ATS as dependent variable. The results are based on block-level trade data, while the variable BS represents the number of trades that fit into a block and BCT denotes the block frequency. The activity controls comprise a stock's volume group (VG) and the order quantity (OQ) per block. VG is either set to 1, 2, or 3, whereas larger values indicate higher trading volumes. Quality controls include the daily mean LnReturn, the corresponding standard deviation SDPrice, and a firm's LnSize as of December 31st, 2017. We report β coefficients, t-statistics (in parentheses), and standard errors for each independent variable. ***, **, and * indicate statistical significance at the 0.1%, 1% and 5% level, respectively.

findings on the TC in subsection 5.1.1, this effect may result from an increasing number of partial executions that comes with smaller blocks. More specifically, we hypothesize that reducing blocks' sizes could intensify imbalances between demand and supply, stretch the remaining quantities of large orders over time, and thereby result in an increasing number of partial executions but also lower the size of each trade. However, whether this rationale holds is subject to the robustness tests that follow in section 5.4. Furthermore, the interaction between VG and BS is negative and statistically significant indicating an inverse relationship between trading volume and the positive impact of larger BSs on the ATS. In consequence, moving to a higher trading volume tertiary (e.g., from the medium to the high volume) is accompanied by a loss of about 2.7 trades (1%). The same holds for the relationship between OQ and BS. However, despite a statistical significance at the 0.1% level, it remains economically negligible.

For BCTs, we observe similar but inverse results. In consequence, the positive and statistically significant coefficients indicate that longer BCTs are beneficial for the number of shares included in a trade. Models 5 to 7 imply that increasing BCT by 1 minute increases the ATS by 0.05 shares. For increasing block frequencies from 10 to 60 minutes, for instance, the ATS grows by about 2.5 shares or 1% compared to mean ATS. However, similar to the impact of the BS, this effect may be driven by order book imbalances. The interactions with a stock's VG is statistically significant (0.1%) and indicates that the positive impact of creating fewer blocks is more pronounced for stocks with a lower trading volume. The interactions with the OQ remain economically insignificant.

Eventually, the interaction between BS and BCT is always negative and significant at the 0.1% level. We interpret this result as a consequence of order book imbalances and hypothesize as follows: If blocks are limited by a smaller BS, a longer BCT leads to a higher amount of submitted orders and therefore improves the balance between buy and sell orders. This results in more balanced order books, reduces remaining quantities, and finally in a higher ATS. Again, imbalance implications are discussed in the robustness section. In total and similar to the other activity measures, R^2_{adj} rises while adding blockchain parameters, interaction effects, and controls and peaks in models 5, 6, and 7 at 0.27. Together with highly significant F-statistics this underlines the explanatory contribution of the BS and BCT, whereas the drop in model 8 illustrates the hetergeneity among the 30 DAX stocks.

5.2. Liquidity

To evaluate liquidity effects, we utilize an adapted version of the Amihud (2002) illiquidity measure (DILLIQ) on the daily and order book imbalances in form of the RQP on the block-level. The DILLIQ examines the response of price to order flow, while RQP captures the ability to trade on a more granular intraday level. In total, the evidence provided in this section indicates that daily liquidity is driven by the BCT and profits from a reduction of the number of blocks per day. On the intraday level on the other hand, we identify an increasing BS as the central determinant of liquidity improvements. However, in both analyses low values for R^2_{adj} indicate incomplete models, while the blurry nature of both measures impedes interpretability. On the other hand, we also obtain robust and highly significant F-statistics across all specifications. In total, this supports the relevance of the BCT and the BS as determinants of daily and intraday liquidity but also highlights the need for more detailed analyses with liquidity measures tailored to the characteristics of decentralized markets. In the following subsections we introduce, discuss, and interpret these findings in detail.

5.2.1. Daily Illiquidity

To assess the impact of the blockchain configuration on a daily level, we utilize the DILLIQ ratio. It measures the logarithmic price change (i.e., return) that comes with 1 EUR of turnover and is equal $18.87 \cdot 10^{-6}$ on average. Note that we follow Amihud (2002) and transform the values in the data panel by scaling them up by a factor of 10^6. Thereby, we aim to improve the interpretability of the small coefficients. Table 6 summarizes the resulting regressions.

First, models 3 and 5 indicate a negative relationship between BS and daily liquidity as increasing the size of blocks is positively correlated with a high DILLIQ. In addition, the VG interaction suggests that the liquidity improvement that comes with smaller blocks is stronger for high volume stocks. At first, this finding seems counter-intuitive but may result from the fact that smaller blocks stretch large trades over time, and therefore improve liquidity on trading days with a lower trading activity. However, both effects are not robust across specifications and fade after adding activity and quality controls in models 5 and 6. Instead, the LnReturn and the SDPrice become statistically and economically significant. The OQ interaction is neither statistically nor economically significant.

In contrast, the BCT coefficients are significant at the 0.1% level and negative throughout all specifications. This implies a robust negative relationship between BCT and illiquitiy and suggests that daily liquidity improves with longer BCTs. More specifically, the full specification in model 6 estimates an improvement of $0.2046 \cdot 10^{-6}$ per minute. For an increase of the block frequency from 10 to 60 minutes, this constitutes an improvement of $10.23 \cdot 10^{-6}$ or 54% relative to the daily average. The interaction term with a stock's VG is positive and significant at the 1% level in model 5 but does not hold robustly after adding quality controls in models 6 to 8. In addition, the interaction with the OQ is neither

Dependent Variable: **DILLIQ** $\cdot 10^6$ **(per Day)**	Size Effect	Time Effect	Blockchain Configuration	Size-Time Interaction	Robustness Market Activity	Full Specification	Full Specification (no TFE)	Full Specification (no FE)
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	13.1725	20.4386 *	22.0338 *	24.7200 *	33.1713 *	-1,668.1469	-1,848.3094	145.4711 **
	(1.33)	(2.04)	(2.19)	(2.36)	(2.10)	(-1.49)	(-1.65)	(2.61)
	9.9310	10.0277	10.0384	10.4640	15.8069	1,119.4426	1,117.5611	55.6558
Blockchain Parameters								
BS	-0.0101		0.6959 ***	-0.5635	4.3834 *	3.8179	3.8362	2.3635
	(-0.06)		(3.42)	(-0.40)	(2.20)	(1.93)	(1.94)	(1.25)
	0.1665		0.2035	1.3998	1.9898	1.9765	1.9765	1.8933
BCT		-0.0572 ***	-0.0849 ***	-0.0945 ***	-0.2156 ***	-0.2046 ***	-0.2043 ***	-0.1959 ***
		(-4.97)	(-6.03)	(-5.37)	(-5.63)	(-5.38)	(-5.37)	(-5.35)
		0.0115	0.0141	0.0176	0.0383	0.0380	0.0380	0.0366
BS·BCT				0.0042	0.0035	0.0039	0.0038	0.0051
				(0.91)	(0.75)	(0.84)	(0.83)	(1.13)
				0.0046	0.0046	0.0046	0.0046	0.0045
Activity Controls								
VG					-8.3860	-67.5199	-74.5467	-14.2910 ***
					(-1.28)	(-1.73)	(-1.91)	(-4.81)
					6.5571	39.1172	39.0447	2.9739
VG·BS					-1.7243 ***	-1.6462	-1.6488	-1.3529 **
					(-3.39)	(-3.26)	(-3.27)	(-2.92)
					0.5080	0.5045	0.5045	0.4630
VG·BCT					0.0568 **	0.0630	0.0632	0.0663 **
					(3.05)	(3.41)	(3.41)	(3.68)
					0.0186	0.0185	0.0185	0.0180
OQ					-0.0000	-0.0000	-0.0000	-0.0000 *
					(-1.10)	(-1.34)	(-1.43)	(-2.10)
					0.0000	0.0000	0.0000	0.0000
OQ·BS					0.0000	0.0000	0.0000	0.0000
					(0.40)	(0.67)	(0.73)	(1.69)
					0.0000	0.0000	0.0000	0.0000
OQ·BCT					-0.0000	-0.0000	-0.0000	-0.0000 *
					(-0.90)	(-1.06)	(-1.19)	(-2.25)
					0.0000	0.0000	0.0000	0.0000
Quality Controls								
LnReturn						-1,295.8555 ***	-1,296.1314 ***	-1,295.8915 ***
						(-65.27)	(-65.28)	(-65.25)
						19.8528	19.8536	19.8605
SDPrice						8.7206 ***	8.8000 ***	10.0039 ***
						(9.84)	(9.93)	(11.45)
						0.8865	0.8863	0.8739
LnSize						74.1777	82.3650	-3.8306
						(1.51)	(1.68)	(-1.62)
						49.1152	49.0351	2.3578
Fixed Effects								
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Intraday Fixed Effects	No	No	No	No	No	No	No	No
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Number of observations	302,493	302,493	302,493	302,493	302,493	302,493	302,493	302,493
Average	18.87	18.87	18.87	18.87	18.87	18.87	18.87	18.87
F-statistics	10.38 ***	11.11 ***	11.13 ***	10.84 ***	9.97 ***	110.84 ***	121.38 ***	373.93 ***
R^2_{adj}	0.0011	0.0011	0.0012	0.0012	0.0012	0.0154	0.0153	0.0146

Table 6: Regression daily Amihud illiquidity measure (DILLIQ)

This table presents β coefficients of models 1 to 8 (see section 4.2) with DILLIQ as dependent variable. A higher DILLIQ indicates lower liquidity (higher illiquidity). The results are based on daily trade data and scaled by the factor 10^6 to improve intrepretability (Amihud, 2002). The variable BS represents the number of trades that fit into a block, while BCT denotes block frequency. The activity controls comprise a stock's volume group (VG) and its daily order quantity (OQ). VG is either set to 1, 2, or 3, while larger values indicate higher trading volumes. Quality controls include the daily mean LnReturn, the corresponding standard deviation SDPrice, and a firm's LnSize as of December 31st, 2017. We report β coefficients, t-statistics (in parentheses), and standard errors for each independent variable and the intercept. ***, **, and * indicate statistical significance at the 0.1%, 1% and 5% level, respectively.

statistically nor economically significant.

Eventually, we do not find any evidence for a relationship between BS and BCT. In combination, these findings indicate that daily liquidity is driven by BCTs, while a block's size seems to play a minor role. However, despite a steady improvement from models 1 to 6, R^2_{adj} remains low across all specifications pointing out that substantial independent variables are missing in the current specification. On the other hand, F-statistics are consistently significant at the 0.1% level and thereby underline relevance of the BCT as a determinant of daily liquidity.

5.2.2. Remaining Quantity Porportion

To measure liquidity on a more granular, intraday level we utilize the RQP. The RQP is defined as ratio of unexecuted to submitted orders and ranges between 0 and 1, while the sample average is equal to 0.5486. If all orders in a block are completely executed, liquidity is high and the RQP equal to 0. A value of 1, on the other hand, is assumed if none of the submitted orders are executed and implies low liquidity. Table 7 presents the regression outputs for models 1 to 8 with RQP as dependent variable.

The BS is statistically significant at the 0.1% level across all and economically large in most specifications and thereby robustly indidcates that larger blocks improve intraday liquidity. More specifically, increasing the BS by 1 lowers the RQP within a block by up to 0.092 (models 5 to 7). Compared to the average RQP of 0.5486 across our sample, this constitutes an improvement of 17%. However, this finding may be driven by the growing number of trades that comes with smaller blocks (see 5.1.1). As a result of the limited capacity of a block, the number of partially executed orders grows and their remaining order quantity spills over to the following blocks – especially when there are large orders on one side of the market. By including activity controls, we are furthermore able to identify a statistically significant (0.1%) and robust alleviating effect of higher trading volumes (VG). This suggests that despite bigger blocks, the liquidity of low-volume stocks is adversely affected by more severe spill over effects among blocks.

The impact of increasing BCTs is characterized by consistently negative and statistically significant but small coefficients. Thus, a higher BCT may be beneficial for liquidity but remains economically negligible. In addition, the significantly negative but also small interaction between VG and BCT suggests that the liquidity improvements that come with longer BCTs are weakly reinforced by higher trading volumes.

Finally, the OQ is statistically significant but economically too small to interpret reasonably for both blockchain parameters. In contrast, the relationship between BS and BCT is positive and statistically significant. As a result and consistent with our ATS findings, liq-

Dependent Variable: RQP (per Block)	Size Effect	Time Effect	Blockchain Configuration	Size-Time Interaction	Robustness Market Activity	Full Specification	Full Specification (no TFE)	Full Specification (no FE)
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.5342 ***	0.6944 ***	0.6894 ***	0.7462 ***	0.7827 ***	-1.2313 ***	-1.8870 ***	0.5118 ***
	(188.61)	(241.48)	(240.84)	(262.90)	(245.32)	(-8.98)	(-13.79)	(102.32)
	0.0028	0.0029	0.0029	0.0028	0.0032	0.1371	0.1368	0.0050
Blockchain Parameters								
BS	-0.0145 ***		-0.0079 ***	-0.0476 ***	-0.0919 ***	-0.0919 ***	-0.0919 ***	-0.0912 ***
	(-474.60)		(-205.79)	(-358.46)	(-275.05)	(-274.85)	(-274.57)	(-279.26)
	0.0000		0.0000	0.0001	0.0003	0.0003	0.0003	0.0003
BCT		-0.0011 ***	-0.0008 ***	-0.0011 ***	-0.0000 ***	-0.0000 ***	-0.0000 **	-0.0001 ***
		(-512.47)	(-279.81)	(-374.44)	(-4.43)	(-4.43)	(-2.97)	(-8.68)
		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BS·BCT				0.0001 ***	0.0002 ***	0.0002 ***	0.0002 ***	0.0002 ***
				(311.98)	(344.97)	(344.79)	(344.09)	(350.11)
				0.0000	0.0000	0.0000	0.0000	0.0000
Activity Controls								
VG					-0.0181 ***	-0.0802 ***	-0.1022 ***	-0.0241 ***
					(-24.83)	(-16.50)	(-21.08)	(-82.41)
					0.0007	0.0049	0.0048	0.0003
VG·BS					0.0150 ***	0.0150 ***	0.0150 ***	0.0146 ***
					(142.55)	(142.51)	(142.53)	(143.08)
					0.0001	0.0001	0.0001	0.0001
VG·BCT					-0.0005 ***	-0.0005 ***	-0.0005 ***	-0.0005 ***
					(-142.09)	(-142.07)	(-141.85)	(-140.70)
					0.0000	0.0000	0.00000342	0.0000
OQ					0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***
					(373.63)	(373.54)	(373.52)	(382.33)
					0.0000	0.0000	0.0000	0.0000
OQ·BS					-0.0000 ***	-0.0000 ***	-0.0000 ***	-0.0000 ***
					(-63.50)	(-63.56)	(-63.42)	(-63.63)
					0.0000	0.0000	0.0000	0.0000
OQ·BCT					-0.0000 ***	-0.0000 ***	-0.0000 ***	-0.0000 ***
					(-18.99)	(-18.87)	(-19.02)	(-19.39)
					0.0000	0.0000	0.0000	0.0000
Quality Controls								
LnReturn						-0.0024	-0.0016 **	-0.0012
						(-1.41)	(-0.92)	(-0.68)
						0.0017	0.0017	0.0017
SDPrice						-0.0001	0.0000 **	0.0001
						(-1.72)	(0.38)	(1.65)
						0.0001	0.0001	0.0001
LnSize						0.0875 ***	0.1147 ***	0.0097 ***
						(14.52)	(19.07)	(45.83)
						0.0060	0.0060	0.0002
Fixed Effects								
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Intraday Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Number of observations	4,546,605	4,546,605	4,546,605	4,546,605	4,546,605	4,546,605	4,546,605	4,546,605
Average	0.5468	0.5468	0.5468	0.5468	0.5468	0.5468	0.5468	0.5468
F-statistics	5,304.63 ***	6,018.15 ***	6,745.97 ***	8,534.76 ***	10,931.90 ***	10,570.40 ***	16,583.20 ***	53,397.30 ***
R^2_{adj}	0.0582	0.0655	0.0742	0.0936	0.1261	0.1261	0.1246	0.1246

Table 7: Regression remaining quantity proportion (RQP)

This table presents β coefficients of models 1 to 8 (see section 4.2) with RQP as dependent variable. A RQP close to 1 indicates low and a value close to 0 high liquidity. The results are based on block-level trade data, while the variable BS represents the number of trades that fit into a block and BCT denotes the block frequency. The activity controls comprise a stock's volume group (VG) and the order quantity (OQ) per block. VG is either set to 1, 2, or 3, while larger values indicate higher trading volumes. Quality controls include the daily mean LnReturn, the corresponding standard deviation SDPrice, and a firm's LnSize as of December 31st, 2017. We report β coefficients, t-statistics (in parentheses), and standard errors for each independent variable and the intercept. ***, **, and * indicate statistical significance at the 0.1%, 1% and 5% level, respectively.

uidity in blockchain configurations with smaller blocks may benefit more from longer BCTs. However, similar to the impact of the block frequency, the effect sizes of the interaction remain small and economically marginal. Overall and in contrast to the daily level, the evidence given in table 7 indicates that intraday liquidity is primarily driven by the capacity of blocks, while their frequency only plays a minuscule role. However, R^2_{adj} is always below 0.13 indicating an omitted variable bias, while strongly significant F-statistics support a minimum explanatory contribution of the coefficients reported in table 7.

5.3. Information

Within the third and last dimension of market quality, we investigate price formation effects by taking a closer look at the BI. More specifically, the BI serves as a means to capture the price change that comes with a block. In total, our analyses suggest that the BI is higher for larger and more frequent blocks, while both effects support each other. In consequence, blockchain configurations with a high throughput (i.e., with a large BS and a short BCT) may also lead to more volatile markets – especially in less active trading times. We will introduce and discuss these findings in detail in the following paragraphs.

5.3.1. Block Impact

The BI is defined as the logarithmic price change that comes with a block and helps us to capture the price effects illustrated in figure 4. In order to improve interpretability, we report the regressions' coefficients in basis points (bps) and neglect block directions (BDs). As a result, we limit our analysis to the absolute block impact (ABI), which considers the only intensity of price changes but not their direction. However, we include BDs in the robustness checks that follow in section 5.4. Table 8 summarizes the β coefficients of the ABI regressions in bps, while the average ABI is equal to 48.71 bps.

With respect to the BS, the β coefficients are statistically significant at the 0.1% level and indicate a robust positive relationship between a block's price effect and its size. In consequence, larger blocks create more intense price movements. In model 6, for instance, 1 additional trade per block raises the intensity of the following price change by 30.40 bps. Relative to the sample average this is equal to an increase of 62%. In addition, the interaction with a stock's VG is negative and statistically significant, indicating a weakening effect of increasing trading volumes. This relation may be explained by the lower volatility of large cap stocks (Fama and French, 1993) but also contradicts previous findings on the relationship between trading volumes and volatility (Jones, Kaul, and Lipson, 1994; Darrat, Rahman, and Zhong, 2003).

Dependent Variable: **ABI $\cdot 10^4$ (per Block)**	Size Effect	Time Effect	Blockchain Configuration	Size-Time Interaction	Robustness Market Activity	Full Specification	Full Specification (no TFE)	Full Specification (no FE)
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	17.8524 ***	59.7563 ***	62.9621 ***	54.3253 ***	24.6481 ***	2,143.5872 ***	2,021.2881 ***	568.0573 ***
	(5.22)	(17.11)	(18.06)	(15.55)	(6.17)	(12.74)	(12.05)	(92.56)
	0.0003	0.0003	0.0003	0.0003	0.0004	0.0168	0.0168	0.0006
Blockchain Parameters								
BS	3.1266 ***		5.0458 ***	11.0837 ***	34.3148 ***	30.4034 ***	30.4776 ***	35.6169 ***
	(84.62)		(107.81)	(67.82)	(81.93)	(74.12)	(74.30)	(88.86)
	0.0000		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BCT		-0.0017	-0.2241 ***	-0.1755 ***	-0.3240 ***	-0.2144 ***	-0.2211 ***	-0.3069 ***
		(-0.65)	(-66.75)	(-48.94)	(-34.62)	(-23.39)	(-24.24)	(-34.81)
		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BS·BCT				-0.0213 ***	-0.0220 ***	-0.0217 ***	-0.0219 ***	-0.0231 ***
				(-38.56)	(-39.38)	(-39.62)	(-39.93)	(-42.63)
				0.0000	0.0000	0.0000	0.0000	0.0000
Activity Controls								
VG					-0.5150	40.2893 ***	35.6300 ***	5.9893 ***
					(-0.56)	(6.76)	(5.99)	(16.68)
					0.0001	0.0006	0.0006	0.0000
VG·BS					-7.6263 ***	-6.9720 ***	-6.9786 ***	-8.5030 ***
					(-57.91)	(-54.07)	(-54.12)	(-67.91)
					0.0000	0.0000	0.0000	0.0000
VG·BCT					0.0211 ***	0.0736 ***	0.0752 ***	0.0928 ***
					(4.94)	(17.55)	(17.94)	(22.92)
					0.0000	0.0000	0.0000	0.0000
OQ					-0.0000	0.0000	0.0000	0.0005 ***
					(-1.01)	(0.37)	(0.72)	(16.32)
					0.0000	0.0000	0.0000	0.0000
OQ·BS					-0.0000 ***	0.0000 ***	0.0000 ***	0.0000 *
					(-4.64)	(7.20)	(7.32)	(2.16)
					0.0000	0.0000	0.0000	0.0000
OQ·BCT					0.0000	-0.0000 ***	-0.0000 ***	-0.0000 ***
					(1.54)	(-12.52)	(-12.65)	(-8.90)
					0.0000	0.0000	0.0000	0.0000
Quality Controls								
LnReturn						80.2880 ***	80.1862 ***	81.4487 ***
						(38.27)	(38.22)	(38.76)
						0.0002	0.0002	0.0002
SDPrice						38.1833 ***	38.1897 ***	36.9332 ***
						(435.89)	(436.24)	(433.88)
						0.0000	0.0000	0.0000
LnSize						-92.0723 ***	-86.5239 ***	-24.2811 ***
						(-12.46)	(-11.74)	(-93.91)
						0.0007	0.0007	0.0000
Fixed Effects								
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Intraday Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Number of observations	4,546,605	4,546,605	4,546,605	4,546,605	4,546,605	4,546,605	4,546,605	4,546,605
Average	48.71	48.71	48.71	48.71	48.71	48.71	48.71	48.71
F-statistics	523.19 ***	387.47 ***	596.51 ***	612.89 ***	634.43 ***	3,725.46 ***	5,879.99 ***	17,742.60 ***
R^2_{adj}	0.0061	0.0045	0.0070	0.0073	0.0083	0.0484	0.0481	0.0448

Table 8: Regression absolute block impact (ABI)

This table presents β coefficients of models 1 to 8 (see section 4.2) with ABI as dependent variable. The results are based on block-level trade data and reported in basis points (bps). The variable BS represents the number of trades that fit into a block and the BCT denotes the block frequency. The activity controls comprise a stock's volume group (VG) and the order quantity (OQ) per block. VG is either set to 1, 2, or 3, while larger values indicate higher trading volumes. Quality controls include the daily mean LnReturn, the daily standard deviation SDPrice, and a firm's LnSize as of December 31st, 2017. We report β coefficients, t-statistics (in parentheses), and standard errors for each independent variable and the intercept. ***, **, and * indicate statistical significance at the 0.1%, 1% and 5% level, respectively.

With respect to the BCT, we observe a robust, statistically significant, and negative relationship. This finding is consistent with the anecdotal evidence depicted in figure 4 and appendix D.3 and indicates that the intensity of price changes increases with the block frequency. More specifically, a shift from 10 to 60 minutes reduces a block's price impact by about 10.72 basis points or 22% (model 6). Similar to the BS effects, we also find evidence for an alleviating effect of a stock's VG as a higher VG weakens the negative effect of a larger BCT on the ABI.

Eventually, we also find evidence for statistically significant and negative BS-BCT-interaction. This implies that lowering the BCT reinforces the impact of a larger BS on the ABI. As a result, more frequent blocks may increase volatility as larger blocks lead to larger price changes between successive blocks. However, this effect is economically small and around 0.02 bps in every model specification. The interaction between both BS and BCT and OQs remain inconclusive and economically insignificant. In addition, R^2_{adj} remains below 0.05 throughout all model specifications, while F-statistics at the 0.1% level indicate significance of the estimated models in total. Also note that both R^2_{adj} and the F-statistic are boosted, when we add quality controls. In combination with the highly significant coefficients, this suggests that the quality controls explain a substantial amount of the BI variation. However, together with the F-statistics, the robustness of both parameters towards all model specifications supports their (at least minor) role as determinants of price fluctuations in decentralized markets.

5.4. Robustness

To ensure the validity of the findings illustrated in the previous section, we test their robustness in several ways: We consider the number of blocks (5.4.1), modify the input sample (5.4.2), take order book imbalances as independent variable into account (5.4.3), examine the impact of BDs on prices (5.4.4), and disentangle the effects of BCT changes. The underlying motivations and analyses are described in the following subsections.

5.4.1. Number of Blocks

In the first robustness test, we focus on the potentially confounding effects of the different number of blocks in the block-level analyses. More specifically, the results for the ATS, RQP, and BI may be endogenously driven by the increasing number of blocks that comes with a higher block frequency (i.e., lower BCT). As a result, 6 blocks of 10 minutes, for instance, aggregate trading that happens within an hour to 1 block from the corresponding 60-minute configuration. In addition, the coefficients of our regressions may be driven by the preponderance of the number of observations of configurations with a lower frequency. To take these concerns into account, we aggregate the block-level data to stock-day-configurations by computing equal-weighted averages (ATS, RQP, and BI) and sums (ATS) of the dependent and equal-weighted averages of all independent variables. Based on the resulting input sample we conduct a full specification regression (model 6) for each new measure. The results confirm and even strengthen our previous findings for all three measures, as R^2_{adj} improves substantially. For the sake of brevity and due to their confirmatory nature, the results of the regressions are reported in table 15 in appendix F.

5.4.2. Alternative Trading Hours

The second robustness check addresses the high number of trading hours at Stuttgart and aims to exclude effects caused by early and late trading phases. For this purpose, we modify the input sample and exclude orders submitted outside of the trading times of the reference market Xetra (Clapham and Zimmermann, 2016). This includes orders submitted before 9 a.m. and after 5.30 p.m. This way, we also eliminate confounding effects linked to the choice to initiate the first auction of a day by the first submitted order. Table 16 in appendix F presents the results of the regression analyses ordered by quality dimensions. Note that we focus on the full specification of our regression model (model 6), which includes all controls, interactions, and fixed effects. For the sake of computation and to further demonstrate the robustness of our findings, we additionally limit the replication of market outcomes to the year 2017.

With respect to market activity, the results with alternative trading hours are largely consistent with our previous findings and thereby confirm the effects identified in section 5.1 in direction and size. In addition, we find a statistically significant and negative relationship between the TC and the BCT, which supports the mixed evidence in section 3. On the other hand, the impact of the BS seems to be slightly lower in the 2017 subsample with alternative trading hours, while the impact of an increasing block frequency on the ATS fades completely. Similarly, both liquidity measures DILLIQ and RQP are robust to our modifications, as well. Moreover, our robustness analysis provides additional evidence for the existence of a negative BS effect and the relevance of the a stock's VG on the daily level (DILLIQ). On the intraday level, all effects are consistent. Eventually, we are able to confirm all ABI effects and find indications for an even stronger impact than estimated by model 6 in table 8.

In total, we do not find any contradicting evidence and can confirm most of the findings from the previous sections. In addition, the regressions with alternative trading hours support some weak and resolve some inconclusive effects. As a result, we argue that our results are not biased by Stuttgart's extended trading hours or by starting trading with the first order of a day.

5.4.3. Additional Controls

The aim of the third robustness analysis is to verify our interpretations and to disentangle the effects of partial executions and order book imbalances on market activity. More specifically, we hypothesize in section 5.1 that some blockchain configurations may facilitate imbalances between demand and supply, and thereby stretch the remaining quantities of large orders over time. As a result, we observe an increasing number of partial executions (TC) with a lower BS, while the TO and the ATS increases with the blocks' size and frequency. In consequence, we reexamine our activity measures by extending our regression model (see equation (8)) with the RQP as an independent variable (see section 4.1.2) to verify this hypothesis. Table 17 in appendix F illustrates the results of the associated regressions for the TC, TO, and ATS.

With respect to the TC, these results support our hypothesis as adding the RQP boosts the impact of the BS, while the RQP and its interaction with both blockchain parameters remains low. In addition, the R^2_{adj} rises from 0.5352 to 0.6615. Consequently, the RQP is an important control but a block's size remains an essential determinant of the number of trades per day. In addition, we find evidence for a moderating role of order book imbalances for turnover. More specifically, the significant coefficients for the RQP and both blockchain interactions indicate the RQP's role as an effect channel and a moderator and facilitator of size and time effects. A similar logic applies to the ATS. However, in contrast the results of the ATS regression remain inconclusive. On one hand, column 3 of table 17 stresses the importance of the RQP as a control and driver of our findings, as R^2_{adj} jumps from 0.2673 to 0.8638. On the other hand, the coefficients of the BS, BCT, BS-BCT interaction, and VG-BS interaction change their sign. As a result and in contrast to table 5, a smaller BS and a shorter BCT may increase the average amount of shares per trade. In total, table 17 in appendix F highlights the role of order book imbalances and underlines that parts of the activity effects presented in section 5.1 may be driven by partial executions.

5.4.4. Block Directions

Fourth, we aim to analyze the role of BDs on price formation and price changes in detail. To do so, we utilize two subsets from the data panel illustrated in table 2. More specifically, we create two new data panels that either include the 2.3 million blocks with a positive (BD = +1) or the 2.2 million blocks with negative (BD = -1) direction. Blocks with a direction of 0 are not included in either panel. To minimize confusion and improve interpretability, we furthermore stay with the ABI as dependent variable in our regressions. In total, the results reported in table 17 in appendix F confirm our findings from section 5.3.1. In addition, they highlight that larger and faster blocks may result in more volatile prices – irrespective of their direction. However, our findings also indicate that the VG is more important for blocks with excess demand, while blocks with excess supply seem substantially more affected by higher BS.

5.4.5. Impact of Block Creation Time Variations

In contrast to the BS, which varies substantially across stocks, the BCT is fixed to either 10, 60, or 300 minutes depending on the underlying blockchain configuration. In consequence, the findings from the previous sections may be driven by increasing BCTs from 10 to 60 minutes, 60 to 300 minutes, or both. In this subsection, we take a closer look at the changes of our 6 MQMs to examine, whether either change has a more pronounced effect. To do so, we compute the change of a MQM (ΔMQM) that comes with an increase of the BCT from 10 to 60 and 60 to 300 minutes and compare the respective daily averages to each other. Table 9 summarizes the results and shows that the time effects identified in this section indeed depend on the change of BCTs[18]. More specifically, mean differences reported in panel A indicate that the impact on the ΔTC, ΔTO, ΔDILLIQ, and ΔBI is more pronounced for increases from 10 to 60 minutes. ΔATS and ΔRQP on the other hand, seem to be more affected by increasing the BCT from 60 to 300 minutes. In addition, panel B confirms these findings in statistical significance, direction, and strength in a multivariate setup with year and stock fixed effects. In total, these findings indicate that the impact of changing block frequencies does not only depend on the direction of the change but also on its severity.

6. Discussion

While our findings highlight the impact of the blockchain configuration on the activity, liquidity, and price formation on decentralized markets they are bound by several limitations. In this section, we discuss our results by illustrating the limitations of the underlying data, the data generation process, the applied market quality measures, and the empirical analyses.

First, our study is based on real-world trading data that reflects the behavioral patterns of (retail) investors, their decisions, and resembles the scale and size of modern financial

[18] In addition, figure 10 in appendix F provides complementary illustrations by the means of boxplots.

Δ MQM	Δ TC	Δ TO	Δ ATS	Δ DILLIQ $\cdot 10^6$	Δ RQP	Δ ABI $\cdot 10^4$
Panel A: Compared means						
Mean ΔMQM$_{1060}$	-31.80	-197,607.00	21.39	-25.1604	-0.0799	-44.0079
Mean ΔMQM$_{60300}$	-8.45	7,242.90	81.29	0.4077	-0.1946	28.9804
Mean difference	-23.35 ***	-204,850.00 ***	-59.91 ***	-25.5681 ***	0.1147 ***	-72.9883 ***
	(-158.22)	(-117.00)	(-52.85)	(-5.74)	(113.6300)	(-47.87)
F-statistics	11.10 ***	1.66 ***	1.41 ***	8.70 ***	1.57 **	1.22 ***
Panel B: Regression						
Intercept	3.73 ***	55,650.40 ***	51.67 ***	6.4368	-0.1559 ***	6.4773
	(8.02)	(-117.93)	(13.49)	(0.43)	(-45.74)	-1.2300
	0.46	1,723.37	3.83	15.0761	0.0034	5.2620
ΔBCT	-22.91 ***	-203,244.16 ***	-61.59 ***	-26.0059 ***	0.1169 ***	-73.6678 ***
	(-170.03)	(-117.93)	(-55.45)	(-5.95)	-118.3200	(-48.28)
	0.13	1,723.37	1.11	4.3714	0.0010	1.5260
Fixed Effects						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	200,156	200,156	200,156	200,156	200,156	200,156
Average	-19.84	-92670.55	52.07	-12.06	-0.14	-6.62
F-statistics	1,782.33 ***	500.35 ***	409.01 ***	4.31 ***	723.84 ***	91.48 ***
R^2_{adj}	0.2323	0.0782	0.0648	0.0006	0.1094	0.0151

Table 9: Robustness – block creation time (BCT) variations
This table reports the results of the assessment of BCT changes on market quality. Panel A shows the results of the compared means analysis, while mean ΔMQM$_{1060}$ and mean ΔMQM$_{60300}$ denote the daily average change in the considered MQM given a shift from 10 to 60 and 60 to 300 minutes, respectively. t-values are computed with the Satterthwaite approximation (note that the Cochran approximation provides consistent results) and reported in parentheses. Panel B provides confirming regressions that take year and stock fixed effects into account. ΔBCT is a binary variable that is equal to 1 for changes from 10 to 60 minutes and equal to 0 for changes from 60 to 300 minutes. For each coefficient, we report t-statistics in parentheses and standard errors below. For both panels (A and B) ***, **, and * indicate statistical significance at the 0.1%, 1% and 5% level, respectively.

markets. However, while this setup offers a realistic environment to evaluate the potential of future applications, the data does not reflect actual decentralized trading behavior. On the other side, the scarcity of decentralized trading data complicates the evaluation of decentralized markets, while keeping a practical perspective. As a result, we perceive our approach as a first educated guess and the best we can do so far. Moreover, the preponderance of price discovery happens on reference markets (Hasbrouck, 1995). For DAX 30 stocks, this reference market is Xetra (Clapham and Zimmermann, 2016). In consequence and consistent with Stuttgart's market position, traders may not fundamentally change their behavior as they rely on information from the reference market to make trading decisions.

Second, integrating blockchain parameters into the trading system of the Stuttgart stock exchange shifts the market model from continuous to periodic trading. Thereby, we create an additional gap between the behavioral patterns (and outcomes) observed in the input sample and the replicated market outcomes. More specifically, the input sample is based on orders submitted to trade in continuous limit order books instead of the periodic auctions of the blockchain-based market mechanism. To minimize the resulting frictions, our market mechanism closely follows Stuttgart's trading rules, while the blockchain parameters are calibrated according to the input sample's executions. In addition, the price-time priority adopted from Stuttgart mitigates timing effects of order submissions and time stamps are utilized as tie-breakers. Nevertheless, in combination with the transparency that comes with the decentralization of the order books, the discrete nature of the trading process may result in different trading decisions and offers the possibility to implement trading strategies that exploit these features. The (public) availability of data blocks and latency-related asymmetry of information distribution that characterize today's blockchain-based system, can facilitate front running (Aune, Krellenstein, O'Hara, and Slama, 2017; Malinova and Park, 2017) or other manipulative strategies, such as spoofing (Viana, 2018).

Third, low R^2_{adj}-values within the liquidity and information dimension point towards incomplete empirical models that suffer from an omitted variable bias. In addition, the DILLIQ and the RQP remain blurry throughout our analyses and robustness tests. In consequence, our findings also highlight the need to develop tailored liquidity measures that take the specific characteristics of decentralized markets into account. The same holds for the information dimension, where the BI constitutes only a first step towards the assessment of price formation in decentralized markets. Nevertheless, F-statistics for all three measures remain significant at the 0.1% level across all model specifications, indicating a basic explanatory contribution of our regressions.

Eventually, our study may suffer from the p-value problem that comes with the size of our data panel. According to Lin, Lucas Jr., and Shmueli (2013), standard errors become extremely small in very large samples and thereby boost statistical significance. In consequence, we follow their recommendation and consider the economic as well as the statistical significance of β coefficients in our interpretation.

However, despite these concerns, we believe that this study makes the best possible approximation on how blockchain technology may affect decentralized trading. In consequence, we are confident to offer initial guidance to the engineers of decentralized markets that supports them in their endeavors to build and improve their trading platforms.

7. Conclusion

In total, this study provides a first analytic assessment of the quality of decentralized (stock) markets by examining the impact of central design parameters – the block size and block creation time – on a market's activity, liquidity, and information processing capability. To examine the influence of parameter variations, we utilize order-level data from the Stuttgart stock exchange to replicate and analyze 5 years of blockchain-based equity trading. Thereby, we contribute a technology-agnostic evaluation of decentralized market platforms that analyzes performance-related quality drivers with data from real-world financial markets and find:

First and with respect to the activity of decentralized markets, we find evidence that smaller blocks lead to a higher number of trades but also limit trading volumes and the number of shares included in a trade. In addition, the higher number of blocks per day that comes with increasing the block frequency seems beneficial for the number of trades and turnover but reduces the average size of trades. As a result, increasing the block sizes offers a means to maximize the throughput of a system. The effect of lowering block creation times on the other hand, remains ambiguous and exposes the engineers of decentralized markets to a trade-off between raising turnover and reducing the average trade size. Second, the liquidity of decentralized markets depends on the block creation time on the daily and the block size on the intraday level. More precisely, daily liquidity seems to profit from a higher block frequency, while increasing a block's capacity proofs to be beneficial on the block-level. In consequence, boosting liquidity goes hand in hand with maximizing the throughput of a system. In addition, market engineers can control liquidity mostly independently on the daily and intraday level. Third and last, we investigate the influence of a blockchain configuration on price formation and our analysis indicates that the price impact of a new block is stronger for bigger and faster blocks. Therefore, blockchain configurations that maximize market activity by increasing block sizes and decreasing block creation times may simultaneously lead to more intense price changes and challenge market engineers to find a balance between throughput and volatility. In general, the significant interactions between blockchain parameters across all quality dimensions call for a joint perspective that takes the adverse effects of changing the block creation time into account. As a result, these findings demonstrate that boosting block size and frequency is no silver bullet to resolve scalability issues. Instead, blockchain and market engineers need to take a holistic perspective that aligns all three dimensions of market quality with the platform's objective to find a balanced blockchain configuration.

However, as an initial assessment, this study faces several limitations: First and foremost, the lack of native decentralized trading data and the resulting data generation process may lead to biased results. More specifically, the integration of blockchain parameters into the trading system of the Stuttgart stock exchange and the blockchain's novel transparency paradigm (Notheisen and Weinhardt, 2018) may change the behavior of traders beyond the scope of our replication. Second, we utilize and adapt measures from traditional market quality literature to evaluate market outcomes. However, the blurry nature of some of the measures – especially in the liquidity and information dimensions – limits the interpretability and generalizability of our findings. In addition and third, low R^2_{adj}-values in some analyses indicate incomplete models. In consequence, future research may focus on the analysis of native decentralized trading data to bridge the gap between the artificial data in this study, the development of tailored quality measures, and the analysis of changing trader behavior. This includes the modelling, measurement, and analysis of behavioral implications and consequences, as well as the detection of manipulative strategies and the development of countermeasures. From a technical perspective, this also comprises the preservation of the decentralized and trust-free character of blockchain-based markets on one hand, while ensuring a sufficient level of privacy on the other hand (Gencer, van Renesse, and Sirer, 2017). Nevertheless, we are confident to provide a fertile ground to researchers and some initial guidance for innovative practitioners with this study.

Appendix A. List of Abbreviations

BS	block size	1
BCT	block creation time	1
HFT	high frequency trader	8
TC	trade count	22
TO	turnover	22
ATS	average trade size	22
DILLIQ	daily Amihud illiquidity measure	23
RQP	remaining quantity proportion	23
BI	block impact	25
MQM	market quality measure	26
VG	volume group	26
OQ	order quantity	26
LnReturn	logarithmic daily return	27
SDPrice	daily standard deviation of the uniform price	27
LnSize	total logarithmic market capitalization	27
ABI	absolute block impact	39
bps	basis points	39
BD	block direction	39

Appendix B. Decentralized Markets in Practice

Name	Transaction object	Functional scope	Technology	Website (whitepaper)
Augur	Expectations	Creating of and trading on prediction markets	Ethereum	https://www.augur.net (✓)
ATLANT	Real estate	Tokenization and trading of subdivided parcels	Ethereum	https://atlant.io (✓)
Bancor	Crypto assets	Trading cryptocurrencies	Bancor protocol	https://www.bancor.network (✓)
Bisq (Bitsquare)	Crypto assets	Trading crypto- and fiat currencies	P2P network (Tor)	https://bisq.network (✓)
BitShares	Financial assets	Trading crypto and financial assets	Graphene	https://bitshares.org (✓, ✓)
CrowdForce	Micro businesses	Offer and pay micro tasks and services	Ethereum	https://token.crowdforce.io (✓)
CryptoBridge	Crypto assets	Trading cryptocurrencies	Graphene	https://crypto-bridge.org (-)
Dmarket	In-game items	Trading platform	Exonum	https://dmarket.io (✓)
Gnosis	Expectations	Creation of and trading on prediction markets	Ethereum	https://gnosis.pm (✓)
IDEX	Financial assets	Real-time trading and blockchain-based account management	Ethereum	https://idex.market (✓)
OpenBazaar	eCommerce	Trading digital/physical goods, services, and cryptocurrencies	Own protocol	https://openbazaar.org (-)
OpenLedger DEX	Crypto assets	Trading cryptocurrencies	Graphene	https://dex.openledger.io (-)
Sharevest	Financial assets	Issuing and trading security tokens	Ethereum	https://www.sharevest.co (✓)
Polymath	Financial assets	Issuing and trading security tokens	Ethereum	https://polymath.network (✓)
Waves Dex	Crypto assets	Trading cryptocurrencies and crypto tokens	Waves platform	https://wavesplatform.com (✓, ✓)

Table 10: Overview of decentralized market platforms

Overview of selected decentralized market platforms including the name of the venture, the type of transaction object, the functional scope implemented in a decentralized fashion, the utilized (blockchain) technology, and a reference to additional information. Checkmarks indicate the availability of whitepapers and contain embedded links to them.

Appendix C. Statistics

DAX Stock	Trading volume [EUR]	Submissions	Executions
High Trading Volume			
Daimler AG	2,878,824,761	170,317	161,167
BASF SE	1,895,009,981	97,310	92,951
Allianz SE	1,751,893,157	83,149	78,932
Volkswagen AG	1,709,763,141	87,879	82,535
Deutsche Bank AG	1,625,199,132	103,769	96,536
Commerzbank AG	1,347,282,920	93,959	87,311
Siemens AG	1,128,144,976	63,834	60,560
Deutsche Telekom AG	1,113,196,399	77,900	74,123
E.ON SE	879,639,827	75,053	70,742
Munich Re AG	790,393,581	38,902	36,975
Total (High)	**15,119,347,874**	**892,072**	**841,832**
Medium Trading Volume			
Bayer AG	753,049,363	40,316	38,342
Deutsche Post AG	710,822,205	47,692	45,601
Deutsche Lufthansa AG	707,565,780	52,246	48,978
BMW AG	588,956,034	35,811	33,910
Infineon Technologies AG	576,222,195	39,339	37,016
SAP SE	539,192,253	38,576	36,694
RWE AG	472,087,701	38,415	36,265
Linde AG	429,160,228	25,347	24,252
Adidas AG	406,272,085	27,746	26,530
Continental AG	371,871,258	18,602	17,710
Total (Medium)	**5,555,199,102**	**364,090**	**345,298**
Low Trading Volume			
thyssenkrupp AG	325,780,643	28,745	27,081
Fresenius SE & Co. KGaA	281,528,879	21,004	20,003
ProSiebenSat.1 Media SE	207,858,196	17,796	16,800
HeidelbergCement AG	188,301,059	12,498	11,962
Fresenius Medical Care AG & Co. KGaA	187,662,133	12,878	12,215
Henkel AG & Co. KGaA	183,770,006	12,005	11,393
Merck KGaA	167,651,636	10,939	10,351
Deutsche Brse AG	159,721,055	11,738	11,125
Vonovia SE	113,569,486	10,396	9,797
Beiersdorf AG	84,097,020	6,283	6,000
Total (Low)	**1,899,940,114**	**144,282**	**136,727**
Total	**22,574,487,089**	**1,400,444**	**1,323,857**

Table 11: Volume groups
Volume groups based on the EUR trading volume, the number of submissions, and the number of executions at the Stuttgart stock exchange during the observation period (2013 to 2017).

Year	2013	2014	2015	2016	2017	Total
Trading Days	253	252	253	237	236	1,231
	Total Submissions					
Total	324,487	272,297	301,193	281,872	220,595	1,400,444
High	207,377	173,235	193,444	189,960	128,056	892,072
Medium	86,008	73,755	78,877	65,611	59,839	364,090
Low	31,102	25,307	28,872	26,301	32,700	144,282
	Submissions per Day					
Total - Average	1,282.56	1,080.54	1,190.49	1,189.33	934.72	1,137.65
Median	1,220.00	1,005.50	1,069.00	1,083.00	876.00	1,060.00
Standard Deviation	360.72	402.92	520.22	720.32	320.50	498.39
High - Average	819.67	687.44	764.60	801.52	542.61	724.67
Median	777.00	630.00	674.00	728.00	512.00	662.00
Standard Deviation	264.24	271.44	364.58	535.85	195.21	359.04
Medium - Average	339.95	292.68	311.77	276.84	253.56	295.77
Median	320.00	263.00	285.00	253.00	235.50	273.00
Standard Deviation	99.70	122.46	135.92	148.37	99.24	125.92
Low - Average	122.93	100.42	114.12	110.97	138.56	117.21
Median	116.00	91.50	103.00	101.00	117.00	106.00
Standard Deviation	44.05	45.10	54.43	62.60	84.39	60.77
	Shares per Trade					
Total - Average	579.24	565.27	478.15	558.14	588.53	551.91
Median	200.00	160.00	130.00	150.00	150.00	150.00
Standard Deviation	1,955.92	1,721.49	1,422.17	1,891.90	1,754.31	1,761.46
High - Average	597.98	598.49	462.84	614.08	711.11	588.14
Median	195.00	160.00	110.00	150.00	170.00	150.00
Standard Deviation	2,043.62	1,808.44	1,474.51	2,161.38	2,077.36	1,921.80
Medium - Average	592.77	562.77	587.57	493.75	476.19	548.77
Median	189.00	170.00	192.00	140.00	120.00	150.00
Standard Deviation	2,028.88	1,743.56	1,493.50	1,254.98	1,339.12	1,629.86
Low - Average	417.81	345.38	281.53	316.11	317.93	336.73
Median	200.00	160.00	110.00	120.00	100.00	150.00
Standard Deviation	818.41	765.61	606.61	778.06	683.28	734.30

Year	2013	2014	2015	2016	2017	Total
Trading Days	253	252	253	237	236	1,231
	Total Executions					
Total	307,771	257,521	286,388	264,048	208,129	1,323,857
High	196,011	163,782	183,782	177,954	120,303	841,832
Medium	82,137	69,788	75,117	61,261	56,995	345,298
Low	29,623	23,951	27,489	24,833	30,831	136,727
	Executions per Day					
Total - Average	1,216.49	1,021.91	1,131.97	1,114.13	881.90	1,075.43
Median	1,155.00	929.00	1,019.00	1,015.00	823.00	997.00
Standard Deviation	355.08	400.30	514.72	697.01	314.47	487.57
High - Average	774.75	649.93	726.41	750.86	509.76	683.86
Median	731.00	587.50	646.00	680.00	473.50	620.00
Standard Deviation	262.23	269.55	359.65	516.36	191.24	350.07
Medium - Average	324.65	276.94	296.91	258.49	241.50	280.50
Median	306.00	246.50	268.00	237.00	222.00	257.00
Standard Deviation	98.03	121.21	135.10	144.80	97.90	124.11
Low - Average	117.09	95.04	108.65	104.78	130.64	111.07
Median	109.00	84.00	98.00	97.00	110.00	100.00
Standard Deviation	43.40	43.97	53.68	60.85	82.56	59.38
	Trading Volume per Day [EUR]					
Total - Average	19,455,634	17,823,060	20,331,201	17,557,332	16,338,639	18,338,332
Median	18,070,182	16,655,422	18,742,236	16,210,178	15,409,822	16,925,251
Standard Deviation	6,661,126	7,736,631	9,671,249	9,550,444	6,449,342	8,241,854
High - Average	12,942,418	12,161,910	13,794,422	12,056,780	10,307,920	12,282,167
Median	11,941,958	11,343,034	12,674,440	10,842,951	9,471,874	11,159,156
Standard Deviation	5,060,658	5,739,640	7,128,774	7,053,992	4,804,935	6,136,795
Medium - Average	4,886,115	4,305,437	5,082,196	4,059,208	4,178,873	4,512,753
Median	4,515,928	3,793,530	4,706,574	3,605,665	3,808,895	4,138,044
Standard Deviation	1,848,190	1,996,051	2,447,861	2,213,432	1,806,268	2,114,017
Low - Average	1,627,102	1,355,713	1,454,584	1,441,344	1,851,846	1,543,412
Median	1,468,654	1,144,763	1,241,672	1,225,662	1,610,711	1,342,409
Standard Deviation	764,644	847,508	779,826	947,779	1,043,229	895,423

Table 12: Detailed summary statistics of the input sample by year and volume group.

Appendix D. Market Mechanism

D.1. Software Structure Market Mechanism

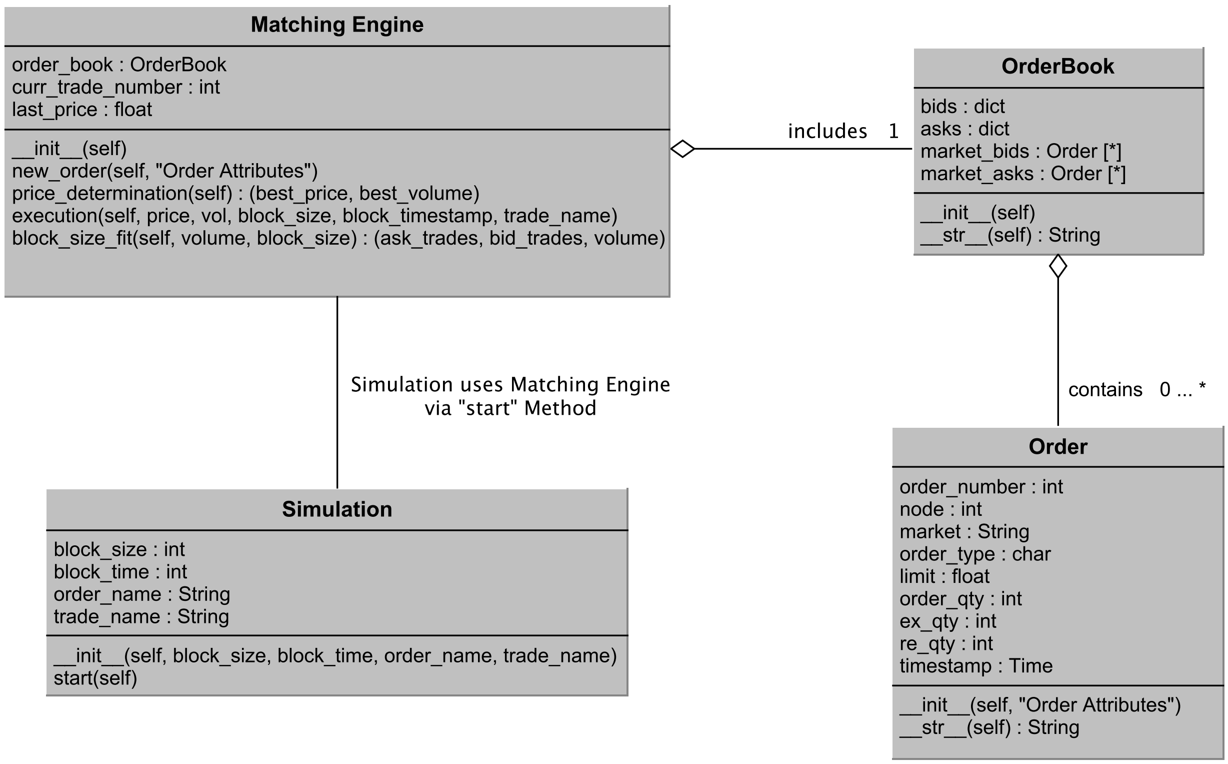


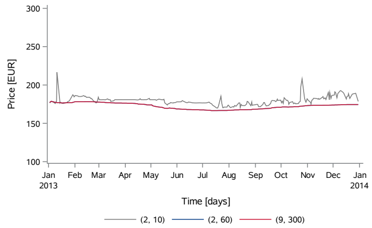
Fig. 6. Class diagram market mechanism

D.2. Data Structure Market Outcomes

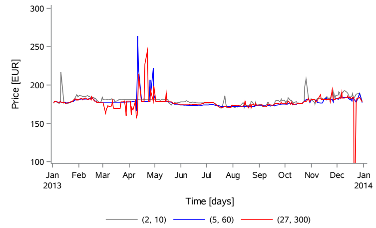
Attribute	**Data type**	**Value (example)**	**Description**
trade_id	Integer	1	Unique trade identifier
order_number	String	1501029450129	Unique identifier for order submission
order_type	Character	K	Either K or V for buy or sell
stock	String	daimler	Unique stock identifier
order_limit	Float	73.33	Order limit (0 for market orders)
order_qty	Integer	10	Order quantity
re_qty	Integer	5	Remaining order quantity
trade_qty	Integer	5	Traded quantity
trade_price	Float	72.78	Price per stock in the trade
timestamp	String	02Jan2013:06:36:26.00	Timestamp of the trade

Table 13: Data structure market outcomes

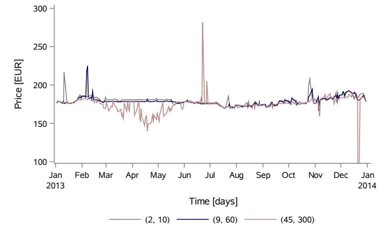
D.3. Market Outcomes



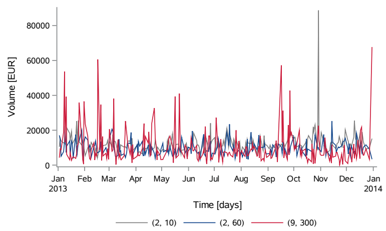
(a) Prices BS = min



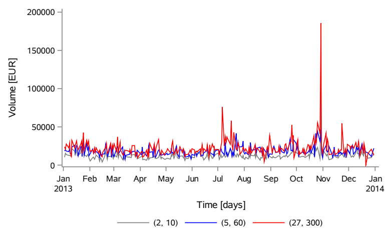
(b) Prices BS = med



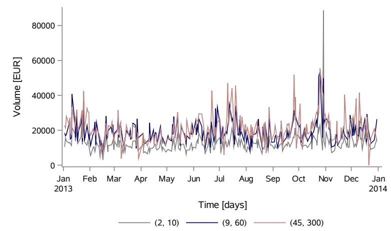
(c) Prices BS = max



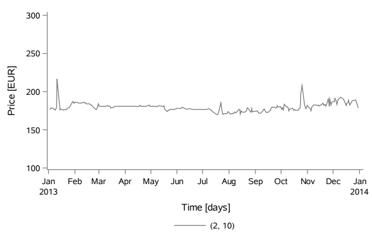
(d) Volumes BS = min



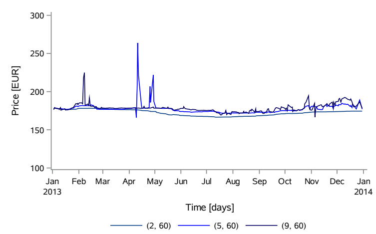
(e) Volumes BS = med



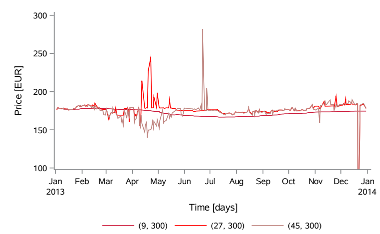
(f) Volumes BS = max



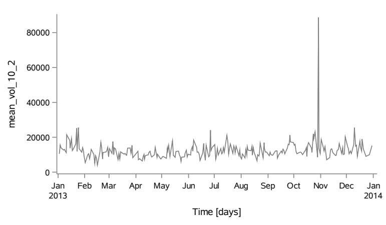
(g) Prices BCT = 10



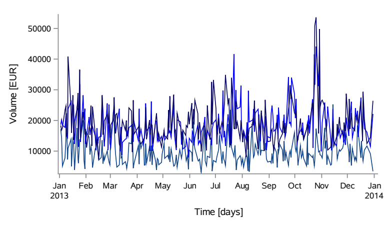
(h) Prices BCT = 60



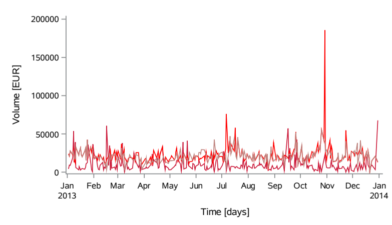
(i) Prices BCT = 300



(j) Volumes BCT = 10

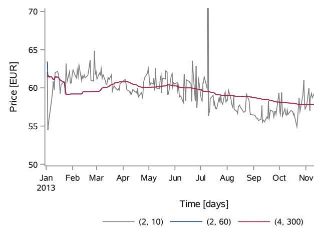


(k) Volumes BCT = 60

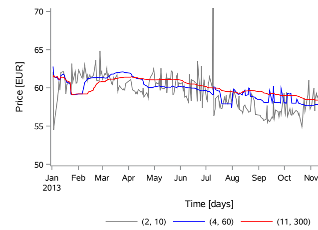


(l) Volumes BCT = 300

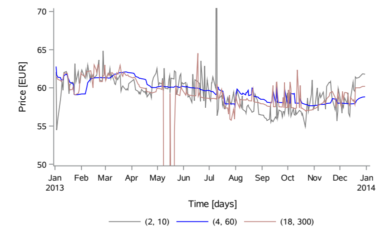
Fig. 7. Comparative statics market outcomes VW AG
Each panel illustrates the replicated trade prices or trading volumes for VW AG in 2013 (253 trading days), while holding either the block size (BS) or the BCT fixed. Prices are computed as daily averages and volumes as daily totals. The line color indicates the respective blockchain configuration (BS, BCT).



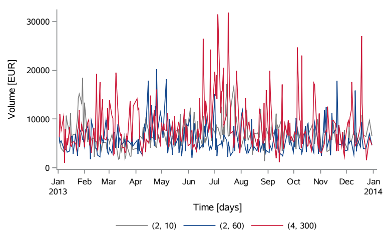
(a) Prices BS = min



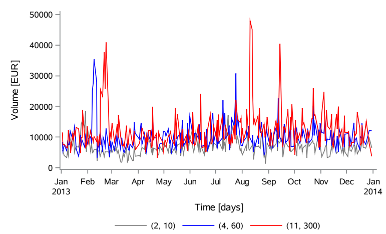
(b) Prices BS = med



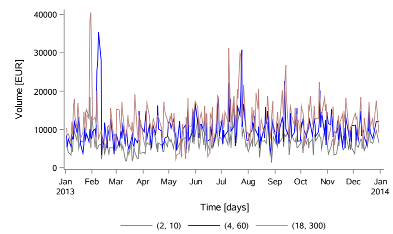
(c) Prices BS = max



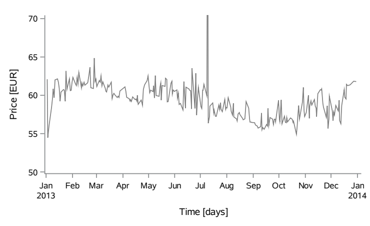
(d) Volumes BS = min



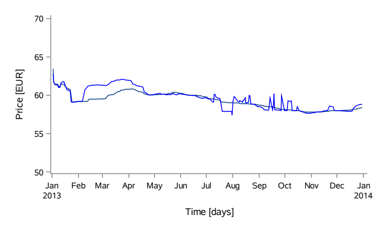
(e) Volumes BS = med



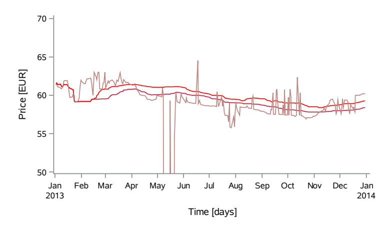
(f) Volumes BS = max



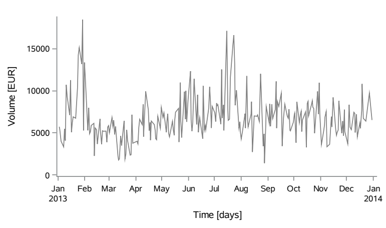
(g) Prices BCT = 10



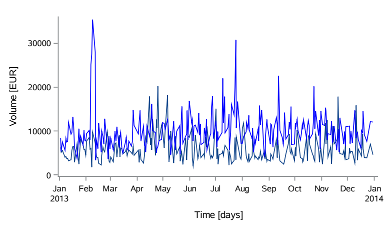
(h) Prices BCT = 60



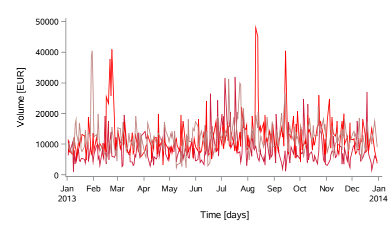
(i) Prices BCT = 300



(j) Volumes BCT = 10



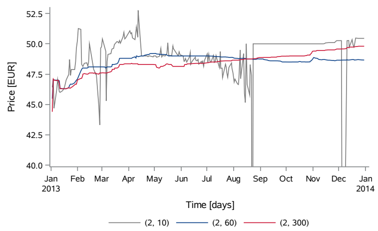
(k) Volumes BCT = 60



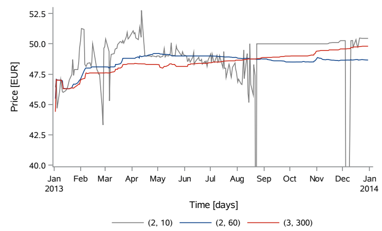
(l) Volumes BCT = 300

Fig. 8. Comparative statics market outcomes SAP SE

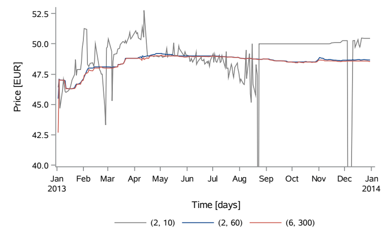
Each panel illustrates the replicated trade prices or trading volumes for SAP SE in 2013 (253 trading days), while holding either the block size (BS) or the BCT fixed. Prices are computed as daily averages and volumes as daily totals. The line color indicates the respective blockchain configuration (BS, BCT).



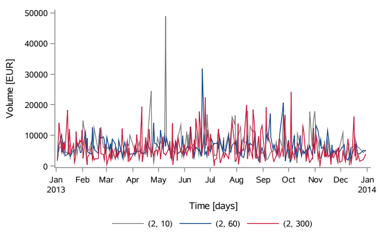
(a) Prices BS = min



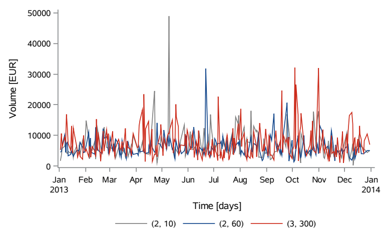
(b) Prices BS = med



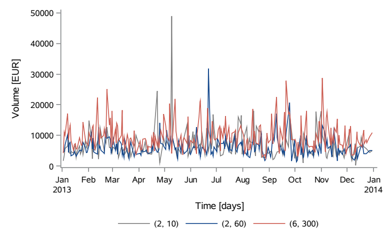
(c) Prices BS = max



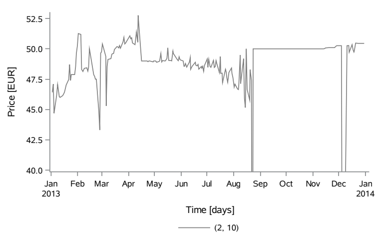
(d) Volumes BS = min



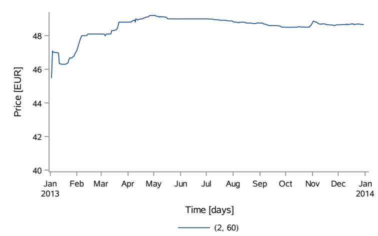
(e) Volumes BS = med



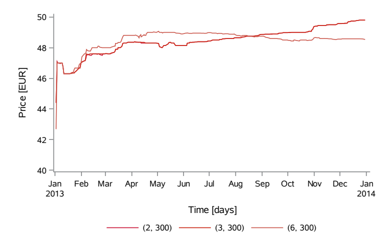
(f) Volumes BS = max



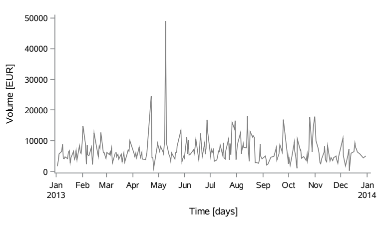
(g) Prices BCT = 10



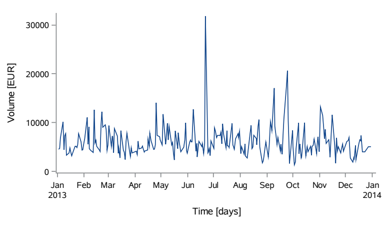
(h) Prices BCT = 60



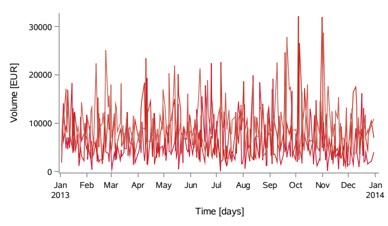
(i) Prices BCT = 300



(j) Volumes BCT = 10



(k) Volumes BCT = 60



(l) Volumes BCT = 300

Fig. 9. Comparative statics market outcomes Deutsche Börse AG

Each panel illustrates the replicated trade prices or trading volumes for Deutsche Börse AG in 2013 (253 trading days), while holding either the block size (BS) or the BCT fixed. Prices are computed as daily averages and volumes as daily totals. The line color indicates the respective blockchain configuration (BS, BCT).

Appendix E. Overview of market quality measures

MQM	Source	Citations	Interpretation	Frequency	Advantages	Disadvantages
Trade count (TC) $TC_{i,d,s} = n_{i,d,s}$	Barclay et al. (2003)	347	TC measures the execution frequency. The higher TC, the higher is the market activity level.	Per day	TC is easy to calculate and to interpret.	TC does neither contain price nor quantity information.
Turnover (TO) $TO_{i,d,s} = \sum_{j=1}^{TC_{i,d,s}} Price_{i,d,s,j} \cdot Quantity^{T}_{i,d,s,j}$	Barclay et al. (2003)	347	TO measures the trading volume in euro. The higher TO, the higher is the market activity level.	Per day	TO is easy to calculate and to interpret and contains information on price and quantity.	The TO interpretation may be distorted by large orders.
Average trade size (ATS) $ATS_{i,b,s} = \frac{\sum_{j=1}^{TC_{i,b,s}} Quantity^{T}_{i,b,s,j}}{TC_{i,b,s}}$	Hendershott et al. (2011)	1,182	ATS measures the amount of shares per trade. The higher ATS, the higher is the market activity level.	Per block	ATS is easy to calculate and to interpret.	ATS does not provide information on the trade frequency.
Daily illiquidity ratio (DILLIQ) $DILLIQ_{i,d,s} = \frac{\lvert Return_{i,d,s} \rvert}{TO_{i,d,s}}$	Amihud (2002), Næs et al. (2011)	7,102	DILLIQ measures the response of price to order flow. The higher DILLIQ, the less liquid is the stock.	Per day	DILLIQ is a robust and simple measure. It does only require daily data.	DILLIQ does not capture microstructure aspects.
Remaining quantity proportion (RQP) $RQP_{i,b,s} = \frac{\sum_{j=1}^{TC_{i,b,s}} Quantity^{R}_{i,b,s,j}}{\sum_{j=1}^{TC_{i,b,s}} Quantity^{S}_{i,b,s,j}}$	Cao et al. (2009), Brogaard et al. (2014)	916	RQP measures the percentage of remaining order quantity within a block. The higher RQP, the lower is the percentage execution.	Per block	RQP is easy to calculate and to interpret on a percentage scale.	The RQP interpretation may be biased by large orders.
Block impact (BI) $BI_{i,b,s} = BD_{i,b,s} \cdot \ln\left(\frac{Price_{i,b,s}}{Price_{i,b-1,s}}\right)$	Hendershott et al. (2011)	1,182	BI indicates the information content of a trade. The higher BI, the higher is the information content of a trade, i.e. the price movement.	Per block	BI offers a simple approximation of the information impact.	A heuristic is needed for determining the BD. More robust measures focus on the trade innovation.

Table 14: Overview of market quality measures
All measures are calculated for each stock i, each blockchain configuration s, and each block b or day d, respectively. The number of citations is reported as of October 31, 2018.

Appendix F. Robustness

Dependent Variable:	**ATS (daily avg)**	**ATS (daily sum)**	**RQP (daily avg)**	**ABI $\cdot 10^4$ (daily avg)**
Independent Variable	(Full Specification, per day)	(Full Specification, per day)	(Full Specification, per day)	(Full Specification, per day)
Intercept	8,741.04 ***	318,017.44 ***	0.5245 *	-417.5691
	(31.32)	(14.07)	(2.26)	(-1.04)
	279.11	22,600.83	0.2321	400.9959
Blockchain Parameters				
BS	28.49 ***	1,509.55 ***	-0.0865 ***	35.6595 ***
	(57.39)	(37.55)	(-209.54)	(50.00)
	0.50	40.20	0.0004	0.7132
BCT	0.08 ***	24.13 ***	-0.0001 **	-0.2204 ***
	(8.37)	(31.50)	(-6.81)	(-16.22)
	0.01	0.77	0.0000	0.0520
BS*BCT	-0.06 ***	-2.22 ***	0.0001 ***	-0.0309 ***
	(-55.41)	(-23.66)	(149.74)	(-18.58)
	0.00	0.09	0.0000	0.0017
Activity Controls				
VG	218.77 ***	14,790.58 ***	0.0035	-57.0188 ***
	(22.43)	(18.73)	(0.43)	(-4.07)
	9.75	789.68	0.0081	14.0108
VG*BS	-2.64 ***	-289.55 ***	0.0140 ***	-7.9369 ***
	(-20.76)	(-28.11)	(132.73)	(-43.42)
	0.13	10.30	0.0001	0.1828
VG*BCT	-0.00	-23.87 ***	-0.0004 ***	0.1081 ***
	(-0.84)	(-63.95)	(-116.00)	(5.50)
	0.00	0.37	0.0000	0.0066
OQ	0.02 ***	2.03 ***	0.0000 ***	0.0011 ***
	(177.88)	(180.66)	(120.62)	(6.68)
	0.00	0.01	0.0000	0.0000
OQ*BS	-0.00 ***	0.04 ***	-0.0000 ***	0.0000 ***
	(-87.29)	(104.79)	(-55.06)	(6.68)
	0.00	0.00	0.0000	0.0000
OQ*BCT	0.00 ***	-0.01 ***	-0.0000 ***	-0.0000 ***
	(65.14)	(-95.13)	(-27.94)	(-12.35)
	0.00	0.00	0.0000	0.0000
Quality Controls				
LnReturn	10.31	-41.31	-0.0034	-87.5039 ***
	(2.08)	(-0.10)	(-0.83)	(-12.30)
	4.95	400.83364	0.0041	7.1118
SDPrice	-1.58 ***	-79.90 ***	-0.0003	64.8309 ***
	(-7.16)	(-4.46)	(-1.61)	(204.04)
	0.22	991.60	0.0002	0.3177
LnSize	-373.47 ***	-14,062.03 ***	0.0079	19.8261
	(-30.50)	(-14.18)	(0.77)	(1.13)
	0.22	991.60	0.0102	17.5935
Fixed Effects				
Year Fixed Effects	Yes	Yes	Yes	Yes
Intraday Fixed Effects	No	No	No	No
Stock Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	302,493	302,493	302,493	302,493
Average	268.69	13,183.86	0.4627	64.29
F-statistics	15,526.20 ***	11,262.20 ***	5,721.88 ***	1,241.77 ***
R^2_{adj}	0.6884	0.6157	0.4487	0.1500

Table 15: Robustness - Number of Blocks
This table presents full specification regressions (model 6) with block-level measures aggregated to stock-day-configurations (equal-weighted averages and totals, i.e. sums). Particularly, the daily sum of the ATS is equal to the daily number of traded shares. We report β coefficients, t-statistics (in parentheses), and standard errors for each variable. ***, **, and * indicate significance at the 0.1%, 1% and 5% level.

Quality Dimension	Activity			Liquidity		Information
Dependent Variable:	**TC**	**TO**	**ATS**	**DILLIQ**	**RQP**	**ABI**
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-108.44	-2,144,752.55	156.71	161.0954	0.7995	269.4001
	(-0.00)	(-0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	345,790.91	4,997,767,543.00	492244.35	8,388,148.8890	245.4898	497,006.6214
Blockchain Parameters						
BS	-0.38 **	54,851.64 ***	20.75 ***	7.6942 **	-0.0864 ***	41.1652 ***
	(-3.27)	(32.42)	(12.77)	(2.71)	(-104.38)	(27.94)
	0.12	1,692.00	1.62	2.8390	0.0008	1.4734
BCT	-0.02 ***	256.96 ***	0.05	-0.3760 ***	-0.0000 **	-0.2945 ***
	(-8.75)	(7.94)	(1.45)	(-6.92)	(-2.61)	(-9.09)
	0.00	32.00	0.04	0.0540	0.0000	0.0324
BS·BCT	0.01 ***	-103.44 ***	-0.05 ***	0.0012	0.0001 ***	-0.0326 ***
	(27.42)	(-26.04)	(-22.28)	(0.18)	(123.52)	(-16.14)
	0.00	4.00	0.00	0.0070	0.0000	0.0020
Activity Controls						
VG	17.37 ***	249,452.82 ***	-41.05	-10.6210	-0.0083	-20.4891
	(0.00)	(0.00)	(-0.00)	(-0.00)	(-0.00)	(-0.00)
	10,755.36	155,448,802.00	15310.60	260,902.0290	7.6356	15,458.7192
VG·BS	-0.57 ***	-6,048.45 ***	-1.63 **	-2.7331 ***	0.0149 ***	-9.4650 ***
	(-18.98)	(-14.04)	(-3.20)	(-3.78)	(57.50)	(-20.52)
	0.03	431.00	0.51	0.7230	0.0003	0.4612
VG·BCT	-0.04 ***	-373.38 ***	0.01	0.1330 ***	-0.0005 ***	0.1109 ***
	(-37.96)	(-23.40)	(0.89)	(4.97)	(-56.09)	(7.40)
	0.00	16.00	0.02	0.0270	0.0000	0.0150
OQ	0.00 ***	0.72 ***	0.05 ***	-0.0000	0.0000 ***	-0.0015 ***
	(56.95)	(45.00)	(313.36)	(-0.69)	(159.06)	(-11.11)
	0.00	0.00	0.00	0.0000	0.0000	0.0001
OQ·BS	0.00 ***	0.189 ***	-0.00 ***	0.0000	-0.0000 ***	0.0001 ***
	(30.92)	(32.98)	(-34.52)	(0.32)	(-29.54)	(6.89)
	0.00	0.00	0.00	0.0000	0.0000	0.0000
OQ·BCT	-0.00 ***	0.004 ***	0.00 ***	-0.0000	-0.0000 ***	-0.0000 *
	(-16.87)	(6.39)	(5.80)	(-0.56)	(-9.62)	(-2.07)
	0.00	0.00	0.00	0.0000	0.0000	0.0000
Quality Controls						
LnReturn	1.85	30754.77 *	-0.19	-453.3191 ***	-0.0064 *	0.0074 ***
	(1.96)	(2.25)	(-0.03)	(-19.80)	(-2.27)	(14.56)
	0.94	13640.00	5.58	22.8930	0.0028	0.0005
SDPrice	1.10 ***	5,017.49 ***	-0.12	11.5977 ***	-0.0015 ***	0.0042 ***
	(19.77)	(6.24)	(-0.32)	(8.60)	(-7.54)	(120.22)
	0.06	804.00	0.39	1.3490	0.0002	0.0000
LnSize	4.75	80,953.96	-0.37	-5.5876	-0.0012	-0.0010
	(0.00)	(0.00)	(-0.00)	(-0.00)	(-0.00)	(-0.00)
	15,028.94	217,215,455.00	21,394.17	364,569.8930	10.6696	2.1601
Fixed Effects						
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Intraday Fixed Effects	No	No	Yes	No	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	59,910	59,910	688,931	59,910	688,931	688,931
Average	30.37	328,524.40	295.17	21.59	0.5603	62.12
F-statistics	1,816.99 ***	1,711.48 ***	5,367.28 ***	21.51 ***	1,750.44 ***	475.22 ***
R^2_{adj}	0.5491	0.5343	0.2968	0.0136	0.1209	0.0360

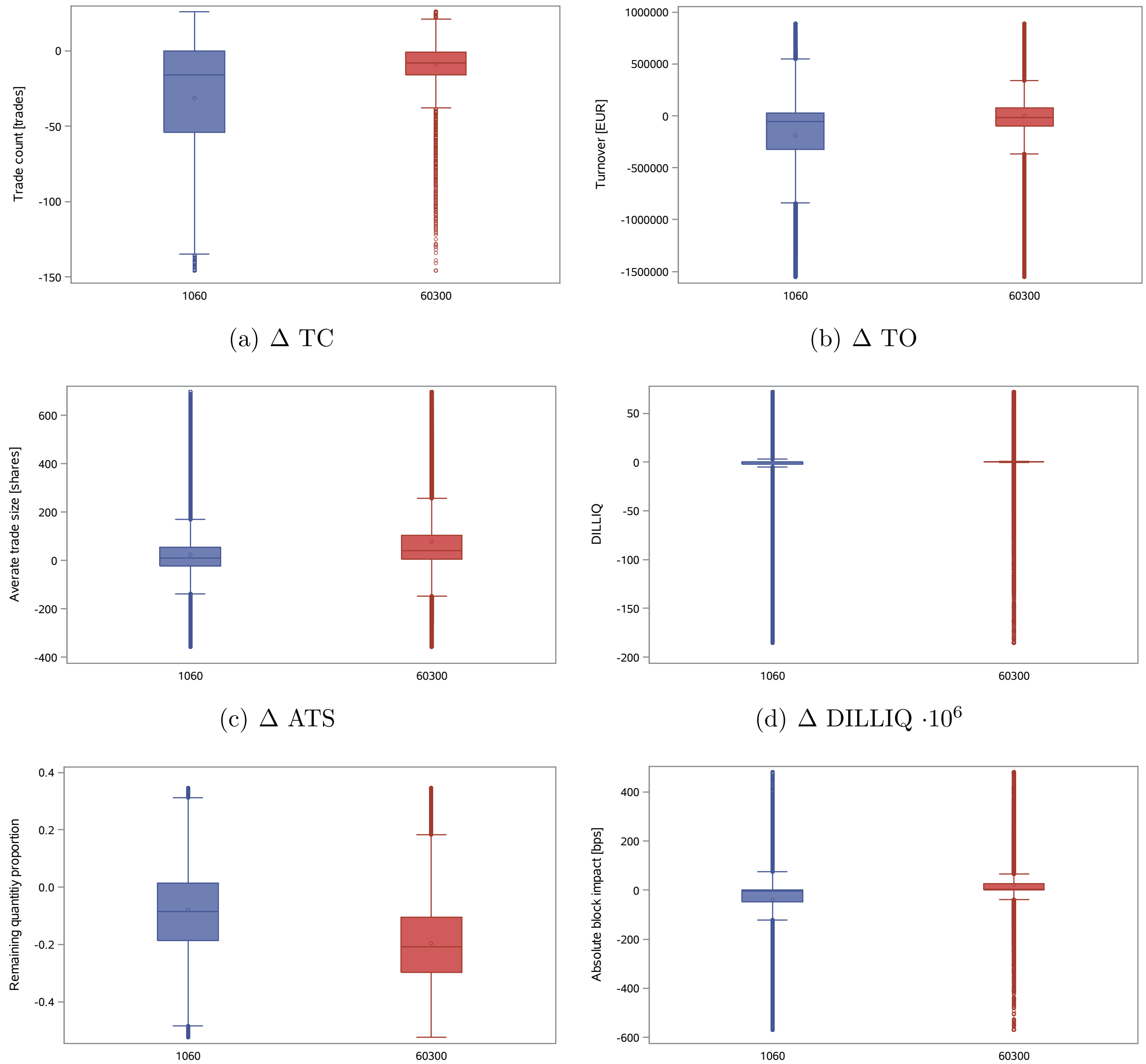
Table 16: Robustness - Alternative trading hours

This table presents full specification regressions (model 6) with a modified data panel for each MQM. Consistent with Xetra's trading hours, we only consider orders submitted between 9 a.m. and 5.30 p.m. to replicate market outcomes for 2017. We report β coefficients, t-statistics (in parentheses), and standard errors for each variable, while ***, **, and * indicate significance at the 0.1%, 1% and 5% level, respectively.

Dependent Variable:	TC	TO	ATS	BI	BI
Independent Variables	(Full Specification with RQP)	(Full Specification with RQP)	(Full Specification with RQP)	(Full Specification BD = +1)	(Full Specification BD = -1)
Intercept	275.90 ***	-2,370,305.00 ***	511.23	2,130.87 ***	-110.83
	(7.80)	(-5.48)	(0.00)	(8.92)	(-0.00)
	35.39	432,425.73	202,521.75	238.98	140,702.75
Blockchain Parameters					
BS	-3.01 ***	37,149.93 ***	-104.75 ***	22.98 ***	44.44 ***
	(-47.12)	(47.61)	(-379.66)	(45.20)	(64.28)
	0.06	780.36	0.28	0.51	0.69
BCT	-0.02 ***	277.21 ***	-0.19 ***	-0.19	-0.23 ***
	(-15.85)	(18.61)	(-30.29)	(-15.83)	(-15.48)
	0.00	14.90	0.01	0.01	0.01
BS·BCT	0.02 ***	-70.23 ***	0.34 ***	-0.02 ***	-0.03 ***
	(104.47)	(-38.87)	(898.16)	(-26.98)	(-32.53)
	0.00	1.81	0.00	0.00	0.00
Activity Controls					
VG	37.09 ***	291,311.63 ***	4.00	34.70 ***	-22.32
	(29.98)	(19.28)	(0.00)	(4.07)	(-0.01)
	1.24	15,113.17	6,299.17	8.53	4,376.37
VG·BS	-0.38 ***	-1,729.68 ***	3.44 ***	-5.03 ***	-10.44 ***
	(-23.27)	(-8.64)	(39.69)	(-31.16)	(-49.01)
	0.02	200.30	0.09	0.16	0.21
VG·BCT	-0.05 ***	-382.91 ***	-0.17 ***	0.06 **	0.10 ***
	(-89.99)	(-51.93)	(-59.65)	(11.46)	(13.26)
	0.00	7.37	0.00	0.01	0.01
OQ	0.00 ***	12.99 ***	0.40 ***	0.00 ***	-0.00 *
	(336.13)	(316.24)	(4758.98)	(0.70)	(-1.97)
	0.00	0.04	0.00	0.00	-
OQ·BS	0.00 ***	0.03 ***	-0.00 ***	0.00 ***	0.00 ***
	(10.77)	(8.88)	(-438.92)	(5.51)	(5.04)
	0.00	0.00	-	-	-
OQ·BCT	-0.00 ***	-0.00 ***	-0.00 ***	-0.00 ***	-0.00 ***
	(-52.24)	(-8.59)	(-1963.0)	(-9.55)	(-7.34)
	0.00	0.00	-	-	-
RQP	-0.00 ***	-12.86 ***	-0.40 ***		
	(-307.49)	(-288.60)	(-4395.3)		
	0.00	0.04	0.00		
RQP·BS	-0.00 ***	-0.15 ***	0.00 ***		
	(-19.37)	(-22.22)	(165.77)		
	0.03	0.01	-		
RQP·BCT	0.00 ***	0.01 ***	0.00 ***		
	(25.67)	(13.61)	(1300.41)		
	0.00	0.00	-		
Quality Controls					
LnReturn	-1.75 **	2,945.91	0.70	0.02 ***	-0.00 ***
	(-2.78)	(0.38)	(0.51)	(72.30)	(-13.08)
	0.63	7,665.10	1.39	0.00	0.00
SDPrice	1.21 ***	10,070.88 ***	0.45 ***	0.00 ***	0.00 ***
	(43.09)	(29.41)	(7.76)	(320.30)	(298.55)
	0.03	342.39	0.06	0.00	0.00
LnSize	-12.22 ***	88,178.38 ***	-10.24	-0.01 ***	0.00
	(-7.87)	(4.65)	(-0.00)	(-8.65)	(0.00)
	1.55	18,972.46	8,802.10	0.00	0.61
Fixed Effects					
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Intraday Fixed Effects	No	No	Yes	Yes	Yes
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of observations	302,493	302,493	4,546,605	2,211,991	2,307,771
Average	39.95	403,507.10	279.40	0.0049	0.0048
F-statistics	12,838.50 ***	12,589.50 ***	436,505.00 ***	2,021.68 ***	1,808.96 ***
R^2_{adj}	0.6615	0.6571	0.8638	0.0537	0.0471

Table 17: Robustness – Additional controls and block direction

This table shows the regression results with RQP as additional control (columns 1 to 3) and for subsets with a positive (column 4) and a negative block direction (column 5). Blocks with a block direction of 0 are excluded. We report β coefficients, t-statistics (in parentheses) and standard errors for each variable, while ***, **, and * indicate significance at the 0.1%, 1% and 5% level, respectively.



(a) Δ TC

(b) Δ TO

(c) Δ ATS

(d) Δ DILLIQ $\cdot 10^6$

(e) Δ RQP

(f) Δ ABI $\cdot 10^4$

Fig. 10. Impact of Block Creation Time Variations – Compared means Δ BCT

This figure provides boxplots that illustrate the market quality changes (Δ MQM) that come with increasing the BCT from 10 to 60 and 60 to 300 minutes respectively. All plots are based on daily averages, while the underlying data was winsorized at the 1% level to improve the visual representation.

References

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Aune, R. T., Krellenstein, A., O'Hara, M., Slama, O., 2017. Footprints on a blockchain: Trading and information leakage in distributed ledgers. The Journal of Trading 12, 5–13.

Barclay, M. J., Hendershott, T., McCormick, D. T., 2003. Competition among trading venues: Information and trading on electronic communications networks. The Journal of Finance 58, 2637–2665.

Brogaard, J., Hendershott, T., Riordan, R., 2014. High-frequency trading and price discovery. The Review of Financial Studies 27, 2267–2306.

Budish, E., Cramton, P., Shim, J., 2014. Implementation details for frequent batch auctions: Slowing down markets to the blink of an eye. The American Economic Review 104, 418–424.

Budish, E., Cramton, P., Shim, J., 2015. The high-frequency trading arms race: Frequent batch auctions as a market design response. The Quarterly Journal of Economics 130, 15471621.

Buterin, V., 2013. A next-generation smart contract and decentralized application platform. Whitepaper. https://github.com/ethereum/wiki/wiki/White-Paper (accessed August 30, 2018).

Cao, C., Hansch, O., Wang, X., 2009. The information content of an open limit-order book. Journal of Futures Markets 29, 16–41.

Chiu, J., Koeppl, T. V., 2018. Blockchain-based settlement for asset trading. SSRN Electronic Journal .

Clapham, B., Zimmermann, K., 2016. Price discovery and convergence in fragmented securities markets. International Journal of Managerial Finance 12, 381–407.

Clark, J., Bonneau, J., Felten, E. W., Kroll, J. A., Miller, A., Narayanan, A., 2014. On decentralizing prediction markets and order books. In: *Workshop on the Economics of Information Security*.

Copeland, T. E., Galai, D., 1983. Information effects on the bid-ask spread. The Journal of Finance 38, 1457–1469.

Darrat, A. F., Rahman, S., Zhong, M., 2003. Intraday trading volume and return volatility of the djia stocks: A note. Journal of Banking & Finance 27, 2035 – 2043.

Deutsche Bundesbank, Deutsche Börse, 2016. Joint Deutsche Bundesbank and Deutsche Börse blockchain prototype. Press release.

Donet, J. A., Prez-Sol, C., Herrera-Joancomart, J., 2014. The Bitcoin P2P network. In: *Financial Cryptography and Data Security*, pp. 87–102.

Economides, N., Schwartz, R. A., 1995. Electronic call market trading. The Journal of Portfolio Management 21, 10–18.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3 – 56.

Farmer, J. D., Skouras, S., 2012. Review of the benefits of a continuous market vs. randomised stop auctions and of alternative priority rules (policy options 7 and 12). Foresight, Government Office for Science.

Fricke, D., Gerig, A., 2018. Too fast or too slow? Determining the optimal speed of financial markets. Quantitative Finance 18, 519–532.

Gencer, A. E., van Renesse, R., Sirer, E. G., 2017. Short paper: Service-oriented sharding for blockchains. In: *International Conference on Financial Cryptography and Data Security*, pp. 393–401.

Harris, L., 2002. Trading and exchanges: Market microstructure for practitioners. Financial Management Association Survey and Synthesis, Oxford University Press.

Hasbrouck, J., 1991a. Measuring the information content of stock trades. The Journal of Finance 46, 179–207.

Hasbrouck, J., 1991b. Security markets, information and liquidity. Financial Practice and Education 1, 7–16.

Hasbrouck, J., 1991c. The summary informativeness of stock trades: An econometric analysis. The Review of Financial Studies 4, 571595.

Hasbrouck, J., 1995. One security, many markets: Determining the contributions to price discovery. The Journal of Finance 50, 1175–1199.

Hawlitschek, F., Notheisen, B., Teubner, T., 2018. The limits of trust-free systems: A literature review on blockchain technology and trust in the sharing economy. Electronic Commerce Research and Applications 29, 50–63.

Hendershott, T., Jones, C. M., Menkveld, A. J., 2011. Does algorithmic trading improve liquidity? The Journal of Finance 66, 1–33.

Hendershott, T., Moulton, P. C., 2011. Automation, speed, and stock market quality: The NYSE's hybrid. Journal of Financial Markets 14, 568–604.

Huang, R. D., Stoll, H. R., 1996. Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE. Journal of Financial Economics 41, 313–357.

Jessel, B., Marshall, T., 2016. Get Bold with Blockchain. Journal of Financial Transformation 43, 15–20.

Jones, C. M., Kaul, G., Lipson, M. L., 1994. Transactions, volume, and volatility. The Review of Financial Studies 7, 631–651.

Kogias, E. K., Jovanovic, P., Gailly, N., Khoffi, I., Gasser, L., Ford, B., 2016. Enhancing Bitcoin security and performance with strong consistency via collective signing. In: *Proceedings of the 25th USENIX Security Symposium*, pp. 279–296.

Kranz, T. T., 2015. Continuous Market Engineering - Focusing Agent Behavior, Interfaces, and Auxiliary Services. Ph.D. thesis, Karlsruhe Institute of Technology.

Lee, L., 2016. New kids on the blockchain: How Bitcoins technology could reinvent the stock market. Hastings Business Law Journal 12, 81–132.

Lin, M., Lucas Jr., H. C., Shmueli, G., 2013. Research commentary - too big to fail: Large samples and the p-value problem. Information Systems Research 24, 906–917.

Madhavan, A., 1992. Trading mechanisms in securities markets. The Journal of Finance 47, 607–641.

Malinova, K., Park, A., 2017. Market Design with Blockchain Technology. SSRN Electronic Journal .

Mills, D. C., et al., 2016. Distributed ledger technology in payments, clearing, and settlement. FEDS Working Paper No. 2016-095 .

Næs, R., Skjeltorp, J. A., Ødegaard, B. A., 2011. Stock market liquidity and the business cycle. The Journal of Finance 66, 139–176.

Nakamoto, S., 2008. Bitcoin: A peer-to-peer electronic cash system. Whitepaper. https://bitcoin.org/bitcoin.pdf (accessed August 30, 2018).

Notheisen, B., Cholewa, J. B., Shanmugam, A. P., 2017a. Trading real-world assets on blockchain. Business & Information Systems Engineering 59, 425–440.

Notheisen, B., Gödde, M., Weinhardt, C., 2017b. Trading stocks on blocks - engineering decentralized markets. In: Maedche, A., vom Brocke, J., Hevner, A. (eds.), *Designing the Digital Transformation*, Springer International Publishing, Cham, pp. 474–478.

Notheisen, B., Hawlitschek, F., Weinhardt, C., 2017c. Breaking down the blockchain hypetowards a blockchain market engineering approach. In: *Proceedings of the 25th European Conference on Information Systems (ECIS)*, pp. 1062–1080.

Notheisen, B., Weinhardt, C., 2018. The blockchain, plums, and lemons - information asymmetries in decentralized markets. SSRN Electronic Journal .

O'Hara, M., 1998. Market Microstructure Theory. Blackwell Publishing Limited.

Pagano, M., Rell, A., 1996. Transparency and liquidity: A comparison of auction and dealer markets with informed trading. The Journal of Finance 51, 579–611.

Pancs, R., 2012. Comparing market structures: Allocative and informational efficiencies of continuous trading, periodic auctions, and dark pools. Technical report, Department of Economics, University of Rochester.

Patel, H., 2014. A pure block chain based decentralized exchange. IACR Cryptology ePrint Archive .

Peterson, M., 2018. Blockchain and the future of financial services. The Journal of Wealth Management 21, 124–131.

Riordan, R., Storkenmaier, A., 2012. Latency, liquidity and price discovery. Journal of Financial Markets 15, 416–437.

Subrahmanyam, A., 1994. Circuit breakers and market volatility: A theoretical perspective. The Journal of Finance 49, 237–254.

Szabo, N., 1997. Formalizing and securing relationships on public networks. First Monday 2.

Urquhart, A., 2016. The inefficiency of Bitcoin. Economics Letters 148, 80–82.

Viana, D., 2018. Two technical images: Blockchain and high-frequency trading. Philosophy & Technology 31, 77–102.

Wah, E., Hurd, D. R., Wellman, M. P., 2016. Strategic market choice: Frequent call markets vs. continuous double auctions for fast and slow traders. EAI Endorsed Transactions on Serious Games 3.

Wei, W. C., 2018. Liquidity and market efficiency in cryptocurrencies. Economics Letters 168, 21–24.

Weinhardt, C., Gimpel, H., 2007. Market Engineering: An Interdisciplinary Research Challenge. In: *Dagstuhl Seminar Proceedings*.

Workie, H., Jain, K., 2017. Distributed ledger technology: Implications of blockchain for the securities industry. Journal of Securities Operations & Custody 9, 347–355.

Yermack, D., 2017. Corporate governance and blockchains. Review of Finance 21, 7–31.

Zhang, S. S., Wagener, M., Storkenmaier, A., Weinhardt, C., 2011. The quality of electronic markets. In: *Proceedings of the 44th Hawaii International Conference on System Sciences*.

Working Paper Series in Economics

recent issues

No. 129 *Benedikt Notheisen, Vincenzo Marino, Daniel Englert and Christof Weinhard:* Trading stocks on blocks: The quality of decentralized markets, February 2019

No. 128 *Francesco D'Acunto, Daniel Hoang, Maritta Paloviita and Michael Weber:* Human frictions in the transmission of economic policy, January 2019

No. 127 *Francesco D'Acunto, Daniel Hoang, Maritta Paloviita and Michael Weber:* IQ, expectations, and choice, January 2019

No. 126 *Francesco D'Acunto, Daniel Hoang, Maritta Paloviita and Michael Weber:* Cognitive abilities and inflation expectations, January 2019

No. 125 *Rebekka Buse, Melanie Schienle and Jörg Urban:* Effectiveness of policy and regulation in European sovereign credit risk markets - A network analysis, January 2019

No. 124 *Chong Liang and Melanie Schienle:* Determination of vector error correction models in high dimensions, January 2019

No. 123 *Rebekka Buse and Melanie Schienle:* Measuring connectedness of euro area sovereign risk, January 2019

No. 122 *Carsten Bormann and Melanie Schienle:* Detecting structural differences in tail dependence of financial time series, January 2019

No. 121 *Christian Conrad and Melanie Schienle:* Testing for an omitted multiplicative long-term component in GARCH models, January 2019

No. 120 *Marta Serra-Garcia and Nora Szech:* The (in)elasticity of moral ignorance, December 2018

No. 119 *Thomas Mariotti, Nikolaus Schweizer, Nora Szech and Jonas von Wangenheim:* Information nudges and self-control, November 2018