Engineering Decentralized Markets
A Blockchain Approach

Zur Erlangung des akademischen Grades eines
Doktors der Wirtschaftswissenschaften

(Dr. rer. pol.)

von der
KIT-Fakultät für Wirtschaftswissenschaften
des Karlsruher Instituts für Technologie (KIT)

genehmigte

DISSERTATION

von

Benedikt Notheisen, M. Sc. Wi.-Ing.

Tag der mündlichen Prüfung: 06.08.2019
Referent: Prof. Dr. Christof Weinhardt
Korreferentin: Prof. Dr. Marliese Uhrig-Homburg
Karlsruhe, 2019

Acknowledgements

I would like to thank Prof. Dr. Christof Weinhardt for the opportunity to pursue my research interests at the Institute of Information Systems and Marketing (IISM) and for his advice and encouragement throughout my dissertation. I would also like to thank Prof. Dr. Marliese Uhrig-Homburg for co-advising my thesis as well as Prof. Dr. Verena Dorner and Prof. Dr. Marc Wouters for serving on my thesis committee. In addition, I am very grateful to Prof. Dr. Andreas Park for the opportunity to visit the University of Toronto and his comments on my work. In particular, I want to thank my colleagues at the IISM, Boerse Stuttgart, and the University of Toronto for numerous inspiring discussions and helpful feedback. Finally and most importantly, my special thanks go to my family and friends for their support, patience, and unconditional backing throughout my life.

Contents

Chapter 1

Introduction

> *"I think that the Internet is going to be one of the major forces for reducing the role of government. The one thing that's missing, but that will soon be developed, is a reliable e-cash - a method whereby on the Internet you can transfer funds from A to B without A knowing B or B knowing A."*
>
> Milton Friedman, 1999

1.1 Motivation

Nine years after Friedman's statement above, Nakamoto (2008) introduced a peer-to-peer electronic cash system called Bitcoin. Bitcoin implements the vision of Milton Friedman (Berthoud, 1999; Sixt, 2017) and offers fully decentralized, pseudonymous online payments that allow users to transfer funds digitally without relying on financial institutions (Nakamoto, 2008). In recent years, the popularity of Bitcoin as an investment opportunity has grown substantially (Glaser et al., 2014; Cheah and Fry, 2015; Dyhrberg, 2016b) and Nakamoto (2008)'s idea has inspired numerous new cryptocurrencies (Bariviera et al., 2017). The underlying blockchain or Distributed Ledger Technology (DLT) combines a distributed and immutable append-only database, a decentralized consensus mechanism, and crypographic elements to create a reliable, transparent, and complete record of past transactions (Notheisen et al., 2017). Despite its novelty, Nakamoto's approach to create unforgeable digital messages (Lamport et al., 1982) resembles the features of previous attempts: It enables transactions without identification (Chaum, 1985) and centralized governance (Shermin, 2017), while digital time-stamping (Haber and Stornetta, 1991) and cryptographic puzzles (Borisov, 2006) prevent double spending.

Smart contracts (Szabo, 1997) extend the functional scope of blockchain and DLT systems beyond cryptocurrencies and support the development of fully decentralized applications and organizations (Peters et al., 2015; Cong and He, 2018).

Today, the blockchain and DLT concept has crossed the peak of the hype cycle (Gartner, 2016, 2018) and presents a new way to conduct, record, and manage transactions without the need to trust in central authorities or intermediaries (Greiner and Hui, 2015; Fröwis and Böhme, 2017). With respect to markets, decentralized applications and organizations promise to redistribute governance to their stakeholders (Yermack, 2017; Beck et al., 2018). From a practical perspective, these features allow market engineers to create distributed system architectures and implement decentralized platforms that replace centralized control with consensually imposed, self-enforcing rules (Beck et al., 2016; Glaser et al., 2019). Practically, blockchain and DLT enables an automated transaction of digital and physical assets, while keeping a valid and transparent record of past interactions (Notheisen et al., 2017). Moreover, fully decentralized market mechanisms unify matching, clearing, and settlement of transactions in a joint step, while changes of ownership can be tracked and audited via the blockchain's log (Notheisen et al., 2017). In combination, these building blocks can form the backbone of decentralized markets and reduce the power of intermediaries that operate, govern, and supervise market platforms (Catalini and Gans, 2016; Risius and Spohrer, 2017; Iansiti and Lakhani, 2017; Tapscott and Tapscott, 2017).

Driven by this disruptive potential, the prospect of cost savings, and the pursuit of efficiency gains, start-ups, established organizations, and market authorities intensify their blockchain activities (e.g., Deutsche Bundesbank and Deutsche Börse, 2016). They join forces, increase their investments in external knowledge acquisition (Pawczuk et al., 2018), and promote internal research and development efforts (Lannquist, 2018) to conquer the 'trust machine' (Economist, 2015). The global industry survey of Pawczuk et al. (2018) for instance, covers more than 1,000 senior executives and indicates that 95% of the surveyed companies will invest in blockchain technology in 2019, while 65% will invest more than 1 million USD. In addition, global venture capital funding exceeded 1,500 million USD in the mid of 2016 (Friedlmaier et al., 2018, p. 3523). These initiatives result in a rapidly growing and increasingly convoluted market for blockchain and DLT solutions and the exploration of numerous use cases in the context of markets (Friedlmaier et al., 2018). Potential applications include the tokenization (i.e., digitization) of assets (Oliveira et al., 2018), notary services (Wörner et al., 2016), identity and digital rights management systems (Fujimura et al., 2015), and registry systems (Fairfield, 2015), amongst others.

The most actively explored fields include the finance (Guo and Liang, 2016), automotive (Bauer et al., 2019), energy (Mengelkamp et al., 2017), and logistics industry (Imeri et al., 2019) amongst others (Pawczuk et al., 2018). Especially in financial markets, there is a growing number of decentralized exchanges (DEXs) that promise their customers to trade in a fair, transparent, and fully decentralized environment (table A.4; Daian et al., 2019).

However, blockchain and DLT is still an emergent technology and its novelty and complexity constitute a challenge for both researchers and practitioners (Glaser and Bezzenberger, 2015). As a result, few success stories, such as Bitcoin or other cryptocurrencies, corresponding exchange and investment services, and Initial Coin Offerings (ICOs) pioneer financial markets (Peters et al., 2015; Pawczuk et al., 2018). On the other hand, engineering decentralized markets is a challenging task that goes beyond offering blockchain-related but still centralized services. As an infrastructure technology, the blockchain lies at the core of market platform and shapes its characteristics, ensures its proper functioning, and influences behavioral patterns on and beyond the market. In consequence, it is crucial to understand both, the technical versatility and limitations of blockchain- and DLT-based market platforms as well as the economic consequences of adoption, to leverage the technology's potential and identify and mitigate adverse side effects. This includes developing a structured approach to engineer decentralized markets, studying the technological design of market platforms, and exploring the resulting economic effects from an individual and market perspective.

In research and practice, the terms blockchain and DLT are often used interchangeably. Formally, DLT "extends the notion of a blockchain to a system type that comprises systems under [the] centralized control [...] of a single organization or a small group of organizations" (Glaser et al., 2019, p. 122). Thus, the mechanisms applied to validate transactions and to retain data consistency might differ from fully decentralized systems. "Besides, the term blockchain is often used [...] to refer to the underlying data structure, [to] a specific type of database system, or [to] the network as a whole including users and smart contracts. In contrast, DLT is neutral regarding technical peculiarities and always refers to the distributed system that tracks changes to data and ensures its consistency through a consensus mechanism among a group of users with potentially conflicting interests" (Glaser et al., 2019, p. 123). In this thesis and in line with the idea of Nakamoto (2008) and seminal paper of Buterin (2013), the term blockchain refers to a publicly accessible peer-to-peer network and comprises a distributed database, a decentralized consensus mechanism to facilitate data consistency, and smart contracts to implement decentralized applications.

1.2 Research Outline

In the spirit of market engineering (Weinhardt and Gimpel, 2007), this thesis aims to shed light on the blockchain's capability to implement and operate decentralized market platforms. It includes the design of a market platform's technological foundation and its functional scope as well as the assessment of the resulting economic characteristics that shape behavioral patterns and market outcomes. Consequently, it is important to understand the relationship between central blockchain features - such as the immutability of transactions, the public availability of historic information, or its discrete nature - and technological and economic platform characteristics in order to exploit the technology's full potential. To take the interdisciplinary nature of this endeavor into account, this thesis integrates conceptual, technological, and economic considerations and rests on a hierarchical three-level approach. Table 1.1 illustrates these three levels, summarizes their focus, and highlights the corresponding research questions.

Level	Focus	Research Questions
1	Conceptual framework	1, 2
2	Technological design	3, 4, 5, 6, 7
3	Economics analyses	8, 9, 10

TABLE 1.1: *Levels and focus of this thesis.*

First, on the conceptual level, blockchain literature is dispersed across disciplines, while studies that integrate technological and economic aspects in the context of markets remain scarce (Notheisen et al., 2017). As a result, the lack of a holistic view impedes the utilization of blockchain technology as a facilitator of decentralized markets. To address this issue, the first research question of this thesis builds on Weinhardt and Gimpel's interdisciplinary market engineering framework to structure the technological elements of blockchain-based platforms within the context of markets.

Research Question 1. *Which pivotal elements and layers define blockchain-based market platforms?*

Besides the platforms' elements, trust plays a central role in the blockchain realm, as the 'trust machine' (Economist, 2015) claims to replace trust with technological system properties (Beck et al., 2017).

In contrast, Information Systems (IS) research illustrates trust as a multi-faceted and interlaced construct that includes users' trust in peers, the platform, and the product (Hawlitschek et al., 2018; Hawlitschek, 2019). The second research question focuses on this tensions and discusses how the behavioral conceptualization of trust in the sharing economy aligns with the blockchain's technological approach.

Research Question 2. *To which extent can the blockchain implement the multi-faceted nature of trust prevalent on the peer-to-peer platforms of today's sharing economy?*

The resulting blockchain engineering framework is based on a structured review of blockchain literature in IS and adjacent fields, illustrates the limits of trust-free systems, and offers a structured approach to guide the creation, communication, and evaluation of decentralized markets.

Second, the technology level utilizes the conceptualization of the characteristics, components, and limitations of blockchain-based platforms and applies the blockchain engineering framework to the use case of decentralized markets. More specifically, it illustrates and evaluates the design, architecture, and features of decentralized markets by means of two proof-of-concept prototypes.

The first prototype implements a transparent transaction system that enables the automated and fully decentralized transaction of real-world assets, such as cars or stocks. It utilizes blockchain technology to provide a valid, transparent, and immutable (i.e., irreversible) record of historic transactions to its users. In combination with peer-based consensus process, these features facilitate trust in the correctness of the transactional record and impede unauthorized transactions and the dissemination of corrupted information. However, the irreversibility and delayed finality of blockchain-based transactions increases transaction risk (Böhme et al., 2015). Especially in case of errors or deceptive counterparties (Böhme et al., 2015) this remains an unsolved issue and leads to the third research question.

Research Question 3. *How can market engineers decrease the risk resulting from the irreversibility of blockchain transactions, while still providing a valid transaction log?*

In addition, the life cycle of complex physical assets, such as cars, often involves multiple stakeholders and comprises a variety of process steps. Integrating these steps in a blockchain-based system may be infeasible, boost complexity and cost, and inhibit performance. To shed light on its feasibility, the fourth research question evaluates the blockchain's ability to implement and operate a transaction system for cars.

Research Question 4. *To which extent can a blockchain-based transaction system store and represent the life-cycle of a car?*

Aside from disintermediation, the blockchain provides a comprehensive registry, while its transparent nature disseminates private information among its users. The fifth research question transfers these characteristics to the economic context of markets with asymmetrically distributed information and asks how it helps uninformed buyers to approximate a car's actual value.

Research Question 5. *Which characteristics of blockchain-based transaction systems affect information asymmetries, and thus the uncertainty about quality in the market for lemons?*

In total, this first proof-of-concept prototype demonstrates the potential and highlights the limitations of decentralized transaction systems. It introduces a mechanism to reduce transaction risk, aims to replace bureaucratic, trust-based registry systems, and utilizes the blockchain to dismantle information asymmetries.

The second prototype narrows the focus to a crucial prerequisite for each transaction - a mechanism to connect demand and supply. However, transferring the continuous design of today's financial market platforms to the blockchain's discrete world is a challenging task (Clark et al., 2014). At the same time, academic approaches remain scarce and lack either a holistic perspective or technical details. Similarly, DEXs refrain from disclosing their specifications to protect business interests. The following research question aims to address these issues by illustrating the software architecture of a blockchain-based, decentralized market mechanism.

Research Question 6. *How can smart contracts implement a decentralized market mechanism that incorporates a double auction, keeps distributed order books, and allows traders to submit limit and market orders?*

Independent of the market mechanism, the motivation to trade stocks on a blockchain is simple: The technology promises to streamline the value chain of securities trading by providing a self-sufficient, intermediary-free, and transparent system with a high transaction speed and low transaction costs (Pinna and Ruttenberg, 2016; Daian et al., 2019). Again, implementing all stages may be infeasible, inefficient, or costly. In consequence, the seventh research question aims to explore the blockchain's capability to implement and operate the value chain of securities trading.

Research Question 7. *To which extent can a blockchain-based market platform operate the value chain of securities trading and which technology features limit performance?*

Overall, the second prototype demonstrates the feasibility and illustrates the design of decentralized market mechanisms by implementing a fully decentralized matching engine as well as distributed order book structures. From a business perspective, it challenges the role of traditional market institutions by enabling users to raise equity and trade stocks intermediary-free.

In combination, both prototypes form the backbone of decentralized markets: The transparent transaction system utilizes fiduciary transaction safeguards to reduce transaction risk. At the same time, the blockchain's transparent, reliable, and complete log supplies interacting parties with information. In between, the intermediary-free market mechanism connects demand and supply, while clearing and settlement become an integral part of the trading process. On the other side, the prototypes highlight the technological limitations of decentralized markets and point towards the blockchain's public transparency paradigm and discrete nature as starting points for economic analyses.

The third and last level of this thesis elaborates these starting points up and investigates the economic impact of the identified technology characteristics on market outcomes. More specifically, it examines how increasing transparency affects behavioral patterns and evaluates the impact of the discrete, block-based nature of database updates on market quality.

The first analysis focuses on a cornerstone of the blockchain's consensus process: The public disclosure of historic transactions. This non-discriminatory form of transparency ensures data integrity and facilitates the validity of database updates in the absence of a central authority. However, in market environments, interacting parties' strategies often depend on different levels of information about their counterparties or the transactional object. As a result, it is crucial to understand whether and how their behavior changes with the blockchain's shift towards public transparency. Especially in market environments with asymmetric information and quality differences increasing transparency may have ambiguous effects, as it reduces uncertainty on one hand but also enables opportunistic users to exploit disclosed information on the other. The following two research questions utilize game theory to explore how behavioral changes affect individuals and how these effects spill over to the market and economy.

Research Question 8. *Which participants of a market with asymmetric information are affected by the blockchain's shift towards public transparency? When and how does their behavior change?*

Research Question 9. *How do the behavioral changes of opportunistic market participants affect their counterparties, market outcomes in total, and the welfare of the economy?*

In line with prior research, the findings of the first analysis indicate that the blockchain's shared record reduces moral hazard, mitigates adverse selection effects, and provides incentives for individual users to behave opportunistically. More specifically, the disclosed information allows them to learn about quality differences and deceive their counterparties to increase their utility. Despite a welfare gain, the market may collapse and future generations are denied access to the market. Practically, these results offer initial guidance for blockchain adoption in markets with information asymmetries and highlight risks that arise from competition, the exposure to irrational behavior, and the implementation of value-adding services within the infrastructure.

Guided by the second prototype, the second analyses furthermore examines the impact of the blockchain's discrete nature – namely the size and frequency of database updates – on a DEX's market quality. This includes the assessment and quantification of market quality effects, the identification of quality drivers and trade-offs, as well as the discussion of practical implications and is summarized in the following research question:

Research Question 10. *How do the size and frequency of database updates (i.e., blocks) impact the activity, liquidity, and price formation on blockchain-based markets?*

Based on five years of trading data, the second analysis indicates that increasing the blocks' capacity and frequency is mostly beneficial for market activity and liquidity. On the other side, faster and bigger blocks facilitate volatility, and thus are no silver bullet to scale decentralized markets.

Finally, the findings of the third and last level illustrate the consequences of conceptual and technological decisions and thereby complement the first and second level of this thesis to form a holistic perspective. In total, the three levels constitute a first step towards the assessment of decentralized markets by illustrating the conceptual components of blockchain-based systems, demonstrating the technological feasibility of market platforms, and highlighting economic risks and side effects of blockchain adoption.

1.3 Structure of the Thesis

The remainder of this thesis is structured as follows: To pave the way, Chapter 2 establishes a fundamental understanding of blockchain technology (Section 2.1) and introduces market engineering as a toolbox to create, evaluate, and shape market platforms (Section 2.2). Adopting the notion of the blockchain as a platform, Chapter 3 leverages a structured review of interdisciplinary blockchain literature to combine technological and economic aspects with the market engineering approach and derive the blockchain engineering framework.

After conceptualizing the characteristics, elements, and limitations of blockchain-based platforms, Chapter 4 applies the blockchain engineering approach to the use case of decentralized markets. More specifically, it introduces and utilizes established Design Science Research (DSR) and blockchain design frameworks (Section 4.1) to illustrate, implement, and verify the design, architecture, and features of an intermediary-free transaction system (Section 4.2) and market mechanism (Section 4.3).

Based on the findings of Section 4.2, Chapter 5 applies game theory to analyze the effect of the blockchain's public transparency paradigm on behavioral patterns and market outcomes. Similarly, Chapter 6 explores the relationship between the discrete nature of blockchain-based market mechanisms illustrated in Section 4.3 and market quality quantitatively.

Finally, Chapter 7 concludes this thesis by summarizing its findings, outlining its contributions, and illustrating the potential for future research.

Appendices A, B, C, and D provide supplementary literature, Gitlab references to the prototypes and illustrations of other software infrastructures, proofs and calculus to support Chapter 5, and additional statistics for Chapter 6. Figure 1.1 illustrates the thesis structure including research questions 1 to 10 accordingly.

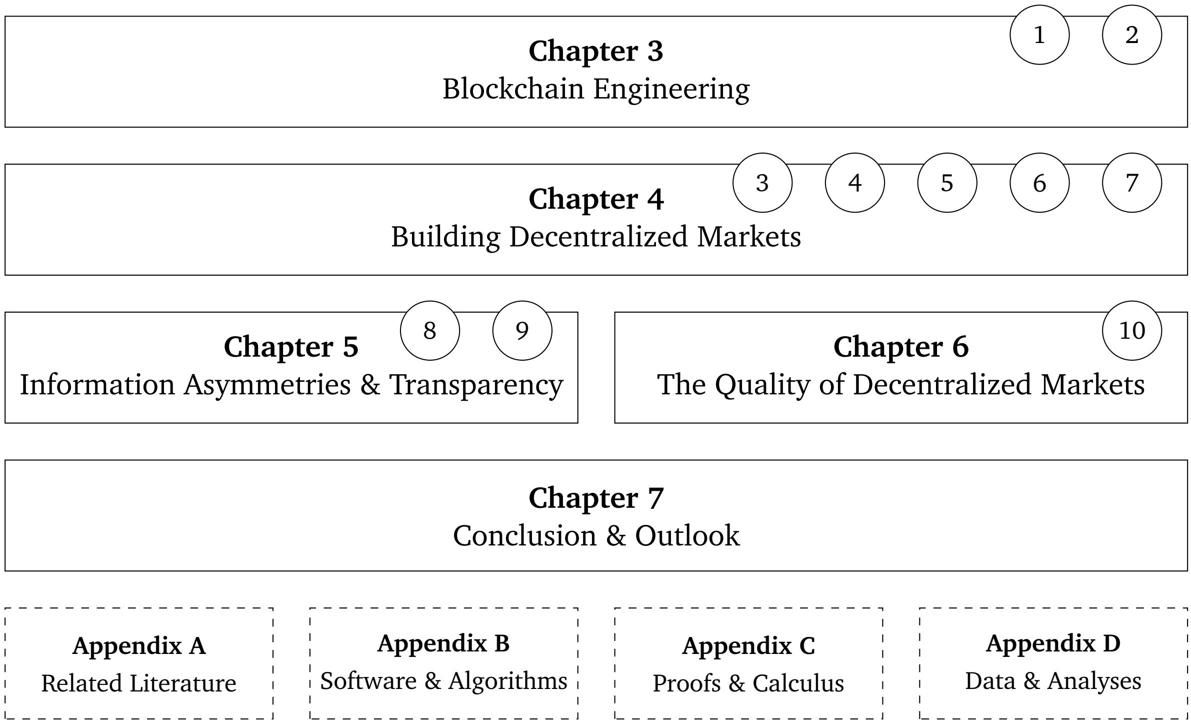


FIGURE 1.1: *Structure of this thesis*
This figure illustrates the structure of this thesis. Solid boxes represent thesis chapters and dashed boxes appendices. Circles map research questions 1 to 10 to chapters 3 to 6.

Chapter 2

Foundations

Engineering decentralized markets is a challenging task. It requires market engineers to go beyond established approaches and utilize peer-to-peer technologies to create platforms that connect users without depending on central authorities, intermediaries, or platforms. One technology that bears the potential to fulfill these requirements and to form the backbone of decentralized markets is the blockchain technology. However, despite the growing adoption (Notheisen et al., 2017), the blockchain term and concept remains opaque for many users. To pave the way for this thesis, Section 2.1 illustrates the basic components of blockchain-based systems (2.1.1) and discusses their capability to function as a platform (2.1.2), while Section 2.2 introduces market engineering as a holistic toolbox to create, evaluate, and shape market platforms.

2.1 Blockchain Basics

"The blockchain was first introduced as a mechanism to prevent double-spending in the peer-to-peer electronic cash system known as Bitcoin. Based on the underlying idea of Nakamoto (2008), blockchain protocols provide an immutable record of transactions by combining a distributed database [with] chronologically ordered and cryptographically interconnected blocks [...] with a decentralized consensus mechanism and cryptographic security measures (Glaser, 2017). The interplay of these elements impedes the dissemination of corrupted information and moderates frictions among potentially conflicting agents without the need for a central governing institution or authority" (Notheisen et al., 2017, p. 426).

In combination with smart contracts (Szabo, 1997), the technology has emerged from its origin in cryptocurrencies and heads to a variety of commercial applications (Nofer et al., 2017).

More specifically, blockchain technology offers a distributed software architecture that has no single point of failure or requirement for centralized governance (Xu et al., 2016). As a result, it enables autonomous, transparent, secure, and tamper-free transactional databases (Glaser, 2017), reduces the complexity of writing contracts (Davidson et al., 2016), facilitates cost-efficient micro transactions (Beck et al., 2016), and allows [...] novel organizational forms and business models (Glaser and Bezzenberger, 2015). From a practical perspective, this leads to "[...] decentralized market and application platforms, notary services (Wörner et al., 2016), digital proof of identity and legitimization (Wörner et al., 2016), digital rights management systems (Fujimura et al., 2015), validated, immutable, and consistent registries (Fairfield, 2015; Glaser, 2017; Xu et al., 2017), and transaction systems that track the ownership of (digital) assets (Fairfield, 2015; Beck et al., 2016)" (Notheisen et al., 2017, p. 426).

Nevertheless, the blockchain is still an emergent technology that faces several limitations: First and foremost, researchers and practitioners still explore the interplay between technical and economic characteristics of blockchain-based systems, whereas the interdisciplinary nature of potential applications requires a rigorous understanding of both (Glaser and Bezzenberger, 2015; Salviotti et al., 2018). "Second, due to the nature as a transaction-based system, smart contract applications cannot trigger themselves but rather require some form of external intervention to execute (Glaser, 2017). Third, [...] blockchain-based systems still face a variety of technical limitations, such as capacity, latency, and query issues (Glaser, 2017; Beck et al., 2016; Wörner et al., 2016). Fourth, there are some drawbacks associated with the technical structure of blockchain protocols, such as the threat of 51% attacks (Nakamoto, 2008; Böhme et al., 2015), increased costs related to the deployed consensus mechanism (Brenig et al., 2016; Beck et al., 2016; O'Dwyer and Malone, 2014), privacy concerns (Kosba et al., 2016; Böhme et al., 2015), and transaction risk (Böhme et al., 2015)" (Notheisen et al., 2017, p. 426).

2.1.1 The Blockchain Concept

"A blockchain is a distributed, immutable, append-only database without a central authority that orders and validates transactions to keep data consistent across multiple nodes. In public blockchain systems, every [...] user can operate a node and access core functionalities by simply downloading and running a client software. In [these] systems, the core functionality is transacting system-inherent tokens" (Glaser et al., 2019, p. 122). For the Bitcoin platform for instance, this is sending a Bitcoin or a fraction thereof from one user to another. To achieve these features, the seminal works of Nakamoto (2008) and Buterin (2013) integrate previous approaches that allow users to transfer assets without identification (Chaum, 1985) and centralized governance (Shermin, 2017), enable the time-stamping of digital documents (Haber and Stornetta, 1991), prevent Sybil attacks (Borisov, 2006), and "formalize and secure relationships" via smart contracts (Szabo, 1997).

Distributed Database Access

The backbone of a blockchain-based system is borne by a distributed database. In distributed databases storage and processing units remain separate, while data is stored redundantly at or linked across different (physical) locations. As a result, managing and maintaining the system's integrity and state across the network follows two paradigms: Replication and duplication (Özsu and Valduriez, 2011). Replication is used to determine data inconsistencies on an ongoing basis and updates the distributed data accordingly. Duplication creates a physical backup of the database. In addition, a (usually centralized) database management system keeps track of the indexing, organizes data, and manages the participating users (Özsu and Valduriez, 2011). In a peer-to-peer setup, data is spread and replicated across multiple users that have equal rights to access and write data. Consequently, all users of the network have the same privileges, pledge their resources to the network, and thereby render central coordination obsolete. In a blockchain-based system, the distributed database is managed by a decentralized database management systems known as decentralized consensus mechanism, comprises a list of transactions called ledger, and is replicated across all nodes of the peer-to-peer network. As a result, the historic record enables each user to verify and validate database updates, to audit past transactions, and to determine the blockchain's current state (Nakamoto, 2008).

The Decentralization of Consensus

The core innovation that comes with blockchain technology is the decentralization of the consensus authority. As a result, agents with different levels of information and potentially conflicting interests can engage in interactions without depending on a central authority. To replace intermediaries, a decentralized consensus mechanism provides a means to achieve an agreement over the validity and order of transactions within the blockchain system's peer-to-peer network. More specifically, consensus mechanisms resolve informational conflicts (Lamport et al., 1982; Chohan, 2017) by creating a Sybil-resistant voting system that ensures a parity between voters and votes (Borisov, 2006; Dinger and Hartenstein, 2006; Xu et al., 2016). To do so, a consensus mechanism creates an artificial barrier that makes participating in the consensus process - i.e., the proposition of a database update and voting on the correctness of updates - costly (). To compensate the peer-to-peer network for this effort, most mechanism grant a reward to the first user that proposes a correct database update. To determine the correctness of the proposed update, the remaining participants of the consensus process check its validity and vote accordingly. Only if a majority of users agrees with the update, it is added to the database and the proposer is rewarded (Mingxiao et al., 2017).

The specific features of a consensus mechanism depend on the system's degree of openness, the characteristics, rationales, and objectives of users, the application environment, and other blockchain design parameters[1]. Proof of Work (POW) - the consensus mechanism of the popular Bitcoin and Ethereum platforms - for instance is designed to achieve a consensual agreement in an open, publicly accessible, and pseudonymous network. By requiring the network participants to solve a randomized cryptographic puzzle, it can tolerate up to 50% of malicious actors (Gervais et al., 2016).

Kroll et al. (2013) and Biais et al. (2018) study Bitcoin's consensus game and analyze the underlying equilibrium strategies of rational, strategic users. More specifically, Kroll et al. (2013) show that complying with the rules of the consensus mechanism is a Nash equilibrium. This implies that compliance is the best strategy given the strategy choices of the other users. However, they also show that there is an infinite number of other equilibria.

[1]A detailed overview of blockchain design dimensions, choices, and characteristics is available in Subsection 4.1.2 of this thesis.

As a result, a malicious user may be able to destabilize the system by pushing it to one of those equilibria. Biais et al. (2018) extend this analysis and model POW-based blockchain protocols as a stochastic game. Consistent with the idea of Nakamoto (2008), they find that extending the longest chain is a Markov perfect equilibrium. However, in line with Kroll et al. (2013) they also stress that interacting via a blockchain-based system is a coordination game, where the presence of multiple equilibria may lead to opportunistic behavior. Eyal and Sirer (2018) for instance illustrate how rational actors could collude with an attacker to take over the majority of computing power of the system and thereby show that Bitcoin's POW is not incentive compatible. In addition, Nayak et al. (2016) highlight that a combination of attacks can amplify threats to Bitcoin's POW consensus process, while Chiu and Koeppl (2017) estimate the welfare loss created by Bitcoin's mining and update scheme.

In consequence, there is a growing number of other consensus mechanisms that aim to resolve the inefficient and costly nature of POW by changing the way costs are generated or by restricting system access (Panarello et al., 2018). Saleh (2018) for instance shows in an extensive form game that Proof of Stake - the most popular alternative to POW - induces consensus in equilibrium by creating an implicit cost for delaying an agreement on new transactions. Proof of Stake creates a barrier and randomizes the right to append new data based on a combination of a user's stake and age (i.e., system membership). In addition, there is a variety of other approaches that go beyond computation-based or time-based proofs and propose permission-based, memory-based, communication-based, and other concepts (Cachin and Vukolic, 2017; Mingxiao et al., 2017). Table A.2 in appendix A.2 summarizes the characteristics of selected approaches, compares their security, latency, and transaction volume, and illustrates current applications.

The Role of Cryptography

Cryptographic hash functions are the glue of blockchain-based systems. They enable users to send and receive transactions, interconnect data blocks to facilitate decentralized time-stamping, allow the efficient assessment of database updates, and empower consensus mechanisms. From a technical perspective, they are deterministic one-way functions that are quick to compute and map input data sets of arbitrary length to an unique output with a fixed length. This output is also known as hash or hash value. As a result, it is impossible to guess the input from the output, two different inputs never lead to the same result, and the same input always leads to the same output (Katz et al., 1997).

From a user perspective, asymmetric cryptography enables the identification of individuals by public keys and the specification and authorization of transactions by the combination of public and private keys. More specifically, a user can utilize the recipient's public key to specify and one of his or her own private keys to sign and send a transaction. After signing a transaction, a private key becomes stale, while the mathematical relationship between a public and the corresponding private key enables the transaction's recipient to validate its correctness (Rivest et al., 1978). In consequence, each user has a unique public and a potentially infinite number of perishable private keys that can be created and managed by a wallet software.

To conduct a blockchain transaction, a user denominates a transactional object, specifies a recipient via a public key, references past transactions to proof ownership, signs the transaction with a private key, and broadcasts it to the peer-to-peer network (Antonopoulos, 2017). Across the network, other users collect, verify, and aggregate broadcasted transactions and propose the resulting data blocks as database updates to their peers (Eyal, 2015). Whenever a new block is proposed, each user checks its validity before casting a vote. In addition, the sequential order of database updates - and thus the timely order of past transactions - is ensured by the cryptographic interconnection of data blocks. Merkle Trees or hash trees summarize the content of each block to a single hash value. This allows the auditing users to traverse the blockchain's historic transaction graph efficiently (Antonopoulos, 2017). If a majority of the users agrees with the proposed update, the proposer appends his or her block to the blockchain, broadcasts the update to the network, and earns a reward (Nakamoto, 2008). Figures 2.1 and 2.2 illustrate this update process and the blockchain's resulting data structure, respectively. Moreover, they highlight the role of of public and private keys.

Besides, crypographic hash functions are an essential building block of the most common consensus mechanism POW. More specifically, Nakamoto (2008)'s approach follows the Hashcash algorithm introduced by Back (2002). Hashcash was initially designed to reduce e-mail spam and requires the sender to include the solution of a costly cryptographic and easy to validate puzzle. As a result, it becomes unprofitable to deliver spam mails on a large scale as there is a small cost attached to each message. In a similar fashion, POW-based consensus protocols require a user to solve a cryptographic puzzle to gain the right to propose a database update and vote on others' updates. This artificially created cost threshold renders the creation of virtual nodes to skew voting unprofitable and thereby reduces the risk of Sybil attacks (Yeow et al., 2018).

Smart Contracts

Smart contracts extend the functional scope of blockchain-based systems and allow the execution of software logic within their distributed environment. Formally, they are programs that are written by individual users and broadcasted to the peer-to-peer network. As a result, they become part of the distributed database and are subsequently available to all users of the system and already deployed contracts. "Smart contracts are triggered through a transaction that is sent either by a user or by another smart contract [...]. This interaction of contracts enables complex systems of interacting services that are implemented in the form of smart contracts. [...] The control over a contract and hence also [...] the implemented service is defined by the creator of the contract. Control can be left to its creator, another user in the system, or no specific entity at all. The latter setup, autonomy of control, renders the contract an autonomous entity or agent in the system who acts according to its programmed logic, no matter who interacts with it" (Glaser et al., 2019, p. 123). From a technical perspective, smart contracts are stored in the blockchain's distributed database and their output becomes part of the consensual agreement of database updates. In consequence, each participating node has to compute a triggered contract's return within the consensus process. From an economic perspective, the utilization of smart contracts also changes the informational environment within markets and organizational applications. Cong and He (2018) investigate the impact of smart contracts on industrial organization and competition by the means of a dynamic model and find that smart contracts reduce information asymmetries and improve welfare and consumer surplus by enhancing market entry and competition. On the other hand, they also highlight that the disclosure of information within the consensus process facilitates collusive behavior.

In practice, different platforms, such as Ethereum (Ethereum, 2016), Hyperledger Fabric (Androulaki et al., 2018; Cachin, 2016), or Corda (Brown et al., 2016) provide software libraries that support smart contracts and enable the implementation of various services, market applications, or generalized functions (Bartoletti and Pompianu, 2017). However, due to its turing complete nature, easy to access scripting language, and open source character, this thesis utilizes the Ethereum platform to implement the building blocks of decentralized markets in a prototypical fashion in Chapter 4.

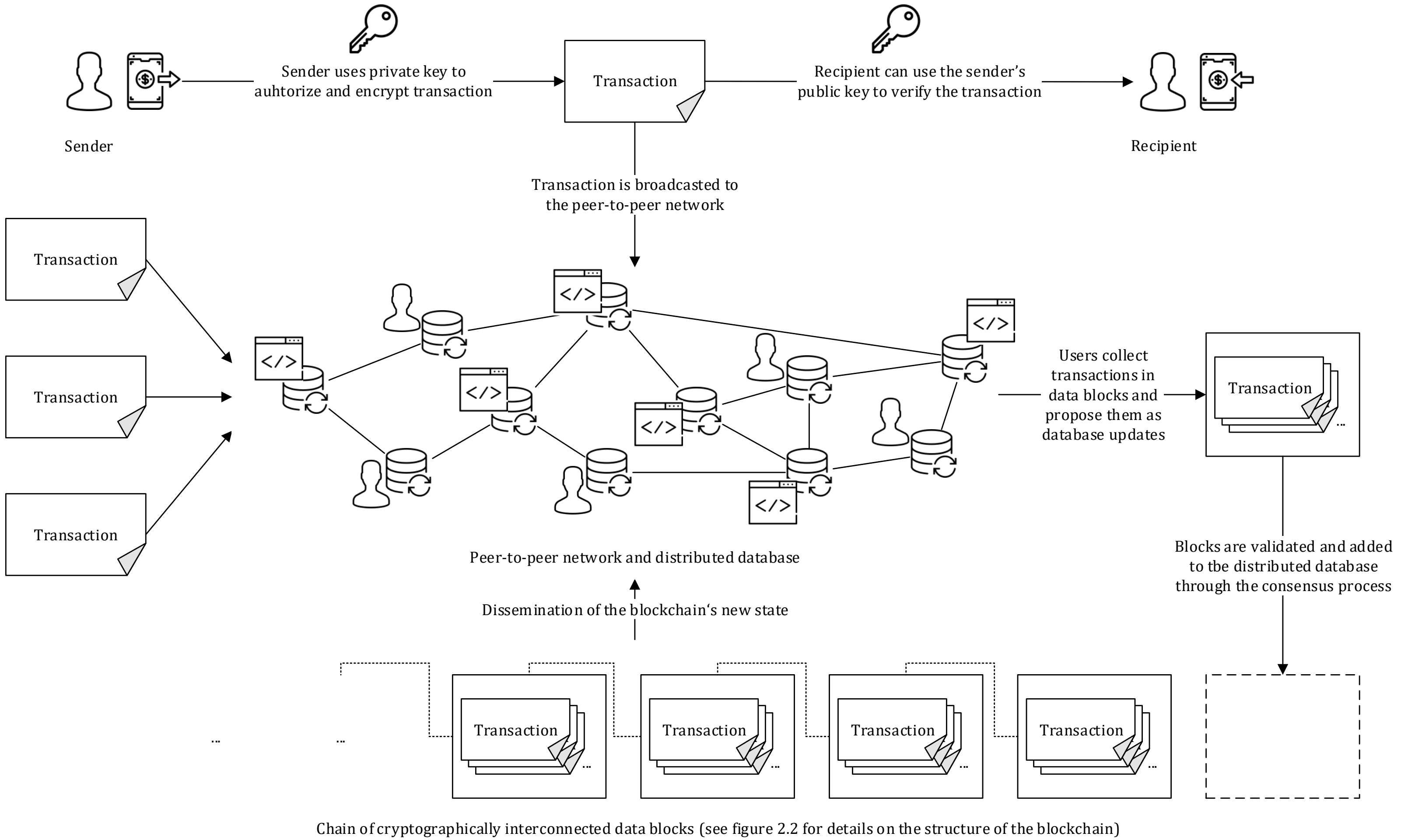


FIGURE 2.1: *Transaction process*

This figure illustrates the process of a blockchain transaction and highlights the involvement of cryptographic elements at each stage. After the transaction is specified and signed by the sender, it is broadcasted to the peer-to-peer network. The network's users collect all new transactions aggregate them into blocks, check their validity, and propose them as a database updates. Eventually, on block is chosen by the consensus mechanism, added to the distributed database, and the blockchain's new state is disseminated through the peer-to-peer network.

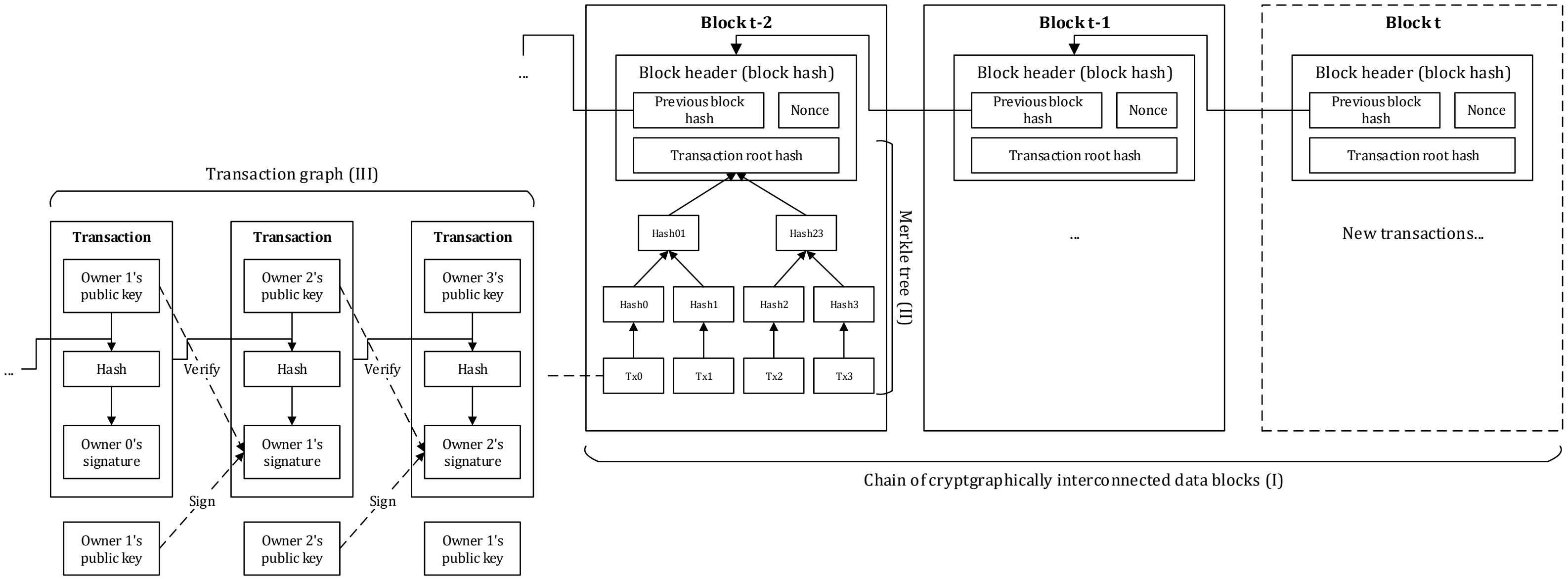


FIGURE 2.2: *Data structure*

This figure is based on Nakamoto (2008) and illustrates the cryptographic connection of blocks and resulting chain that forms the blockchain's distributed database (I). In addition, it highlights how merkle trees summarize transactions within a block (II) and how public and private keys span the historic transaction graph (III). t *denotes the current and* $t-n$ *with* $n \in \{1, \ldots, N\}$ *the preceding blocks.*

2.1.2 Blockchain as a Platform

This subsection is based on the book chapter "Blockchain as Platform". The chapter is co-authored by Florian Glaser and Florian Hawlitschek and was published in Business Transformation with Blockchain - Volume I in November 2018. Direct citations are highlighted by double quotes.

Publication details:
Glaser, F., Hawlitschek, F. & Notheisen, B.[2]*,*
Blockchain as a Platform,
Business Transformation through Blockchain, Volume I, First Edition, Palgrave Macmillan, November 2018, ISBN 978-3-319-98911-2,
https://doi.org/10.1007/978-3-319-98911-2_4.

Introduction

"Digitalization is a ubiquitous term and refers to the digitization of processes and information alongside improvements, innovations, and reinventions that are enabled by increasingly powerful information technology. Today, nearly every industry sector is affected by digitalization and is facing threats and opportunities through new possibilities. With the rise of the digitalization, the platform approach has become the dominant strategy for large companies to operate an extensible, digital medium of exchange for products, information, and services. A large share of companies with the highest market capitalization based their business on platforms (e.g., Apple, Alphabet, Amazon). The earlier evolutionary stages of today's digital platforms were two-sided markets, where two groups of users exchanged goods and every internet user could take the role of either a buyer or a seller (e.g., eBay). Over the last decades, it became a common decision to open up a platform to third-party service developers who could reuse the platform's core functionality to build complementary components. This opening up of platforms is referred to as 'permissionless innovation' (de Reuver et al., 2017). A digital platform is defined as 'a system that can be programmed and therefore customized by outside developers users and in that way, adapted to countless needs and niches that the platforms original developers could not have possibly contemplated' (Parker and Van Alstyne, 2018).

[2]Authors are listed in alphabetical order.

Given the definition above, we can derive features that distinguish a platform from a two-sided market: The openness to innovation through third-party developers. That is, platforms provide Application Programming Interface (API)s which grant developers access to core functionalities provided by the platform for integration of extended functionality, external services, or platforms. A recently emerging type of digital platforms is blockchain systems. Although they can be considered platforms according to the discussed definition, they [...] differ with respect to the provision of their core functionality."

The characteristics and properties outlined in section 2.1.1 "render blockchains a potential infrastructure for various (novel) business models in today's digital platform economy, ranging from [peer-to-peer] sharing and [peer-to-peer] lending, over autonomous asset registries, to completely crowd-based financing and investing. Although blockchain technology has been around for nearly a decade (Nakamoto, 2008), few sociotechnical challenges have been sufficiently researched and few best practices to address key challenges have been developed. The goal of this [section] is to arrange blockchain technology within the concept of institutions and explain and discuss two resulting key challenges, namely, governance and trust, of such decentralized and potentially autonomous service systems, by drawing upon research on incumbent digital platform models."

Blockchain Systems as Open Digital Platforms

"From an abstract perspective, blockchain systems can be analyzed on two distinct layers: the fabric layer and the decentralized application layer (dapp or application layer) according to Glaser (2017) [and Notheisen et al. (2017)]. The fabric layer comprises the [peer-to-peer] communication, consensus, and database management components. The application layer includes all services and features implemented in the form of smart contracts and is relying upon the functionalities provided by the fabric layer. Application layer services can be (re)used by other users in the same blockchain system. A smart contract-based service, for example, can require services of other smart contracts or might require token transactions on the underlying level for performing its service.[3] Both layers of a blockchain system are providing core functionalities that are open to be used or extended by users of the system. Hence, blockchains are open platforms, and therefore research on and knowledge about digital platforms and blockchain share a common ground.

[3] The layers of blockchain systems and their respective components are explained and illustrated in Chapter 3 and figures 3.2 and 3.3 in detail.

A crucial difference to digital platforms is, however, that blockchains do not provide a common API to interact with service interfaces, but the possibility to deploy code onto the platform's fabric layer which is shared by all users. To set up a smart contract, a user has to attach code to a transaction and send the transaction into the network. Other nodes in the system receive the transaction attach it to the blockchain of transactions according to the consensus mechanism and can thereafter retrieve the code of the contract from the blockchain database. Thus, once a smart contract is deployed in the blockchain, its code is available at every node for execution whenever a user calls the contract. Put differently, the functionality of the entire platform can be extended by any user through deployment of smart contracts onto the fabric layer. Incumbent digital platforms are usually governed by larger corporations or organizations that have full control over additional features provided for the platform. The governing company is in control of the technical APIs of its platform or in control of the extensions that are available and published for the platform. For example, Google governs its android platform's Playstore, and Apple is in control of iOS' App Store, while Facebook is in control of its platform's APIs. In summary, blockchains' core functionalities are solely developed and operated by a multitude of open-source developers (that develop the fabric layer) and participants (miners that validate transactions) in a globally distributed system with extending functionality provided by users (on the application layer). There does not have to be a single organization or corporation that is coordinating the development or overseeing the operations of the fabric layer. Although, in practice, a crowd/privately funded organization is often in charge of coordinating the selection and implementation of future features of a fabric layer.

While this holds for the fabric layer, smart contracts can be written by any participant who might be a single user, a nonprofit organization, or a corporation. These properties render a blockchain system a decentralized, open digital platform that provides a set of core functionalities for others to build upon, which is, however, changing over time through contributions of arbitrary other users. This allows blockchain-based platforms to function as a decentralized institution that enables and implements new forms of governance mechanisms. However, the distributed nature of such systems also requires a new form of governance mechanisms as neither the fabric layer nor the application layer has a central authority that can deliberately impose binding processes. Given the inherently distributed nature of public blockchain systems, previous approaches might apply to some degree but are challenged by these new and pervasive sociotechnical interaction mechanisms. The openness of public blockchain systems further implies that smart contract code can be developed and deployed by any participant.

Relying upon services provided by publicly available smart contracts requires trust. On the one hand, the user has to trust in the correctness of the code. This requires the user to trust the developer of the code and the code that it performs exactly the way the user expects it to do. The alignment of expectations and reality regarding performed functionality of code might be possible for simple contracts but becomes nearly impossible for complex service networks that are composed of a multitude of interacting contracts.

If these trust requirements are fulfilled, the actual execution of the code in its unchanged version is comparably reliable, that is, trust-free, as the code is deployed into a large distributed system and once deployed cannot easily be manipulated or changed. This resembles the actual meaning of a stipulated enforcement of a smart contract as by proposed by Szabo (1997). However, this trust-free property is limited to the consensus regarding smart contract code execution and data that is generated within the blockchain system (i.e., trust in system information about token transactions between users). As soon as external data might be required for a smart contract to execute (e.g., sensor data, financial time series data, or any other data describing the state of the physical world), additional trust into the externally provided data is needed. These two issues induce two severe sociotechnical challenges, governance and trust, if blockchains are to become ubiquitous and utility-bearing parts of our future digital economies and societies. The remainder of this section discusses these two challenges in [...] sociotechnical and socioeconomic contexts."

The Blockchain's Institutional Characteristics and Governance Implications

"Institutions form the core of any governance mechanism. To create a rudimentary understanding of institutions and how they work, this section gives a brief introduction to the field of institutional economics, builds on this foundation to arrange blockchain technology within the concept of institutions, and discusses the resulting governance implications."

The role of institutions. "To provide a common starting point, we follow North (1991) and define institutions as '[...] humanly devised constraints that structure political, economic, and social interaction' (North, 1991, p. 1). As such, they consist of both formal and informal rules that take the behavior of individuals into account.

These behavioral factors comprise the impact of agency costs (Jensen and Meckling, 1976), the consequences of separation of ownership and control (Fama and Jensen, 1983), the relevance of property rights associated with interactions (Demsetz, 1967), the social costs generated by external effects (Coase, 2013), and the impact of transaction and coordination costs on organizational structures (Williamson, 1979).

$$X \rightarrow Y, \; in \; C. \tag{2.1}$$

The purpose of institutions is to structure interactions and organize human behavior by constraining action spaces, attributing a set of possible reactions to possible actions, and collectively assigning a function to objects. We can formalize this perception by the saying X counts as Y in C where X stands for the domain of physical and nonphysical objects that are allowed by the institution (i.e., the action spaces), while Y is the function assigned to them. C represents the institutional environment that defines the manifestation of X and Y and the relationship between them. It restricts the available set of actions in X by specifying which objects belong to X and assigns a possible set of functions Y to these objects. These enabling rules are embedded in the transformation function and allow individuals to act within a specific spectrum. Both restricting and enabling rules are equally important as they depend on each other. This way, institutions impose consistency on human activities, which allow interacting parties to '[...] create stable expectations about the behavior of others' (Hodgson, 2006). The resulting order of social [...] interactions reduces [information and enforcement activities,] as institutions prescribe the behavior of individuals [...] (Coase, 1937; Jensen and Meckling, 1976; Williamson, 1979).

As highlighted before, institutions can be formal or informal, and thus do not require an explicit representation in order to exist and be relevant (Hodgson, 2006). In addition, they form either directly or indirectly as a result of the combined effort of a society and its individuals (Tuomela, 1995). Formal institutions are written rules that prescribe specific behavior and provide a basis to enforce it. In case of violations, they also specify sanctions that allow a (centralized or decentralized) authority to enforce the previously agreed arrangement. Informal institutions, on the other hand, are usually not available in an explicit form and manifest on the basis of reciprocity as individuals implicitly agree on them by behaving accordingly. In addition, enforcement is not specified in advance, and instead violators are punished by spontaneous feedback of the society (e.g., by exclusion). Independent of their formal or informal nature, institutions can form either spontaneously, which is when their existence leads to an improvement for a society as a whole (Foss, 1996), or as a result of a conscious design (Smith, 2003).

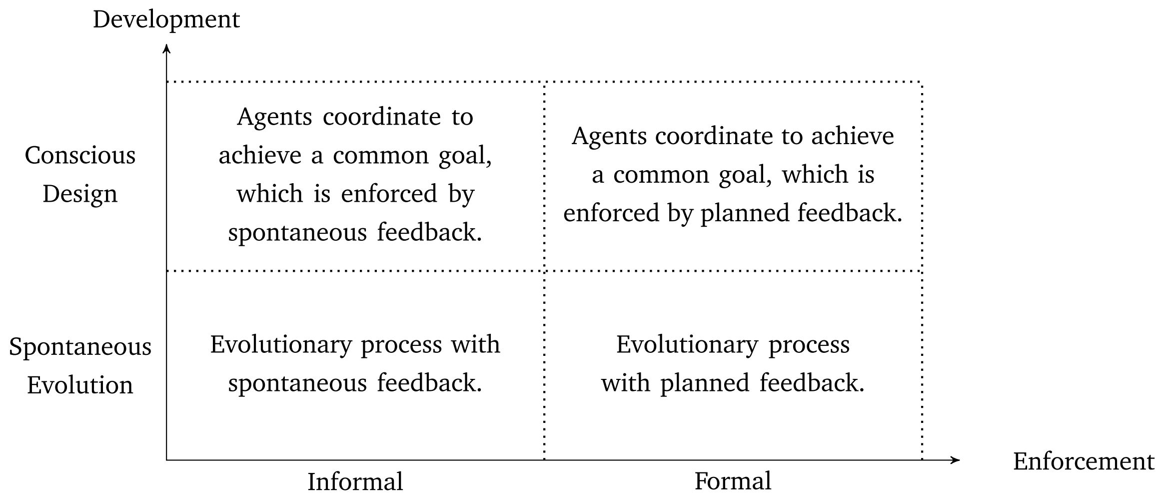


FIGURE 2.3: *The dimensions of institutions.*

In the case of a conscious design, the individual agents that form a society negotiate rules to govern interactions in their social and economic life in order to reach some superordinate goal. Figure 2.3 summarizes the dimensions of institutions and illustrates their assorted characteristics. It is important to note that institutions - irrespective of their level of formalization and their origin - are not fixed and are subject to change as societies evolve over time (Ostrom, 1986):

$$X(t) \rightarrow Y(t),\ in\ C, \tag{2.2}$$

To ensure that they adapt accordingly, rules have to be renegotiated or adapt implicitly, as the sociotechnical and economic environment evolves continuously and interacting individuals change their behavior."

The blochchain as an institution. "Based on the understanding of the role, characteristics, and key components of institutions developed in [the previous paragraph], we apply this understanding to blockhchain-based platforms.

First, we will take look at the key components, namely restricting and enabling rules, that span the governing scope and define the fashion of order an institution establishes. Transferring this concept to blockchain systems, the fabric layer restricts the action spaces of its users by setting the boundaries of the technical infrastructure, thus constraining the scope of possible application scenarios.

[...] The fabric layer specifies the characteristics of a blockchain system and thus determines its application domain and scope of governance. Building on the fabric layer, the application layer empowers individuals to shape the way they interact with each other. It enables users to assign a function the generalized IT artifact defined by the fabric layer and engage in concrete interactions, by allowing users to tokenize values, provide and use services, and conduct transactions. The fabric layer of the Bitcoin blockchain, for instance, is specified to conduct transactions between pseudonymous counterparties without a central intermediary, while allowing only a highly limited incorporation of program/software logic via Opcodes. In consequence, the action space is constrained to actions related to transferring some number-values between users. However, this limited functionality enables its users to use Bitcoin as a peer-to-peer payment system. In other words, it allows the users of Bitcoin to act within a given spectrum and provides a common understanding of the Bitcoin system as an electronic cash system. In contrast, the Ethereum blockchain goes beyond the concept of a pure cryptocurrency and incorporates a shared global infrastructure that allows the implementation of smart contracts by itentional design. As a result, it enables a variety of assigned functions that range from the simple functionality of a cryptocurrency known as Ether, over transaction systems (Notheisen et al., 2017) to decentralized autonomous organizations (Jentzsch, 2016) and market places (Notheisen et al., 2017). This functional scope has multiple advantages, such as the automation of governance, but also impedes the development of a common understanding of its assigned function(s).

Second, we arrange the blockchain protocol, which includes fabric and the application layer, as well as adjacent processes such as protocol development and maintenance within the institutional dimensions introduced (see figure 2.3), in order to highlight and understand the multi-faceted nature of blockchain-based platforms. The fabric layer, which forms the technological foundation of each blockchain system, is usually the result of a conscious design of a small group of core developers that coordinates to achieve a common goal, such as providing a fully decentralized electronic cash system in the case of Bitcoin. The resulting system aims to contribute to a collectively determined goal of society by reducing the coordination efforts of individual agents required to achieve this goal. With respect to blockchain technology, such a goal could be the transfer of assets between interacting parties without relying on a central authority. However, whether a specific blockchain fabric becomes widespread standard or fails to establish in the institutional landscape cannot be enforced by the protocol itself but is rather determined implicitly by its actual use.

If a user does not agree with the proposed protocol, he or she can provide an update to the system to which other users can switch if they prefer the proposed update. As a result, the compliance with a specific blockchain fabric is enforced via a the network effects based on the implicit vote of users by joining a proposed protocol or protocol update or stick with the incumbent system version. In addition, blockchain fabrics that have the reputation of not functioning well or giving unfair advantages to a specific group of users are also punished by social feedback (that is a bad reputation), which in turn leads to an absence of users. In most cases, the fabric layer is maintained and updated by an open source community or an organization that is based on an open source community (examples include the Bitcoin Foundation or the Ethereum Foundation). These maintenance mechanisms form as a result of an evolutionary cultural process within the specific communities and often build on the altruistic aspiration to improve the underlying protocols. To comply with specific rules, customs, and manners within these communities are usually enforced by social feedback. The application layer, which embeds payment services, smart contracts, and other functionalities, results from the conscious design of the fabric layer, which enforces the compliance of interacting agents with their previous commitments based technical specification of the blockchain system (Beck et al., 2018). More specifically, individual agents can only engage in a transaction with assets for which they can provide a verifiable proof of ownership (for example by referencing to received transactions stored in older blocks) and the settlement of a transaction takes place as a direct consequence of the consensus mechanism. The same logic applies for contractual agreements implemented in smart contracts and non-monetary transactions within more complex smart contract-based platforms. Figure 2.4 summarizes and illustrates the arrangement of the blockchain's institutional characteristics within the dimension of institutions [...]. In total, this illustrates how blockchain systems resemble the key components of institutions and highlights the enforcement channels that blockchain technology utilizes in order to govern the interactions of individual users of an open platform."

Implications for platform governance. "As a result of its institutional and technological features, blockchain technology has the potential to reshape the way platforms, in general, are governed. The following section highlights a potential path of such a transformation along the core value propositions of blockchain technology - the improvement in transparency resulting from the current and complete record, the decentralization of consensus authority, and the automation of enforcement. Eventually, we illustrate how platform governance might change in the future.

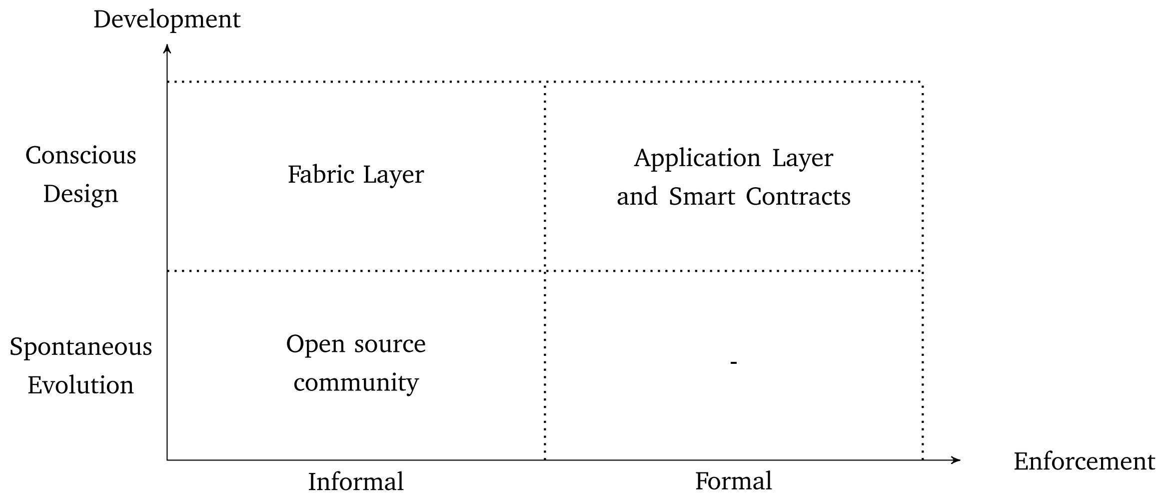


FIGURE 2.4: *The institutional dimensions of blockchain-based platforms.*

First, the more current and more complete information about ownership structures (Yermack, 2017) facilitates the dissemination of information among platform users in real-time and allows them to make more informed decisions. The resulting technical establishment of the accountability of individual users (Beck et al., 2018), leads to a reduction of the uncertainties that interacting parties face under asymmetric information (Notheisen et al., 2017). Further, it mitigates free-rider problems (Yermack, 2017) that arise in economically and socially opaque environments. In addition, the historical record of interactions reveals entanglements among individuals thereby disclosing potential conflicts of interest (Yermack, 2017) that might impede platform efficiency. However, the increase in transparency also raises some issues with respect to the incentives of users to contribute to the consensual agreement, as the disclosure of formerly private information reduces the rents individuals were able to generate from this informational monopoly. Furthermore, the visibility of unique identifiers and related transactional histories raises privacy concerns (Beck et al., 2018; Böhme et al., 2015) that need be considered when designing blockchain-based platforms.

Second, the decentralization of consensus facilitates the decentralization of decision rights (Beck et al., 2018) and enables the resolution of disagreements and conflicts without the involvement of a centralized arbitrator (Beck et al., 2018). As a result of this diffusion of authority, individuals themselves, supported by the scrutiny and wisdom of the crowd, become the sources of authenticity (Morabito, 2017). In combination with the irreversibility of transactions, this shift ensures the correctness [of the] database.

In addition, the reliability and quality of the stored information does not depend on the judgment and ability of costly auditors and data integrity becomes independent of the integrity of individuals (Yermack, 2017). However, the absence of a central authority and the resulting transmission of decision rights and consensus authority to the heterogeneous crowd of individual platform users requires an effective alignment of individual incentives and collective interests (Beck et al., 2018). When the incentives to participate in the costly consensus process are not properly aligned with the users' individual interests and motivations, their contributions may be insufficient or even malicious, which eventually threatens the integrity of the entire platform (Beck et al., 2018).

Third, [...] blockchain technology automates the enforcement of agreements between interacting parties. These agreements can range from simple monetary transactions at a single point in time, such as in the Bitcoin system, to a contractual nexus of multiple interactions between multiple parties at multiple points in time. Smart contracts provide a tool to govern such complex interaction patterns by autonomously enforcing the rules defined by the ecosystem of the platform and the agreements specified in multilateral negotiations and encoded in the smart contract itself (Beck et al., 2018). The resulting automation of enforcement enables leaner and simpler contracts (for example fewer covenants in debt contracts (Yermack, 2017)), reduces opportunistic behavior of individuals, such as balance sheet fining, and alleviates the scope of manipulative actions (Yermack, 2017). In addition, it facilitates the replacement of (government) entities that manage property rights of physical and digital assets by blockchain-based equivalents (Morabito, 2017).

However, it is important to keep in mind that blockchain technology and smart contracts will not be able the replace the negotiation of agreements. Instead, lawyers will no longer draft extensive paper documents but rather encode the results of their negotiation in self-executing legal documents based on smart contracts (Morabito, 2017). So while the blockchain may be able to reduce coordination costs, this negotiation process might entail a substantial amount of new coordination costs (Beck et al., 2018). An important prerequisite for these new coordintation costs is some sort of common language that allows lawyers and developers a joint understanding of the concluded agreement (Al Khalil et al., 2017). In addition, the finality of the data stored on the blockchain, leaves no chance to correct undesired outcomes or to react to unexpected events. The resulting immediateness of transactions and triggered agreements increases transaction risks (Böhme et al., 2015) and can cause hazardous feedback loops (Paech, 2017) as smart contracts cannot be breached (Morabito, 2017).

Besides the potentially beneficial impact of blockchains on the governance of platforms, maintaining and updating the underlying blockchain infrastructure, especially on the level of the fabric layer, raises new governance problems itself (Yermack, 2017). One way to maintain a blockchain system is to utilize the open source community as a governance institution (see figure 2.4). In such a governance system, a change in the source code of the fabric layer can be initiated by every user and system-wide adoption requires a majority of nodes to implement the update on their device. This passive process of adoption puts powerful individuals in a dominating position and makes blockchain-based platforms vulnerable to sabotage by malicious users that distribute updates that favor themselves by exploiting collective action problems (Yermack, 2017). The distribution of such asymmetrically favorable updates might be detrimental to other, less powerful users, and are pronounced in systems with more heterogeneous user bases (Paech, 2017) and on platforms, where individuals show more distinct collusive tendencies. The empirical findings of Wang et al. (2017) reflect this imbalance and indicate that while individuals value decentralization within the application layer, they do not value decentralization with respect to the governance of a fabric layer (Wang et al., 2017). In consequence, it remains necessary to delegate the responsibility for maintaining the network and to ensure compliance with the socio-economic and legal environment a platform operates in to some governing entity (Paech, 2017). Although the increase in transparency, the decentralization of authority, and the automation of enforcement shifts trust towards a more technical, algorithmic notion (Lustig and Nardi, 2015), the trust of users in the governing entity still plays a crucial role in order to ensure the efficacy and efficiency of blockchain-based platforms."

Trust in Blockchain Systems

"Many of the governance features highlighted in the previous section build the trust-free nature of blockchain technology. The term trust-free refers to the ability of blockchain technology to 'create an immutable, consensually agreed, and publicly available record of past transactions that is governed by the whole system' (Hawlitschek et al., 2018) and therefore should be considered a mainly technological feature in the first place. In addition, [...] trust still plays an important role with respect to the governance of the system. This section builds on these presumptions, elaborates the trust-free property and discusses, which trust relationships prevail or even gain importance in blockchain-based platforms.

Blockchain systems are increasingly taken into consideration to form the basis of different types of digital platforms. Given the characteristics of blockchain technology, it is possible to assume that as long as the platform remains a closed-up, purely technical ecosystem, it can be in fact considered trust-free (Glaser, 2017). However, such purely technical platforms do rarely exist in the real world. Instead they form the basis for a variety of whole microeconomies that need to be managed by platform providers (Parker and Van Alstyne, 2018). This shifts the purely technical view on blockchain-based platforms to a sociotechnical perspective (de Reuver et al., 2017). As a result, the notion of a trust-free blockchain system as underlying infrastructure for platforms should be critically assessed and discussed. Leaving the realm of blockchain systems as purely technical concepts, it is viable to revise the notions of trust and trust-freeness in greater detail. Across disciplines, trust is usually considered as 'a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another' (Rousseau et al., 1998, p. 395). Therefore, trust-freeness is a property that is hard, if not impossible to achieve for a platform (notwithstanding the use of blockchain systems as a technological basis). From the perspective of IS research, different trust relationships matter for users. For example, users need to trust the IS, the provider of the IS, the internet (as an enabler for using an IS), as well as the community of internet users (Söllner et al., 2016). We propose that the same holds true for platform users. In fact, the trust relationships in a platform microeconomy can even be more complex – especially for the case of two-sided markets. The notion of blockchain-based platforms for peer-to-peer sharing is not only in the center of the (popular) scientific discussion (Hawlitschek et al., 2018), it has already begun to enter the global market. The Universal Sharing Network (USN) of the German company slock.it, for example, can be considered as a digital platform with an extensible codebase (de Reuver et al., 2017). In contrast to most posterchild examples of the sharing economy, such as Airbnb or BlaBlaCar, the USN is based on an open source infrastructure on which blockchain application modules can be deployed, enabling third parties to onboard any object to the USN[4].

In the following we will outline which trust relationships matter for blockchain-based platforms. We guide and exemplify these considerations based on an example of a peer-to-peer sharing economy platform and [...] illustrate why even blockchain systems require trust. The engineering of two-sided markets is a particularly difficult task, since markets need to attract participants that take both the roles of consumers and providers in order to facilitate market growth and stability (Teubner et al., 2017).

[4]See https://slock.it/usn.html.

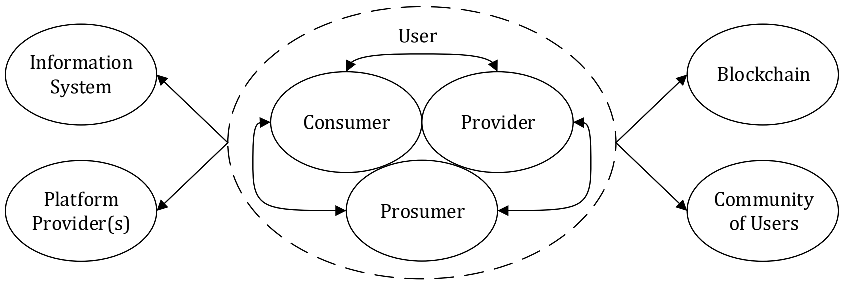


FIGURE 2.5: *Trust targets for blockchain users (based on Söllner et al., 2016).*

Therefore, a set of different user perspectives has to be taken into account to understand the different trust relationships in two-sided blockchain-based markets in detail (see 2.5). In contrast to ISs with a rather homogeneous user base, at least two different user types need to be distinguished, that is, consumers and providers. Since two-sided platforms may well benefit from a possible dual role of users acting as both, consumer and provider (Stummer et al., 2018), it is also worthwhile to extend this categorization by a third type: The prosumers (Ritzer et al., 2012). Obviously, the segmentation of the user role in at least two sub-types is accompanied by a need for trust between these roles. Especially in the context of peer-to-peer sharing, interpersonal trust plays a significant role (Hawlitschek et al., 2018; ter Huurne et al., 2017). In particular, sharing economy platform users need to belief in each other's ability, benevolence, and integrity to develop transaction intentions (Hawlitschek et al., 2016). Furthermore, following the work of Söllner et al. (2016), a set of further trust targets is relevant to understand the use of information systems. For blockchain-based information systems, we adapt and summarize these targets as the information system itself, the platform provider(s), the platform's blockchain infrastructure, and the community of users.

Trust in the information system includes both layers of the blockchain system, that is the application layer and the fabric layer. Therefore trust in the IS is a rather broad concept comprising multiple aspects, such as the tokenization of the ecosystem value, the immutable decentralized database, the decentralized permissioning, as well as autonomous and user controlled services. Importantly, the perception of the trustworthiness of the different layers and corresponding components, will largely depend on the user type. While inexperienced and less tech-savvy users may perceive the IS mainly through the presentation layer, expert-users may have the ability to dig deeper into layers and evaluate the blockchain system's components.

Blockchain systems and their components are operated by both open source developers (developing the fabric layer) and participants in a globally distributed system (developing on the application layer). Consequently the community of open source developers can be considered as the blockchain platform providers. Trust in the platform provider(s), is therefore necessary to prevent an absence of users (for example due to the perception of unfair or fraudulent implementation). In the same way, the participants in a globally distributed system can be considered as the community of users. Following Söllner et al. (2016), we argue that blockchain systems can only provide effective support to their users, if the community of users offers valuable services or information. Thus trust in the community of users describes an individual's belief that the community of users provides services and information reliably, benevolently and with integrity. Finally, users of a blockchain system need to trust the underlying technology itself [...]. Trust in the blockchain becomes necessary due to the high complexity of the technology. Since in most cases users will not be able to fully understand the mechanics of the underlying blockchain technology, they will need to trust in its reliability [(Lustig and Nardi, 2015)]. This is [similar to] institution-based trust in the internet (Söllner et al., 2016)."

Concluding Remarks

"The institutional characteristics of blockchain technology help to structure and organize the interactions on these platforms by facilitating a common understanding of a platform's functionalities and imposing consistency to individual users' behavior. In this context, the fabric layer, which usually results from the conscious design of an informal group of developers and is maintained by spontaneously evolving open source communities, sets the boundaries for interactions of users and the scope of application domains. The concrete manifestation of the fabric layer and thus the characteristics of a platform, is determined implicitly by the informal feedback of user adoption. Building on the fabric layer, the application layer enables individual users to implement various features based on smart contracts. The services and applications resulting from this conscious design reshape governance mechanisms within platforms and redefine how users interact with each other. Their transparent, autonomous, and distributed nature has the potential to reduce the negative effects of information asymmetries, democratize decision processes, secure property rights, simplify contracting and enforcement, and limit opportunistic behavior. However, these features also increase transaction risks and raise privacy concerns.

In combination with the governance of a blockchain-based platform, mastering these challenges requires a new notion of trust. The core dimensions of this new notion of trust are the trust in the IS and the deployed algorithms, trust in the providers of the platform infrastructure (that is the blockchain providers), and trust in the community of users. It is this user and developer base that maintains and secures the fabric layer, which fuels the variety of applications and services build atop the application layer. This trust remains a central facilitator of the adoption of blockchain-based platforms, in particular when it comes to intersections with the real world and the governance of the system itself."

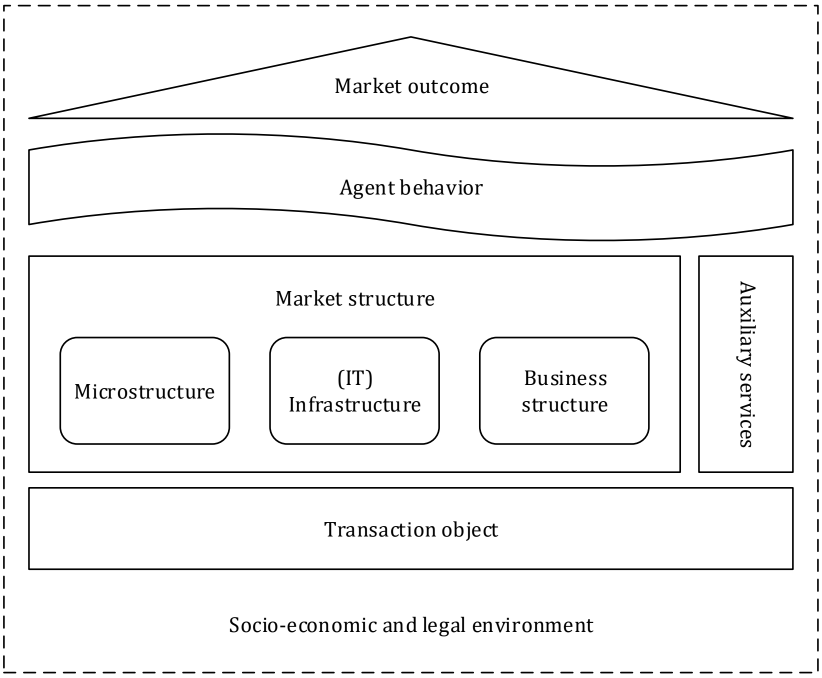
2.2 Market Engineering

"The economic environment evolves, but is also designed" (Roth, 2002, p. 1431). However, shaping markets within their economic environment is a complex task that requires knowledge and methods from multiple fields. More specifically, it requires a shift away from the dominant analytic ex-post view of economics towards a joint perspective that combines traditional game theory and mechanism design with experimental, computational, and engineering approaches. This way, we can create an interdisciplinary and formative view on the organization of economic interactions (Roth, 2002). In addition, market design goes beyond a conceptual approach and should investigate the cause-effect relationship between a market's features and its outcomes to identify relevant trade-offs (Roth, 2002).

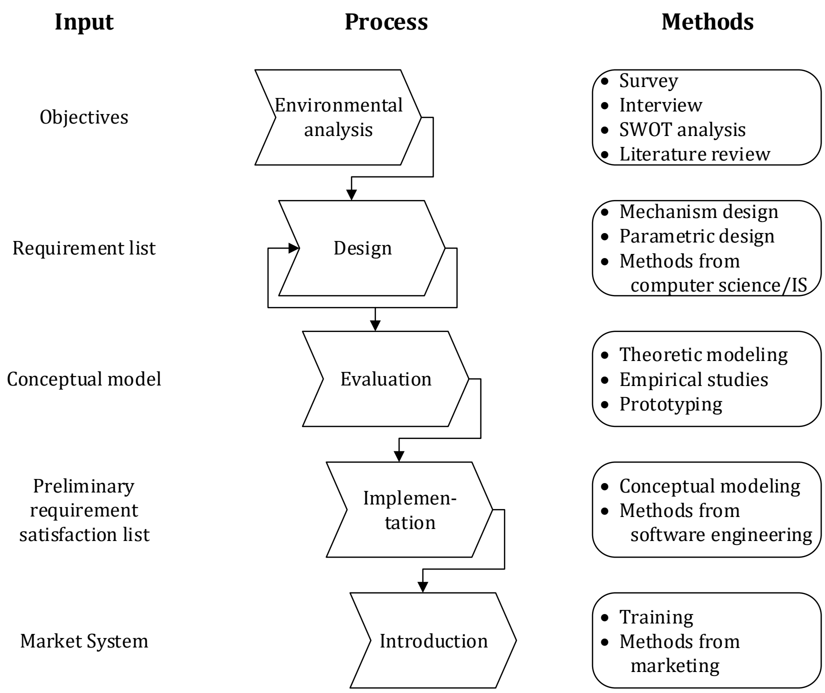
Market engineering builds on this notion to create a structured and systematic approach that offers a toolbox to market designers that helps them to analyze, design, and evaluate (electronic) market platforms within their institutional environment (Weinhardt et al., 2003). As a result, it provides "[...] an integrated, [holistic] view on markets, a multiplicity of methodologies, an interdisciplinary approach, and the understanding that details matter" (Weinhardt and Gimpel, 2007; Gimpel et al., 2008). However, in contrast to Roth (2002)'s notion of market design, market engineering comprises a concrete framework that describes the elements and steps a market designer or engineer should consider in his or her endeavor. Figure 2.6 illustrates the resulting market engineering framework in detail.

The market engineering object (figure, 2.6 panel A) comprises a transaction object, the market structure, auxiliary services, agent behavior, as well as market outcomes and embeds these components within the market's socio-economic and legal environment. This environment is defined by laws, rules, and regulations as well as social norms and outside of the market engineer's control. As a result, it is assumed as given and forms the institutional environment of the market platform at hand. Within this environment, the market engineer aims to achieve a specific market outcome (e.g., maximize activity, liquidity, or information aggregation) by designing the market structure, corresponding auxiliary services, and the underlying transaction object. A market's structure is defined by its microstructure, its (IT) infrastructure, and its business structure. The microstructure defines the core of the market mechanism by connecting demand and supply and determines the price and allocation of the transaction object. The business structure on the other hand, describes the way market operators generate revenue, for instance in form of trading fees. Eventually, the (IT) infrastructure comprises the technical framework that supports the market and implements the micro- and business structure, embeds auxiliary services, and provides an interface that allows agents to connect to the market platform. Auxiliary services are services that are not a core part of the market mechanism but support agents in their interactions. According to Gimpel et al. (2008), these services include decision support and reputation systems or the clearing and settlement of transactions. However, all of these components affect market outcomes only indirectly as the actual agents' behavior lies beyond the market engineer's control. Instead, it depends on the design of the transaction object, market structure, and auxiliary services as well as the agents' characteristics and (economic) rationales. In consequence, the market engineer has to anticipate behavioral patterns in order to achieve the desired outcomes.

Within this framework, the market engineering process (figure 2.6, panel B) describes the steps necessary to create a market. It builds on established methods from software engineering (e.g., waterfall model), combines sequential and iterative elements, and guides the market engineer in his or her creative task (Weinhardt and Gimpel, 2007). More specifically, it illustrates each stage of the engineering process, the corresponding inputs, as well as a selection of potential methods. In the first step, the objectives form the input for a detailed environmental analysis in order to elicit requirements the market platform should meet. Based on the resulting requirement list, the market engineer derives an initial market design with the help of methods from mechanism and parametric design, computer science, and IS. In the evaluation stage, theoretical models, empirical studies, and prototyping are used to evaluate and refine the conceptual design iteratively.



(A) *Market engineering object*



(B) *Market engineering process (selection)*

FIGURE 2.6: *Market engineering framework (Weinhardt and Gimpel, 2007; Gimpel et al., 2008).*

If all requirements are met, the implementation stage follows. The implementation stage builds on a preliminary requirement satisfaction list and comprises the creation of the market platform. Finally, the market engineering process terminates with the introduction of the implemented market platform.

Due to its general perspective and comprehensive nature, the market engineering approach is not bound to a specific application domain or a specific type of market. Instead, it has been successfully applied to a multitude of domains and has proven its efficacy and efficiency in energy (e.g., Dauer et al., 2016; Mengelkamp et al., 2018), prediction (e.g., Kranz, 2015; Kloker et al., 2018), financial (e.g., Burghardt and Weinhardt, 2008; Zhang et al., 2011; Riordan et al., 2013), and other market-based applications (e.g., Luckner et al., 2005; Teschner et al., 2014; Kranz et al., 2015). However, despite the possibility to reiterate in the evaluation stage, the development of a market remains static and does not take changes of market participants or the market's environment explicitly into account. In consequence, the notions of agile (Block, 2010) and continuous (Kranz, 2015) market engineering extend the basic concept introduced above with a dynamic perspective and enables continuous monitoring and improvement.

Agile Market Engineering

Agile market engineering was introduced by Block (2010) and constitutes an advancement of the market engineering approach. As such, it details and extends the development process illustrated in panle B of figure 2.6b by taking the complexity of real-world markets into account. As a result, it facilitates short, lightweight, and incremental development cycles and enables its users to implement an iterative and flexible design-and-build strategy. In addition, Block (2010) evaluates his approach in 5 real-world use cases to create a "[...] collection of best practices, experiences, and tools [...]". Figure 2.8 outlines the agile market engineering process and its 3 phases: The pre-development phase, the development phase, and the operation phase. In the pre-development phase, the business owner assesses the market environment and develops a market vision (I), derives initial requirements with the help of a market expert (II), and evaluates the applicability of existing platforms with the help of a market engineer and the market developer (III). The resulting set of initial requirements initiates the development phase. Within this second phase, the business owner prioritizes the collected requirements (IV), concretizes them, and chooses the most important ones for implementation together with a market expert (V).

In the third and final step of the development phase, the business owner, the market expert, the market developer, and the change manager jointly design, implement, and test the current version of the market platform (VI). Note that the steps of the development phase can be repeated multiple times until the tests yield the desired results. With the release of the market platform, we eventually move on to the continuous operation phase. This phase comprises the actual deployment of the platform by the market operator and the market developer (VII). After the deployment, the business owner, market operator, and market expert observe market activity and outcomes to ensure a proper functioning (VIII). If this is not the case, they add or revise requirements based on their observations (IX) and reenter the development phase.

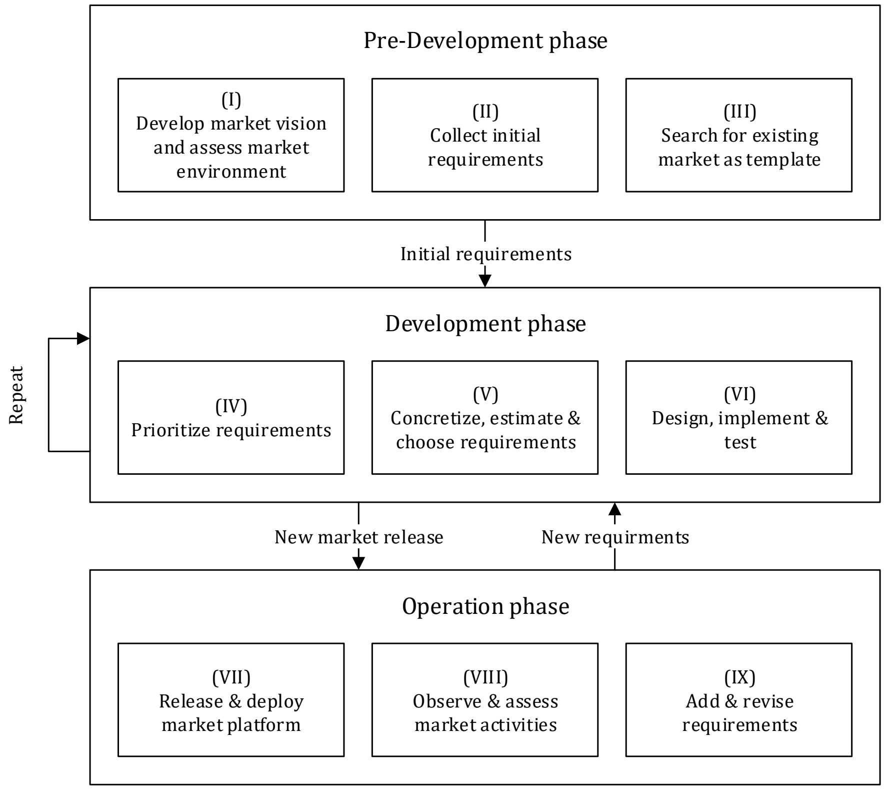


FIGURE 2.7: *Agile market engineering process (Block, 2010).*

Continuous Market Engineering

Similar to agile market engineering, the continuous market engineering approach extends the market engineering framework from figure 2.6 with a continuous view on operation, monitoring, and refinement. However, in contrast to agile market engineering this perspective includes the monitoring of an operating market and emphasizes the assessment of deviations and the following redesign. More precisely, the introduction and operation of a market platform is complemented by a monitoring step. This step comprises the continuous assessment of technical aspects (e.g., the performance of hard- and software), market outcomes (e.g., by activity, liquidity, and information measures (Zhang et al., 2011)), the behavior of traders and other market participants, as well as the impact (and changes) of the socio-economic and legal environment. According to Kranz (2015), there are two events that trigger a deviation analysis: First, the observed performance measures indicate a deviation from the market's normal functioning. If this is the case, the deviation analysis furthermore aims to identify the reasons for the deviation and initiates the redesign to make adjustments. The second trigger are changes in the market's objectives. Consequently, the deviation analysis evaluates the available market parameters and initiates the redesign step accordingly. In both cases, the redesign is followed by an evaluation that assesses the functionality, acceptance, and outcome of the adjusted market structure before the implementation. After the successful implementation, the new release of the market platform is reintroduced and monitoring starts again.

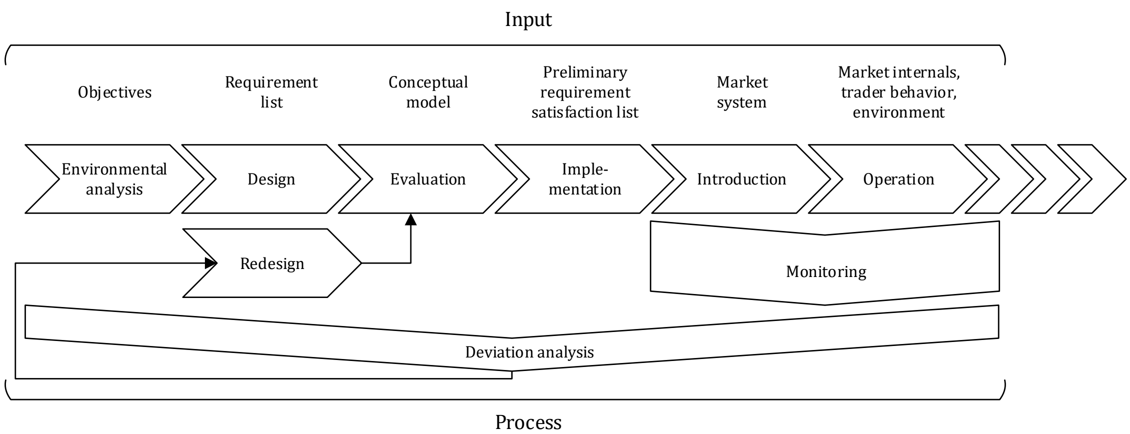


FIGURE 2.8: *Continuous market engineering process (Kranz, 2015).*

Chapter 3

Blockchain Engineering

This chapter is based the articles "Breaking Down the Blockchain Hype - Towards a Blockchain Market Engineering Approach" and "The limits of trust-free systems: A literature review on blockchain technology and trust in the sharing economy". "Breaking Down the Blockchain Hype" is co-authored by Florian Hawlitschek and Christof Weinhardt and was published in the proceedings of the 25^{th} *European Conference on Information Systems (ECIS) 2017. "The Limits of trust-free systems" is co-authored by Florian Hawlitschek and Timm Teubner and was published in the May 2018 issue of Electronic Commerce Research and Applications. In addition, an earlier version was presented as a short paper on the* 17^{th} *International Conference on Group Decision and Negotiation 2017. Direct citations are highlighted by double quotes, while Sections 3.2, 3.3, 3.4, and 3.6 are based on the first, Section 3.5 on the second, and Sections 3.1 and 3.7 on both papers.*

Publication details:

Notheisen, B., Hawlitschek, F. & Weinhardt, C.,
Breaking Down the Blockchain Hype - Towards a Blockchain Market Engineering Approach,
Proceedings of the 25^{th} *European Conference on Information Systems (ECIS), 2017,*
pp. 1062–1080,
https://aisel.aisnet.org/ecis2017_rp/69.

Hawlitschek, F., Notheisen, B. & Teubner, T.,
The limits of trust-free systems: A literature review on blockchain technology and trust in the sharing economy,
Electronic Commerce Research and Applications, May-June 2018, Volume 29, pp. 50-63,
https://doi.org/10.1016/j.elerap.2018.03.005.

3.1 Introduction

"Driven by the expectations about the disruptive and transformational impact on business, the blockchain hype is just about to reach the peak of the Gartner Hype Cycle for Emerging Technologies (Gartner, 2016). While start-ups as well as established companies like Deutsche Börse and the Deutsche Bundesbank put a considerable amount of effort in the development of pioneering blockchain-based market solutions (Deutsche Bundesbank and Deutsche Börse, 2016), many researchers and practitioners still struggle to grasp the true potential of the blockchain (Beck et al., 2016). Since '[...] the technical protocols and implementations [of distributed ledgers, decentralized consensus systems, and decentralized applications based on smart contracts] are quite complex' (Glaser and Bezzenberger, 2015), the engineering and implementation of sophisticated market settings is a nontrivial problem that requires knowledge from various disciplines (Gimpel et al., 2008). The IS community, focusing on both, the IT artifact (i.e., blockchain technology) and the surrounding (economic) structures and contexts (Benbasat and Zmud, 2003) is therefore particularly well suited to conflate and extend the work from different technological and economic disciplines to interdisciplinary research approaches (Giaglis and Kypriotaki, 2014).

So far however, IS research on blockchain-based solutions is still in an early stage and mainly focuses on use case analyses and design science aspects of proof-of-concept prototypes (Beck et al., 2016). At the same time, research approaches and findings are dispersed across a variety of other disciplines such as computer science or economics and finance and therefore would benefit from an interdisciplinary view on a macro level (Giaglis and Kypriotaki, 2014)" (Notheisen et al., 2017, p. 1063) In consequence, we formulate the following first research question:

Research Question 1. *Which pivotal elements and layers define blockchain-based market platforms?*

Besides the elements, layers, and structure of blockchain-based platforms, trust plays a crucial role in engineering decentralized markets. "In recent years, [the blockchain] was sometimes denoted a trust-free technology (Beck et al., 2016) [...]. Trust-free systems rest on the idea to utilize blockchain technology to automatically create an immutable, consensually agreed, and publicly available record of past transactions [...] (Greiner and Hui, 2015). [This] enables verified and transparent [interactions] without the need for a central authority or institution (Nakamoto, 2008; Alt and Puschmann, 2016).

[As a result,] the business model of platforms such as Airbnb and Uber [and] their role as intermediaries between peers and private resources, [is threatened by] the blockchain (Avital et al., 2016) [...]. In fact, several cooperatives such as Lazooz or Share & Charge have set out to establish decentralized sharing platforms with remarkable success in first crowdfunding campaigns (Sundararajan, 2016)" (Hawlitschek et al., 2018, p. 50 - 51). However, against the backdrop of trust as interlaced construct that comprises the relationships between peers, platforms, and products (Hawlitschek, 2019), the question arises whether 'trust-free' blockchain technology will be able to implement this multi-faceted, behavioral nature (Section 2.1.2; Hawlitschek et al., 2018).

Research Question 2. *To which extent can the blockchain implement the multi-faceted nature of trust prevalent on the peer-to-peer platforms of today's sharing economy?*

To answer these questions, this chapter builds on the notion of the blockchain as a market platform (Section 2.1.2) and combines technological aspects with the market engineering approach (Section 2.2) to derive an interdisciplinary framework. To do so, we analyze the growing body of interdisciplinary blockchain research by the means of a comprehensive structured literature review and provide a concept-centric overview. The findings of this review "[...] indicate a strong dispersion with regard to the focus, methodology and specific issues addressed in present IS research, emphasizing the need for a structured approach to guide future research. Based on these findings, we [integrate a technological and a market perspective to derive an] interdisciplinary blockchain engineering framework. [...] The framework differentiates between four layers, and takes [...] the socio-economic and legal environment, the characteristics of the deployed blockchain protocol (i.e., the IT-infrastructure), the application's micro and business structure, as well as the outcomes of the (economic) agents' behaviors" (Notheisen et al., 2017, p. 1063) into account. This way, we aim to support researchers and practitioners "[...] in analyzing and designing the elements of blockchain-based markets on an individual and global level. In addition, [it goes] beyond a purely analytic perspective and provides a toolbox to support the active construction of blockchain-based ecosystems and infrastructures" (Notheisen et al., 2017, p. 1062). Eventually, we extend the blockchain engineering framework by a trust perspective and challenge the claim of the blockchain as a trust-free technology (e.g., Beck et al., 2016). More specifically, we adopt the notion of blockchain-based trust from Section 2.1.2 and discuss, how this behavioral perspective aligns with the blockchain's technological approach (Hawlitschek et al., 2018).

3.2 Literature Review Methodology

"To explore blockchain-related research in the field of IS, we follow the guidelines of Vom Brocke et al. (2009), Webster and Watson (2002), and Cooper (1988) to conduct an exhaustive and selective concept-centric review of literature [...] on blockchain technology. We focus on tangible research results but also shed light on applied research methods to provide a structured overview of the central concepts of blockchain research and the current status of the field. The literature search and selection, as well as the classification process will be described in the following.

In order to ensure the relevance and quality of the reviewed publications, we focus on the top eight peer-reviewed, scientific IS journals from the AIS Senior Scholars' Basket[5] and selected IS conferences[6]. To identify relevant literature, we follow a four step approach based on Webster and Watson (2002), as depicted in figure 3.1.

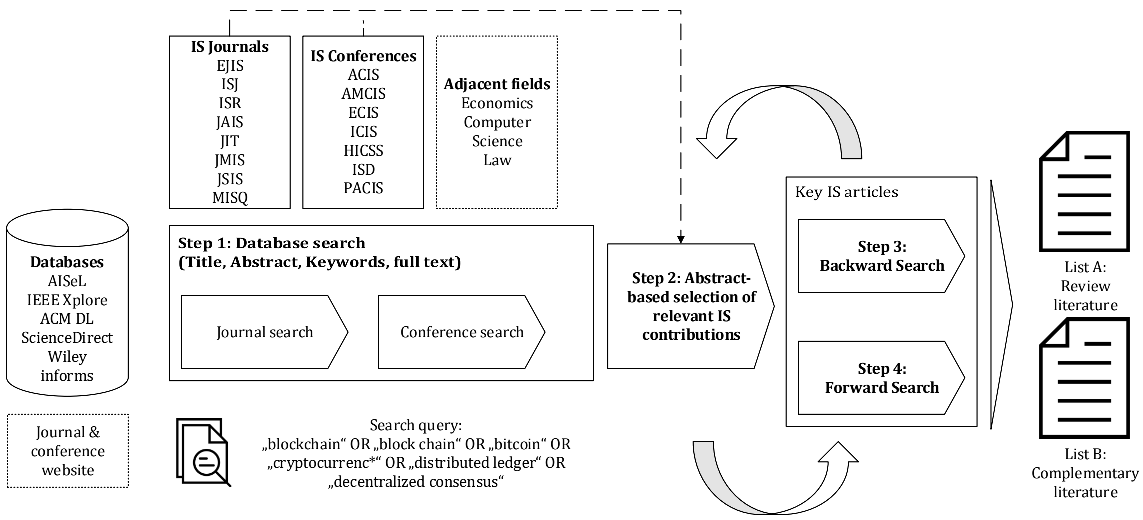


FIGURE 3.1: *Literature search and selection process*

"This figure displays the four-step approach employed in the literature search and selection process. In the first step, we conducted an extensive database search to identify key articles in the top eight peer-reviewed, scientific IS journals, recommended IS conferences, and adjacent fields. In Step 2, we selected articles for the detailed review. Based on those, we performed backward and forward searches in step 3 and 4, respectively. We repeated steps 2, 3, and 4 until our search did not yield any new results" (Notheisen et al., 2017, p. 1065).

[5] See https://aisnet.org/?SeniorScholarBasket.

[6] See http://www.acphis.org.au/index.php/is-conference-ranking.

First, we selected a comprehensive set of scientific databases, such as AISeL, IEEE Xplore, ACM DL, EBSCO Business Source Premier, ScienceDirect, the Wiley Online Library, and in-forms. Within these databases, we searched titles, keywords, abstracts, and full texts by applying the following search string: *blockchain* OR *block chain* OR *bitcoin* OR *cryptocurrenc∗* OR *distributed ledger* OR *decentralized consensus*. Since blockchain technology was introduced in 2008 (Nakamoto, 2008), we limited the search to dates later than January 1, 2008. The first database queries were conducted in June 2016. However, to take the most recent articles into account, we updated the search between the 16th and the 20th of November 2016. Whenever there were no database entries for one of the selected IS journals or conferences, we checked the journals' or conferences' websites [...].

To account for the interdisciplinary nature of the field of IS we furthermore extended our search scope to adjacent fields such as economics and finance, computer science, and law. Within those fields, we exclude publications not labeled as research papers, such as research commentaries, keynotes, news, editorials, extended abstracts, book reviews, PhD-theses, or posters. The review of literature in adjacent fields preserves a complementary character and does not claim to be a complete overview of existing blockchain-related research.

In the second step, we selected a primary set of relevant IS research papers by reviewing each paper's abstract, as suggested by Vom Brocke et al. (2009). Studies that did not contain any of the keywords previously specified in the search query in their abstract or that did not have a primary focus on blockchain research were not considered any further.

For the remaining papers we third, performed a backward and fourth, a forward search. IS articles identified in these steps were added to the selection of relevant literature and both a back-ward and forward search were performed again. Articles that were not published in one of the top eight IS journals or one of the selected conferences were added to the list of adjacent re-search efforts and excluded from the IS review. We repeated the steps 2, 3, and 4 until we did not find any new articles. Eventually, we obtained two lists of publications related to blockchain research. List A contains all IS articles included in our structured review, whereas list B contains all articles excluded in step 2 of the search process as well as all complementing articles from adjacent fields."

3.3 Literature Review Results

3.3.1 Summary Statistics and Research Perspectives

"The literature search process yielded a total of 427 articles, whereof 1 was published in the Senior Scholars' Basket of Eight and 49 in one of the selected IS conferences. Furthermore 29 complementary papers were published in other renowned IS journals such as *Business & Information Systems Engineering* and *Communications of the Association for Information Systems*, or specialized IS conferences. The exclusion of papers only vaguely related to distributed ledgers and blockchain technology, resulted in a list of 26 IS conference papers and no IS journal contributions. Table 3.1 depicts the distribution of the relevant articles across (complementary) journals and conferences.

IS Literature	**Hits**	**Relevant**
Management Information Systems Quarterly (MISQ)	1	0
Australasian Conferences on Information Systems (ACIS)	1	1
Americas Conference on Information Systems (AMCIS)	12	5
European Conference in Information Systems (ECIS)	17	12
International Conference on Information Systems (ICIS)	8	3
Hawaii International Conference on System Science (HICSS)	8	3
International Conference on Information System Development (ISD)	0	0
Pacific Asia Conference on Information Systems (PACIS)	3	2
Total	**50**	**26**

TABLE 3.1: *Core IS literature*
"This table shows the number of articles published in the core IS journals and conferences and differentiates between found (hits) and relevant contributions" (Notheisen et al., 2017, p. 1066).

In Table 3.2, we display the chronological distribution of articles across different fields, starting with the introduction of the blockchain in 2008. Similar to economics and finance, the number of IS publications, remained substantially low until 2014, while the fields of computer science and legal studies started to pick up the topic one year earlier in 2013. These developments seem to coincide with the increasing popularity of Bitcoin, which exceeded the weekly moving average of 50,000 transactions per day at the beginning of 2013 Overall, 86.4% of blockchain-related research was published within the year 2014 or later. In total, articles published in the field of computer science account for more than half of the publications related to blockchain today. The IS community contributes a comparatively small share of 19.4%.

Before summarizing the most important insights from the IS literature, we will give a brief overview on the different views on blockchain from the perspectives of economics and finance, computer science and informatics, and legal sciences in the subsequent paragraph. While researchers in the field of economics and finance mainly concentrate on the characteristics of cryptocurrency markets by analyzing Bitcoin price formation, market efficiency (Nadarajah and Chu, 2017; Fry and Cheah, 2016; Dyhrberg, 2016a), or portfolio diversification effects (Dyhrberg, 2016b; Brière et al., 2015; Bouri et al., 2016), blockchain research in computer science is quite diverse. While some efforts aim to improve the performance of mining technology (Dev, 2014) or solve scalability issues (Karame, 2016), others assess the technology's potential aside of cryptocurrencies (Xu et al., 2016; Hari and Lakshman, 2016). However, one of the most discussed topics is privacy and security (Zyskind et al., 2015; Kosba et al., 2016; Gervais et al., 2016; Eyal, 2015). In turn, research in the field of law follows two major streams: The first one analyzes the use of cryptocurrencies for criminal activities, such as funding terrorism, online black markets, or white-collar crimes (Irwin and Milad, 2016; Barratt, 2015; Marian, 2013). The second stream focuses on the calls for regulatory actions and the need for legal innovations in the face of cryptocurrency markets and blockchain applications (Farmer, 2014; Burleson, 2013; Varriale, 2013; Gump and Leonard, 2016)."

Year	**IS Journals**	**IS Conf.**	**Complimentary outlets**					**Total**	
			IS	**Eco**	**CS**	**Law**	**Total**	**Abs.**	**Rel.**
2008	0	0	0	0	3	0	3	**3**	**0.7%**
2009	0	0	0	0	1	0	1	**1**	**0.2%**
2010	0	0	0	0	1	0	1	**1**	**0.2%**
2011	0	2	0	3	7	0	10	**12**	**2.8%**
2012	0	4	0	1	7	1	9	**13**	**3.0%**
2013	0	0	0	2	21	4	27	**27**	**6.3%**
2014	1	11	4	15	34	9	62	**74**	**17.3%**
2015	0	19	9	36	56	3	104	**123**	**28.8%**
2016	0	13	16	46	83	14	159	**172**	**40.3%**
2017	0	0	0	1	0	0	1	**1**	**0.2%**
Total Abs.	**1**	**49**	29	104	213	31	377	**427**	
Total Rel.	**0.2%**	**11.5%**	7.7%	24.4%	49.9%	7.3%	88.3%		

TABLE 3.2: *Summary statistics literature search process*
"This table provides a chronological distribution over all research perspectives, namely IS, economics and finance (Eco), computer science and informatics (CS), and legal sciences (Law)" (Notheisen et al., 2017, p. 1066).

3.3.2 Literature Classification

"As a basis for the [...] literature review, we performed a keyword analysis on the relevant IS literature (list A) identified in the literature search and selection process. In a first step, we calculated the Levenshtein or edit distance (Levenshtein, 1965) between all keywords, in order to measure the number of morphological changes required to transform a random keyword into a search keyword. This allowed us not only to account for transpositions and similar keywords, such as *cryptocurrencies* and *cryptocurrency* but also to identify subsets of keywords, such as *Bitcoin* and *Bitcoins*. For clustering, we then joined the strings with '[...] the minimum number of insertions, deletions and substitutions to make both strings equal' (Navarro, 2001). In the second step, we then grouped keywords related to similar concepts, such as Bitcoin and cryptocurrencies for instance. Based on these groupings we devised the following four concepts: *Blockchain technology*, *Trust-free economic systems*, *Bitcoin & cryptocurrencies*, and *Financial Service Innovation & FinTech*. All papers that addressed more than one of the identified concepts or emphasized blockchain or Bitcoin as a use case in the context of another concept (e.g., payment systems) were assigned to their primary field of interest."

3.3.3 Blockchain in the Information Systems Literature

"As stated in the previous section, we identified four central areas of interest within the most important IS journals and conferences related to blockchain — *Blockchain technology*, *Trust-free economic systems*, *Bitcoin & cryptocurrencies*, and *Financial service innovation & FinTech*. Table A.3 [in appendix A.3] depicts the allocation of the most relevant IS articles within the corresponding concept matrix." A brief summary of the reviewed literature and the resulting implications are outlined in the following paragraphs. For a more detailed review of the underlying literature, we kindly refer to Notheisen et al. (2017).

In total, "[...] blockchain in IS literature is an emerging research area with a huge potential, which calls for further attention (Gomber et al., 2016). While to date, issues related to blockchain are scarcely discussed in top tier IS journals, conference proceedings increasingly started to broach the issues of blockchain-based technologies (table 3.2) but mainly focus on taxonomy development (Glaser and Bezzenberger, 2015), industry frameworks (Brenig et al., 2016), use case analyses (Wörner et al., 2016), and design science aspects of smart contract-based prototypes (Beck et al., 2016).

Moreover, most of these studies put an increased focus on entrepreneurial (Connolly and Begg, 2015) (Ingram et al., 2015; Ingram and Morisse, 2016; Kazan et al., 2015) and user-specific issues (Glaser et al., 2014; Mai et al., 2015; Hur et al., 2015) related to Bitcoin but rarely go beyond this use case. Other research streams addressing blockchain technology itself or the role of blockchain in the context of trust-free economic systems deliver first valuable insights on how the blockchain might be understood and leveraged as an IT artifact, inter alia enabling a shift from trust in institutions to trust in algorithms (Lustig and Nardi, 2015). In addition, research methodologies range from empirical models (Glaser et al., 2014), over semi-structured interviews (Ingram et al., 2015) and surveys (Lustig and Nardi, 2015), to case studies and DSR-based prototyping (Beck et al., 2016). At the same time, research approaches and findings are dispersed across a variety of other disciplines such as computer science (50%), economics and finance (24%), and law (7%). IS accounts only for 19% of the journal and conference proceedings listed in table 3.2.

While the application of blockchain technology in a variety of financial or other market settings is broadly discussed in the public press (Kassin, 2016) and exhibits an increasing relevance in the business context (Consultancy.uk, 2016), IS research on decentralized economic systems is still in its infancy. Literature on blockchain-based financial market innovation primarily deals with the competitive impact of FinTech start-ups on established financial service providers, neglecting technological aspects of blockchain-based economic systems."

In consequence, "[...] our findings indicate that IS research rarely goes beyond Bitcoin-related topics and exhibits a strong dispersion with regard to the focus, methodology and specific issues addressed. Without a structured alignment of these different views on blockchain, it is difficult to put existing research results into perspective and to derive clear managerial or research implications. In order to take the lead in this emerging, interdisciplinary research area, efforts should be focused on the central issues of understanding the potential of blockchain technology as an IT artifact in different (financial) market scenarios. In combination with the rising relevance of FinTech, the complexity and multidimensional nature of this issue, a structured approach to guide future research efforts is imperative. We hence, propose the interdisciplinary research framework of market engineering (Weinhardt et al., 2003; Weinhardt and Gimpel, 2007; Gimpel et al., 2008) that helps to structure and understand the characteristics of blockchain-based markets and ecosystems and provides a guideline for the design, implementation, and analyses of blockchain-based platforms and applications."

3.4 Towards a Blockchain Engineering Approach

"The [market engineering] framework provides a holistic view and supports the active construction of markets by taking the socio-economic and legal environment, market microstructure, IT infrastructure, and business structure, as well as the decisions and behavior of agents, and the resulting outcomes into account. [Formally, it constitutes] 'the process of consciously setting up or restructuring a market in order to make it an effective and efficient means for carrying out exchange transactions' (Weinhardt and Gimpel, 2007, p. 6). Offering an interdisciplinary, holistic toolbox to systematically analyze, structure, design, and construct the elements of market platforms, to identify areas of application, and to develop theoretically founded design and evaluation procedures, the market engineering approach, is well suited to guide research on developing blockchain-based markets.

Based on the market engineering framework (Weinhardt et al., 2003; Weinhardt and Gimpel, 2007; Gimpel et al., 2008), we aim to provide an unified guideline to evaluate past and consciously structure future blockchain research. In contrast to Glaser (2017), whose primary focus is on technological aspects, we suggest a theoretical foundation framework for the blockchain as an IT artifact in the field of economic applications. In doing so, we support the identification of applications and areas, in which blockchain-based economic systems offer effective and efficient solutions. We furthermore build on the descriptive frameworks of Glaser and Bezzenberger (2015) and Brenig et al. (2016) (i.e., a taxonomy system, knowledge bases for common concepts, and use case analyses on a global level). We extend these approaches by going beyond the provision of pure classification schemes and instead suggest a means to actively support the construction of blockchain-based infrastructures on the micro and macro level.

In Figure 3.2, we introduce the blockchain [...] engineering framework, which provides an integrated, holistic view of interconnected and pivotal elements of blockchain-based platforms and surrounding factors. To account for the openness of the technology and its capability to pervade multiple elements of the market engineering framework, we follow Glaser (2017) and add a multi-layer perspective. As the basic macro layer, the environment layer captures legal, social and economic constraints determined by the field of application, legal requirements, the transaction object, and other external contingencies. It is important to note that the transaction object is not limited to a physical object but rather is an abstraction and includes any form of information or object that is transacted over the blockchain network.

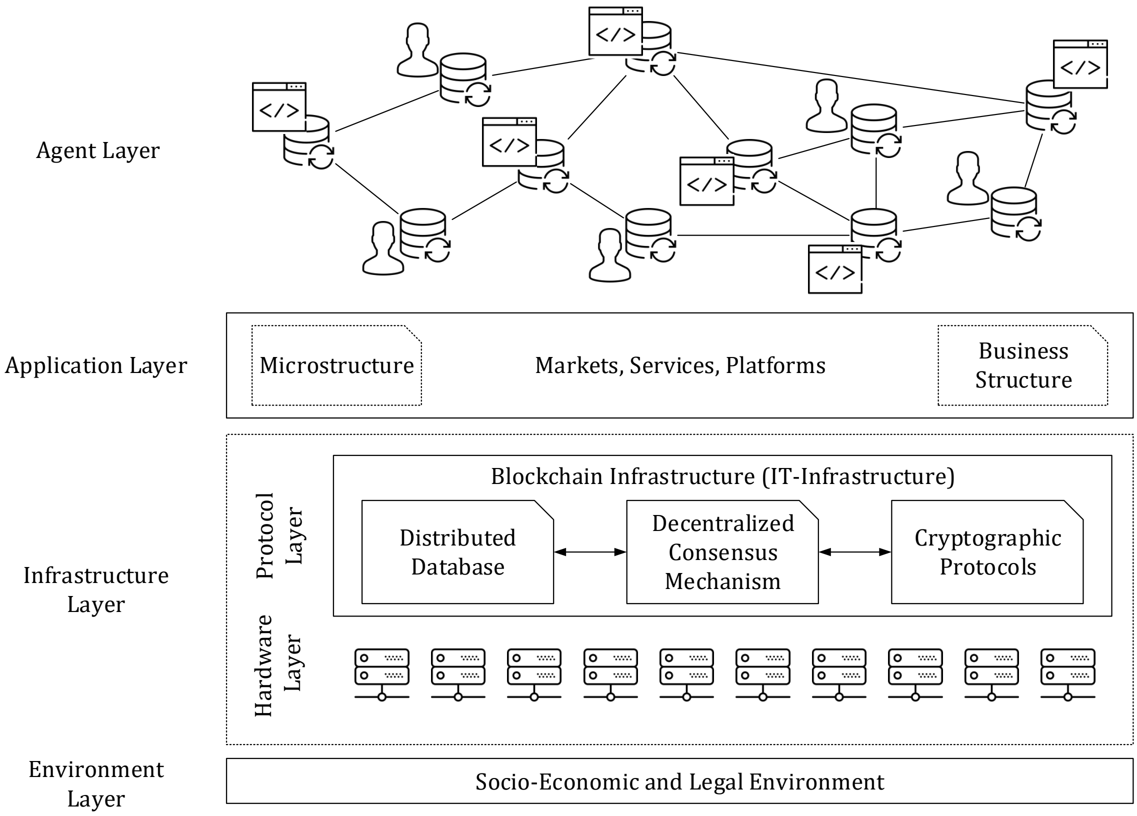


FIGURE 3.2: *Blockchain engineering framework*
"This figure shows the blockchain engineering framework and its pivotal elements and layers" (Notheisen et al., 2017, p. 1073).

Building on the environment layer, the infrastructure layer implements the blockchain protocol, and thus specifies the characteristics of the virtual machine eventually running the application logic. Within the infrastructure layer, we differentiate between the protocol layer and the hardware layer. The hardware layer comprises a heterogeneous crowd of interconnected devices that [...] constitute the runtime environment of the decentralized system. The protocol layer, also known as fabric layer (Glaser, 2017), implements the actual code of the blockchain protocol and thus facilitates the communication between the nodes, enforces agreements, and determines the level of security. In short, the protocol layer defines the basic elements of the IT artifact, i.e. the distributed database, the consensus algorithm, and the cryptographic protocol, that enable the tokenization of economic value and the implementation of decentralized applications on a micro level.

Together, the hardware and the software layer form the backbone of the distributed system and provide the foundation of the microeconomic design, i.e. the micro- and business structure, of potential applications in the application layer. Based on these realized applications, the characteristics and behavior of the interacting economic agents – human and artificial - within the created ecosystem can be analyzed. In combination with the environment layer, which defines the foundation, the agent layer allows the analyses of market outcomes, application performance, or other system properties from a macroeconomic perspective. In addition, the agent layer allows the study of the individual's behavior from a microeconomic perspective. One aspect for instance, is the agent's incentive to participate in the process of truth revelation, which can range from monetary incentives, like in the Bitcoin system, over asymmetrically distributed information or conflicts of interest, such as in the 'Market for Lemons' (Akerlof, 1970), to simply decreasing transaction costs (Davidson et al., 2016)."

3.5 The Limits of Trust-free Systems

3.5.1 Engineering Blockchain-based Trust

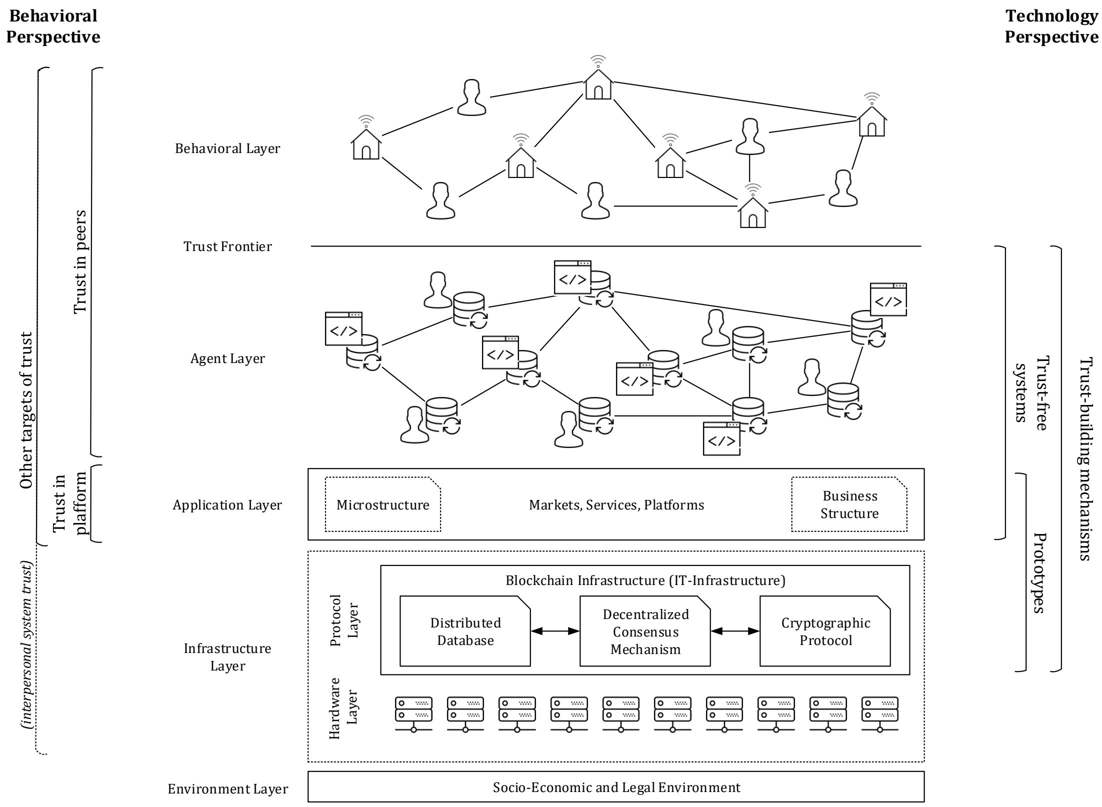


FIGURE 3.3: *Extended blockchain engineering framework*
The framework displayed in this figure extends the framework from Section 3.4 with the role of trust HawlitschekECRA.2018. More specifically, the trust frontier highlights the differences between the behavioral conceptualization of trust in the sharing economy and the implementation of trust-free systems on the technology level.

"A central issue in current literature on [trust in] the sharing economy and blockchain is the ambiguous use of central terms [...]. A consequence of this trend is the ongoing speculation and hype around possible applications of the blockchain technology that may fail to live up to existing expectations (Notheisen et al., 2017). In order to guide future research on trust-related issues at the interplay of the sharing economy and blockchain technology, a common typology for the different conceptualizations of trust is required."

To take these facets into account, we build on the blockchain engineering framework introduced in the previous section and add a behavioral and a technological perspective on trust (see figure 3.3). More specifically, the review of Hawlitschek et al. (2018)[7] "[...] indicates that the trust-free property builds on the synergetic collection of technological features located in the infrastructure layer and application layer. Therefore, the notion of trust-free systems applies well to the logic of the blockchain engineering framework, as long as it operates as a closed ecosystem within its technical boundaries (Glaser, 2017). Particularly, this includes transactions carried out in the agent layer of the framework. Importantly, the agent layer itself captures the virtual representations of both human or computer agents within the blockchain-based system. However, in many use-cases for blockchain technology, it is crucial to take the actual interaction of agents in the real-world into account. This means that behavior outside the closed blockchain ecosystem needs to translate into the agent layer (Notheisen et al., 2017; Glaser, 2017). For example, peers in a sharing economy scenario need to interact with each other, with (smart) products, and/or the platform. The corresponding issue of reliably transferring information on such real-world interactions to the virtual representations within the blockchain-based system emphasizes the boundaries of technical systems that operate trust-free in theory. We consequently extend the framework [introduced in Section 3.4] by an additional behavioral layer that is separated from the agent layer by a trust frontier. It allows a behavioral perspective on the rather technical idea of trust-free (peer-to-peer) platforms and paves the way for a structured analysis of different targets of trust from a behavioral perspective.

Most trust conceptualizations that are addressed in the sharing economy literature describe the relationships between human agents (i.e., peers) with each other, the platform, and potentially a product or other targets. In consequence, the literature on trust is widely grounded in the behavioral layer. However, some contributions are located in the agent layer (if, for instance, profiles or ratings are discussed as a means of virtual user or product representation) and also in the application layer (in case the target for trust is the platform). This is well reflected in the typical notion of online matching, offline interaction, and online rating on sharing economy platforms (Hawlitschek et al., 2016). The relevance of the infrastructure layer is only discussed in one case.

[7]The structured dual literature review of Hawlitschek et al. (2018) offers a detailed analysis of the behavioral and technological conceptualization of trust in the sharing economy and the blockchain realm.

Specifically, Keymolen (2013)'s conceptualization of interpersonal system trust goes beyond the translation of offline cues to an online environment (e.g., through representation in the agent layer). The author suggests to take into account the peculiarities of the underlying online technology. In particular, it is recommended to 'evaluate the techniques employed to build, use, and maintain the platforms' (Keymolen, 2013).

In contrast, the reviewed blockchain literature conceptualizes trust mostly in the lower technology-based layers, and thus does not cross the trust frontier. An exception is the study of Sas and Khairuddin (2015), which dips into the behavioral layer and attempts to elicit the main trust challenges of Bitcoin users and the related mitigation strategies. In their assessment, the authors find that a core element of dealing with dishonest counterparties is a transactional limitation on those embedded in a credible institutional or social environment. In the light of [the extended blockchain engineering framework illustrated in figure 3.3], this highlights the importance to connect virtual action spaces with actual behavioral patterns to establish trust between [interacting] parties and to cross the trust frontier."

In total, "[...] the concepts of trust for the sharing economy and for blockchain technology differ substantially and [...] there exists an obvious tension. On the one hand, trust in the sharing economy is widely regarded as a complex concept with multiple stakeholders, targets, and dimensions [(Hawlitschek, 2019; Mittendorf, 2016; Möhlmann, 2016; Tussyadiah, 2016)]. On the other hand, the promise of the blockchain as a trust-free technology points at the replacement of trusted third parties such as platform intermediaries. The difference that lies in these mainly distinct concepts has important implications for theory and practice. First, in order to successfully contribute to theory on trust in different contexts, it is of utmost importance for sharing economy and blockchain related research to agree on a set of common concepts and expressions and to relate those to established work. Since both fields of research are relatively young, it is all the more necessary to critically assess and discuss the promises derived from nonacademic literature and media, from a scientific, well-structured and theory-grounded point of view. Second, established platform operators and developers of blockchain-based platforms need to be aware of the fact that blockchain technology in and by itself is not able to provide an environment that renders trust-building outside the closed blockchain ecosystem obsolete. Third, in order to leverage the advantages of a trust-free blockchain-based platform, means of overcoming the trust-frontier between the closed technical system and the actual physical world need to be further developed by both researchers and practitioners."

3.5.2 Overcoming the Trust Frontier

"While we agree with the general notion of the blockchain's potential to replace central infrastructures as well as intermediary and payment services [(Glaser, 2017)], we suggest a more critical view on the actual closedness of complex [...] ecosystems. Based on [the] literature review [of Hawlitschek et al. (2018)], we argue that the sharing economy as a complex phenomenon with socio-technical characteristics (John, 2013), can usually not be regarded as a fully self-contained or closed ecosystem that only relies on transactions and information generated within its own boundaries (Glaser, 2017). We propose the concept of the trust frontier that separates interactions in the behavioral layer from their representation in the agent layer. Since human interactions in the real world are very difficult to integrate in a closed blockchain-based ecosystem without the need for a 'trusted interface' (Glaser, 2017, p. 1550), sharing transactions with actual human interaction cannot be carried out in a completely trust-free manner.

A recent study on commons-oriented sharing ecosystems finds that 'when it comes to more complex social relationships, involving sharing of resources and assets, blockchain technology alone does not suffice for people to develop trusted interactions' (Pazaitis et al., 2017, p. 6). The authors suggest to address this issue by introducing an additional trust layer based on human relations, that is, a reputation system nourished by a community-based evaluation process (Pazaitis et al., 2017). Using participatory evaluation as a first step towards a trusted interface to blockchain-based ecosystems may, however, entail a set of potential drawbacks. Not only did the authors report that users stated a sense of discomfort for evaluating certain contributions of others, [...] empowering the crowd [also] entails the risk of unintended consequences and even misbehavior (Wilson et al., 2017).

The German start-up slock.it circumvents the problem of integrating behavioral aspects in the blockchain system, by reversing the challenge [...]. Instead of developing a trusted interface, [they extend] the reach of the closed blockchain system by integrating smart products in a blockchain-based internet of things. Therefore, mainly behavioral aspects related to shared products and not necessarily to other peers need to be considered. However, this strategy does not resolve or overcome the trust frontier but rather shifts it towards the real world, leaving the question of trusted interfaces for human behavior unaffected. As a result of the current scarcity of functional trusted interfaces to blockchain-based [...] ecosystems, the sharing economy is unlikely to run completely trust-free in the near future.

Even if [...] trusted interfaces for overcoming the trust frontier would be available, replacing trust in a platform provider with the provision of blockchain-based algorithmic authority raises several issues concerning trust in algorithms (Ahangama and Poo, 2016; Lustig and Nardi, 2015). A user's individual degree of trust in algorithms and her willingness to rely on blockchain technology may well depend on the technical knowledge, experience, and affinity. While smart contracts that organize sharing economy transactions can in theory be reviewed by each individual capable of reading their specifications and thus may operate trust-free, less tech-savvy users have to trust in the algorithm itself or rather the programmers or actors providing the code and making the algorithm 'run smoothly' (Lustig and Nardi, 2015, p. 751) and legally compliant (Al Khalil et al., 2017). As suggested by Lustig and Nardi (2015), this kind of trust in algorithms may require regulation, the development of social norms, and a common language between developers and lawyers (Al Khalil et al., 2017) that further complicate the successful development of platforms based on blockchain technology."

3.6 Research Gap Blockchain Engineering

"Overall, we perceive the blockchain as a decentralized infrastructure that not only supports markets [and other] forms of platform-based applications [but has the potential to reshape] the role of trust [(Hawlitschek, 2019)]. Within this scope, the blockchain [...] engineering framework [provides] a guideline, to direct future research in the field of IS and supports researchers and practitioners to identify key concepts of blockchain-based economic systems in their endeavors. However, these key concepts should not be limited to specific elements of our framework but also take dependencies, interactions, and reciprocal relationships among the respective elements into account. Moreover, we encourage the blockchain community to go beyond a pure engineering perspective and include all stakeholders, such as users, regulatory bodies, and other third parties in their interdisciplinary analyses. In addition, IS researchers should go beyond the known use cases and adopt blockchain as an IT artifact to connect human and artificial agents on a decentralized level. [Closing this research gap may] include [...] DSR approaches to explore the [design and] technological capabilities of blockchain-based [...]" systems (Chapter 4) and trusted interfaces as well as theoretical and empirical studies to assess user behavior (Chapter 5), the interplay between technological and economic system characteristics, and the impact on market outcomes (Chapter 6).

3.7 Concluding Remarks

"The blockchain is a truly fascinating technology with a set of characteristics that have the potential to transform and disrupt a variety of different industries, such as financial markets (Fanning and Centers, 2016), transaction and asset management systems (Ruault, 2016), or the sharing economy (Sundararajan, 2016). However, in order to transition from a buzzword at the top of the Gartner Hype Cycle (Gartner, 2016) to an established technological basis for real-world [(market) platforms], blockchain technology still has a long way to go" (Notheisen et al., 2017, p. 1074). As demonstrated in the literature reviews of Notheisen et al. (2017) and Hawlitschek et al. (2018), "[...] IS research can play a leading role in facilitating and shaping this transition [...]. However, in order to make a valuable contribution [...], IS researchers may profit from a common language and approach to structure their research efforts, put them into perspective with respect to the elements of blockchain systems, and position their work in relation to other contributions. In order to help and guide [them] in doing so, [this chapter introduces and extends] the blockchain [...] engineering framework" (Notheisen et al., 2017, p. 1074). It comprises five layers – the environment layer, the infrastructure layer, the application layer, the agent layer, and the behavioral layer. "The environment layer forms an ambient fundament that incorporates social, legal, and economic surroundings and norms and constrains the action spaces available within the other layers. Building on this foundation, the infrastructure layer forms the technological backbone of the blockchain system. It consists of the protocol layer, which implements the core blockchain elements [...] and connects the heterogeneous crowd of devices of the hardware layer with a specific application context. The resulting application layer realizes the features and rules that form a platform, market, or service [and determines] interaction of human and computer agents [in the real-world behavioral layer]. [...] The trust-free property builds on the synergetic collection of technological features located in the infrastructure layer and application layer" (Hawlitschek et al., 2018, p. 59). However, the behavioral and technological conceptualizations of trust differ substantially. On one side, trust is perceived as a complex and interlaced construct with a multitude of stakeholders, targets, and dimensions. On the other side, the trust-free character of blockchain-based systems focuses on technological details, while neglecting the actual behavioral patterns of interacting agents. In consequence, overcoming the resulting trust frontier between the application and the behavioral layer is paramount to realize the promise of fully decentralized markets.

Chapter 4

Building Decentralized Markets

After conceptualizing the elements, layers, and limitations of blockchain-based platforms in Chapter 3, the blockchain engineering approach is applied to the use case of decentralized markets in this chapter. More specifically, we illustrate and verify the design, architecture, and features of decentralized markets and implement their core building blocks - a transparent transaction system and a intermediary-free market mechanism - by the means of proof-of-concept prototypes.

To guide the creation of these IT artifacts and demonstrate their validity, efficacy, and utility, we apply established guidelines from DSR. To take blockchain-specific characteristics into account, these approaches are furthermore complemented by tailored blockchain design frameworks. Section 4.1 summarizes these design principles, outlines implications, and thereby paves the way to implement the building blocks of decentralized markets in the two subsequent sections.

Section 4.2 implements "[...] a blockchain-based proof-of-concept prototype that enables the automated transaction of [digital and] real-world assets, such as cars, and provides a valid, transparent, and immutable record of vehicle history to market participants, authorities, and other third parties" (Notheisen et al., 2017, p. 425). The resulting transaction system aims to replace "[...] trust-based, centralized, and bureaucratic [registries] with a tamper-free and autonomous transactional database [...] that comprises a secure registration and transaction process" (Notheisen et al., 2017, p. 425). In addition, it comprises "[...] a built-in mechanism to reduce transaction risk resulting from the irreversibility of transactions in blockchain-based systems" (Notheisen et al., 2017, p. 425).

As a result, the prototype "[...] proposes a novel approach to mitigate adverse selection effects in lemon markets by providing a reliable, transparent, and complete record of each marketable asset's history" (Notheisen et al., 2017, p. 425). In total, Section 4.2 illustrates a possible system design, demonstrates the potential of a decentralized transaction system, and highlights technological limitations (e.g., scalability) and economic implications (e.g., transparency). A detailed analysis of the transparency effects that come with such systems follows in Chapter 5.

Section 4.3 extends this transaction system with an essential prerequisite to implement fully decentralized markets: A mechanism to connect demand and supply without a central authority. The resulting proof-of-concept prototype challenges the role of traditional intermediaries and proposes a market framework that enables users to raise equity and trade stocks in an intermediary-free environment. The resulting IT artifact implements the software structure of a decentralized market place, demonstrates "[...] the feasibility of decentralized market mechanisms, and highlights potential use cases as well as limitations" (Notheisen et al., 2017, p. 474). Again, an economic analysis of the impact on market outcomes and market quality follows in Chapter 6.

Eventually, Section 4.4 merges Section 4.2 and Section 4.3 to illustrate the concept of decentralized markets. In addition, full versions of the implemented prototypes and the corresponding testing procedures are available on Gitlab. Appendix B provides an overview of the associated repository, briefly describes the stored smart contracts and testing procedures, and offers references to the directories and code files.

4.1 Design Principles

4.1.1 Design Science Approach

To guide the creation, evaluation, and presentation of the IT artifacts presented in this chapter, we build on established theories and guidelines from the field of DSR. More specifically, we follow the guidelines proposed by Hevner et al. (2004) and search for a solution to a practical problem or challenge. These problems are explained in detail and formulated as research questions in each section respectively. The resulting IT artifacts are proof-of-concept prototypes that aim to illustrate how one could implement the building blocks of decentralized markets in a trust-free fashion.

Throughout the development process, we ensure our research's rigor by adopting the guidelines introduced by Hevner et al. (2004) and by complementing them with additional DSR frameworks (Peffers et al., 2007; March and Smith, 1995) as well as blockchain-specific approaches (Xu et al., 2017, 2016; Wüst and Gervais, 2017). More specifically, we build on existing knowledge gathered from the field of blockchain-based economic systems in Chapter 3 and iteratively adapt the prototypes throughout the development process (Peffers et al., 2007). In order to ensure the efficacy and efficiency within the building phase, we perform detailed requirements analyses within each use case and continuously reevaluate the artifacts within each iteration (March and Smith, 1995). To evaluate the resulting solutions and to demonstrate each prototype's utility, quality, and efficacy, we furthermore apply structural and functional testing procedures (Hevner et al., 2004). Figure 4.1 illustrates the integrated development process. Embedding the development into the artifact's application environment ensures its relevance and the application of the existing knowledge base facilitates the rigor in its creation. In addition, it illustrates the iterative cycle of building and evaluation phases that form the development process.

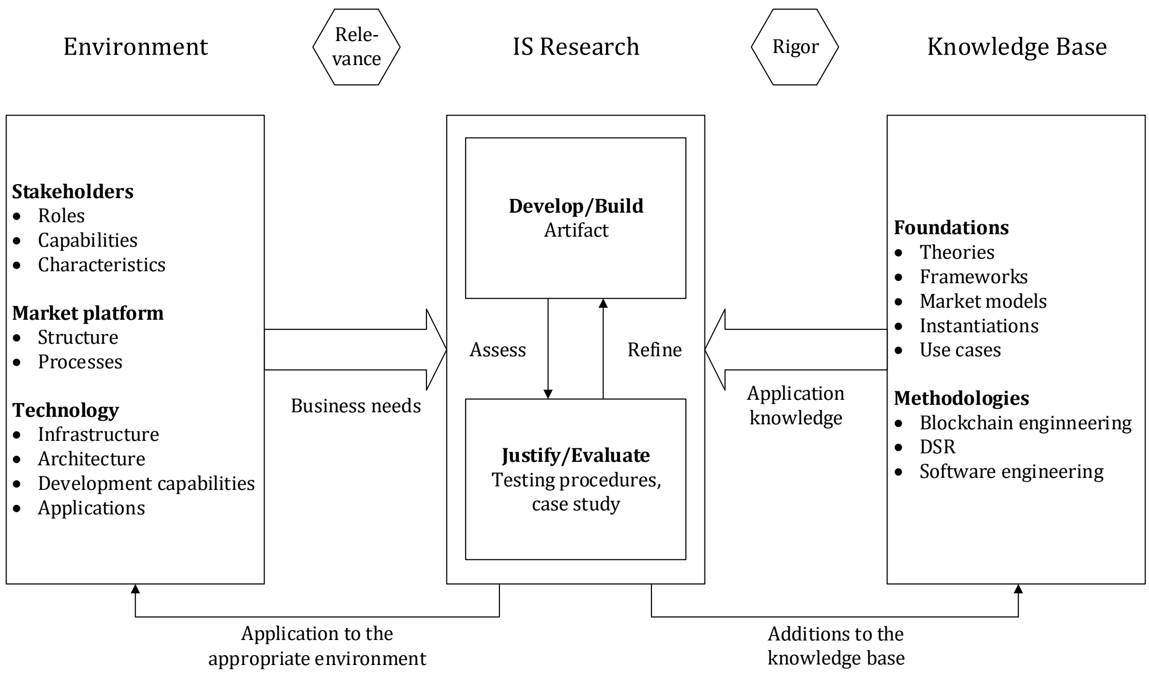


FIGURE 4.1: *DSR approach artifact development*
Iterative DSR approach applied to guide the development of the IT artifacts in Chapter 4 (adapted from Hevner et al., 2004).

Eventually, we aim to maximize the impact of our research by presenting our results to both, technology- and management-oriented audiences. To do so, we structure the following sections according to Gregor and Hevner (2013) and illustrate the underlying economic principles as well as the artifacts' architectural features. Figure 4.2 illustrates the resulting structure of Sections 4.2 and 4.3 and summarizes the content and purpose of each subsection briefly. By these means, we hope to make our findings accessible to both researchers and practitioners alike.

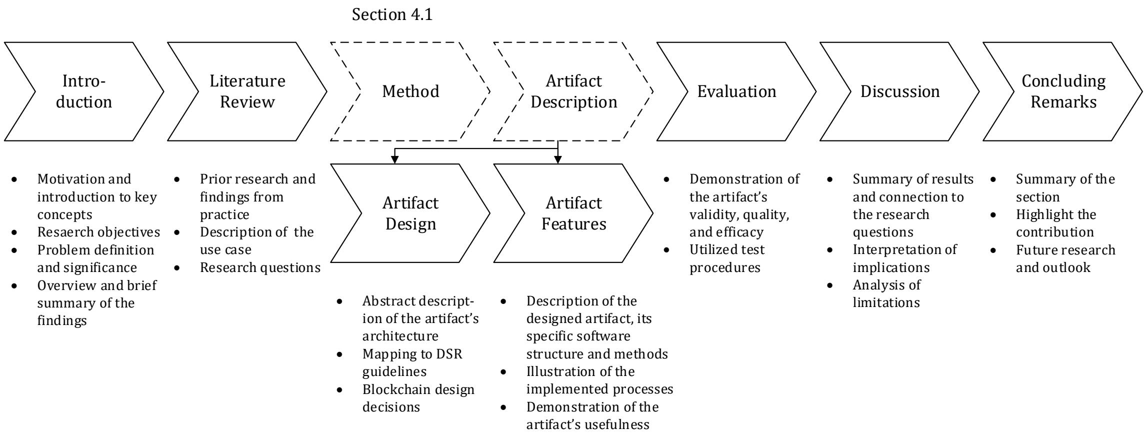


FIGURE 4.2: *Structure and content of Chapter 4*
This figure is based on Gregor and Hevner (2013) and illustrates the structure and content of Sections 4.2 and 4.3. Dashed lines indicate adaptions: To prevent redundancy and pave the way, the DSR approach is outlined in the preceeding Section 4.1. To provide a detailed artifact description, Sections 4.2 and 4.3 differentiate between the generalized design and specific features.

4.1.2 Blockchain Design

To guide the blockchain-specific aspects of the design of the prototypes in Sections 4.2 and 4.3, we utilize and combine the frameworks introduced by Wüst and Gervais (2017), Xu et al. (2016), Xu et al. (2017). Wüst and Gervais (2017) examine under which circumstances a particular scenario is reasonably solvable with blockchain technology. The resulting framework supports us in the assessment of the blockchain's general appropriateness and allows the elimination of infeasible use cases before the implementation of a prototype. Xu et al. (2016) consider the blockchain as a software connector that enables decentralized data sharing among interacting parties in the absence of trust.

Building on this paradigm, they differentiate between different blockchain and application design decisions to elaborate on the implications and trade-offs associated with specific choices. In consequence, we use this framework to explicitly guide our design decisions in the artifact development. Xu et al. (2017) propose an indicative conceptual model that aims to support the assessment of design implications. Their framework captures central design parameters of the blockchain systems via a taxonomy and enables users to compare different blockchain configurations with respect to the implementation of fundamental blockchain properties, cost efficiency, performance, and flexibility. As a result, we use the study of Xu et al. (2017) to assess the implications of our design decisions.

To provide a brief overview of potential blockchain configurations and discuss the resulting implications, we break the associated design decisions down into distinct design choices. These mutually exclusive choices build on academic literature about blockchain design (Wüst and Gervais, 2017; Xu et al., 2016, 2017) and specifications extracted from the most popular publicly available blockchain platforms (i.e., Ethereum, Hyperledger Fabric, and R3's Corda). The five resulting design dimensions include network characteristics, data storage, scalability, architectural features, and the deployment model. Table 4.1 summarizes the design decisions associated with each dimension and indicates choices.

Design dimensions	Design decisions	Design choices		
Network characteristics	Degree of centralization	Centralized	Intermediate	Decentralized
	Access rights	Private	Hybrid	Public
	Access control	Permissioned	Permissionless	
Data storage	Privacy	Sensitive data	No sensitive data	
	Immutability	No changes or deletions	Changes or deletions preferred	Changes or deletions required
	Location	On-Chain	Mixed	Off-Chain
	Instances	Single chain	Multiple chains	
Scalability	Tasks/second	Low	Medium	High
	Cost/task	Low	Medium	High
	Computation	On-Chain	Mixed	Off-Chain
Architectural features	Consensus	Not needed	Security focus	Performance focus
	Incentives	Not required	Optional	Needed
	External validation	Automated	Ad-hoc	No validation
Deployment model	Hardware deployment	On premise	Third-party cloud	Blockchain-as-a-service
	Protocol development & maintenance	Insourcing	Mix	Outsourcing

TABLE 4.1: *Blockchain design dimensions, decisions, and choices*
This table summarizes possible blockchain design dimensions, decisions, and choices within the artifact development. It is based on Xu et al. (2016), Xu et al. (2017), and Wüst and Gervais (2017) and the specifications of popular blockchain platforms. Note that infeasible configurations, such as a fully centralized public network, a public network without a consensus mechanism or no incentives, the deletion of on-chain data, or a high scalability in combination with on-chain storage and computation are not considered in this overview.

Network characteristics. Network characteristics focus on system access and its degree of centralization. In research and practice, it is common to differentiate between public, hybrid or consortium, and private networks. The decentralized character of public blockchains offers high levels of transparency and facilitates an equal distribution of rights among all users but impedes performance (Guo and Liang, 2016). In a fully centralized and private network on the other hand, the users rely on a central authority to mediate transactions, manage memberships, or illegitimate malicious parties (Xu et al., 2017). As a result, performance increases, while the provision of database updates is limited to a central authority (Xu et al., 2017). In addition, commercial applications often require privacy levels that go beyond the cryptographic means available in public blockchains. A hybrid blockchain allows intermediate levels of centralization as users that know and potentially trust each other form a consortium. In such network setups, only a few users may write data, whereas the others can only read it. However, the ability to append new information depends on the access rights granted to each user. In a permissioned blockchain, a specific set of users acts as gatekeepers that restrict read and write access (Xu et al., 2017). In consequence, permission management is essential to control access rights and authorize (new) users. In contrast, permissionless systems restrict neither the right to write or read nor the ability to join the network thereby facilitating true peer-to-peer interactions and the balance of power among users (Wüst and Gervais, 2017).

Data storage. With respect to data storage, the the community of blockchain users needs to consider where and how data should be stored and whether data privacy is important for them or not. Especially in commercial or corporate scenarios, data privacy may be crucial as sharing sensitive information entails significant strategic and legal risks. On the other side, transparency and immutability are essential to ensure the integrity of the data stored on the blockchain. Hence, there is an inherent trade-off between privacy and transparency in every use case (Wüst and Gervais, 2017). Potential measures to account for privacy concerns include the encryption of on-chain data or refraining from storing sensitive data on-chain. However, this may lead to a loss of functionalities and jeopardizes data quality. Beyond that, other approaches do not resolve privacy issues but offer anonymity, while at the same time providing enough transparency for any node to verify data transactions (Sasson et al., 2014). Similarly using private or permissioned blockchains does not prevent users from seeing the stored information. In consequence, the best way to keep data private is to store it off-chain or setting up separate blockchains that run in parallel, and thus limit disclosure (Wüst and Gervais, 2017).

A second feature that is essential for data integrity is immutability. It ensures the availability of a precise and verifiable audit trail for historical transactions thereby alleviating the need for trust. However, there are situations in which data may change or needs deletion (Catalini and Gans, 2016). Changes to the blockchain are realized by creating new transactions, which are appended to the database (Xu et al., 2016). Incorrect or expired entries are not replaced, and thus deleting data is a problem. In consequence, data immutability does not only pose challenges from a business perspective but also includes legal risks. Potential solutions to this issue propose to store sensitive data off-chain keeping it erasable (Xu et al., 2016). In addition, limiting on-chain storage to meta-data, critical data, and hashes mitigates problems due to the blockchain's growing size (Xu et al., 2017).

Scalability. Scalability is one of the most discussed limitations of blockchain technology and depends on a multitude of factors, such as the number of network participants, the orthogonality of their interests, network characteristics, data storage, and security requirements (Vukolić, 2016). As result of this multi-faceted nature, assessing scalability includes many aspects that require individual measures. To assess the number of tasks a system can process per second, we need to differentiate between submission and validation throughput. The submission throughput represents the maximum number of transactions (e.g., in form of process steps) submitted per second. The validation throughput - which determines the actual processing speed - relates to the maximum number of transactions validated per second. Latency refers to the time between submission and validation. On average, Xu et al. (2017) claim, current public blockchains are able to process 3-20 transactions per second. This is in line with the anecdotal evidence extracted from the small sample of blockchain platforms considered in this section as well. However, due to the trade-off between security and performance, the simpler consensus mechanisms applied in private or hybrid networks can improve scalability. In addition, current research explores means to improve performance across all network types (Vukolić, 2016). Besides task performance, the blockchain designers should also consider the costs per transaction that result from the consensus process (e.g., in form of electricity consumption (O'Dwyer and Malone, 2014; de Vries, 2018)) and infrastructure investments (e.g., blockchain development and maintenance or the provision of storage capacity). An essential inhibitor of performance and driver of costs is the implementation of applications via smart contracts. These applications rely on on-chain computations within the blockchain network, and therefore limit performance and increase costs significantly. Consequently, shifting computational efforts off-chain, while keeping the verification of the results on-chain constitutes an efficient means to improve a systems throughput (Xu et al., 2016).

Architectural features. The architectural features of a use case set the way consensus between participating users is achieved. At the core of each blockchain, the consensus mechanism mediates conflicts and defines the rules that ensure that a newly added transaction is valid (Xu et al., 2016). Due to the trade-off between a network's openness and a system's integrity, different forms of consensus mechanisms are required to achieve a specific level of security and data quality. Today, the most common approach is POW - an expensive mechanism that enables a high Sybil resistance in public networks. However, there is a rising number of alternatives that solve the consensus challenge efficiently, such as proof-of-stake or practical byzantine fault tolerance (Xu et al., 2017). For hybrid blockchains, one can assign consensus duties to authorized nodes in favor of scalability (Xu et al., 2016). In private blockchains, a central authority may replace a consensus mechanism in its original sense. However, in any setup an important prerequisite of the consensus process is the users' motivation to participate. Especially in open and conflict-laden scenarios, it may be important to introduce explicit incentives (e.g., in form of monetary rewards or reputation systems) to facilitate honest behavior among participants. However, if there are implicit incentives, such as the reduction of information asymmetries or increased process efficiency, explicit incentives may play a minor role (Notheisen et al., 2017). Irrespective of the way consensus is reached, the integrity of the blockchain is limited to its digital boundaries (Xu et al., 2017; Glaser, 2017). As a result, a use case may require external validations. In the case of digitized value networks, existing workflows can integrate this procedure via validation oracles (Xu et al., 2016). If on the other hand automation is not possible or impractical, one can fall back to ad-hoc validations by human arbitrators (Xu et al., 2016).

Deployment model. Eventually, after the specification is considered, a deployment model needs to be chosen. This decision determines the amount of blockchain-specific skills and knowledge required, and thus comprises a substantial strategic component. Blockchain-as-a-service models offer an easy access but may impede building up own blockchain competencies (Xu et al., 2017). An intermediate solution are cloud-based services offered by third-party infrastructure providers. However, if a use case embodies an essential driver of one of the users' competitive advantage a deployment on premise may be the preferable choice. The same considerations also remain relevant for the development and maintenance of the blockchain protocol and smart contract-based applications. Eventually and consistent with previous IS research, the decision to in- or outsource development strongly depends on the exposure of the stakeholders core competencies (Quinn and Hilmer, 1994) and the quality of the service provider (Lee and Kim, 1999).

4.2 A Transparent Transaction System

This section is based on the article "Trading Real-World Assets on Blockchain An Application of Trust-Free Transaction Systems in the Market for Lemons". It is co-authored by Jacob Benjamin Cholewa and Arun Prasad Shanmugam and was published in Business & Information Systems Engineering in December 2017. Direct citations are highlighted by double quotes.

Publication details:
Notheisen, B., Cholewa, J. B. & Shanmugam, A. P.,
Trading Real-World Assets on Blockchain - An Application of Trust-Free Transaction Systems in the Market for Lemons,
Business & Information Systems Engineering (BISE), December 2017, Volume 59, Issue 6, pp. 425–440,
https://doi.org/10.1007/s12599-017-0499-8.

4.2.1 Introduction

"In this [section], we utilize the use case of the Danish Motor Register (DMR) to present a new way to record, manage, and track the status of ownership of physical assets, such as cars, and develop, implement, and evaluate a blockchain-based transaction system that aims to replace centralized institutions as trusted third parties. We choose Denmark as it is a technologically advanced nation and a front-runner in the digitalization of governmental services to illustrate the benefits of blockchain-based systems with respect to public registry and transaction systems. In collaboration with the Danish tax authority SKAT, we explore the potential of a blockchain-based car register and illustrate how it might be able to replace traditional trust-based, centralized, and bureaucratic systems.

Within this scope, the contribution of our research is threefold: First, we introduce a built-in mechanism to reduce transaction risk associated with the irreversibility of blockchain transactions (Böhme et al., 2015). Second, we address the challenges of providing and maintaining a complete and consistent public record of vehicle history by replacing a traditional register with a blockchain-based alternative that includes a secure registration and transaction process. In doing so, we illustrate how to replace a potentially expensive, trust-based, incomplete, and inconsistent bureaucratic registry with an autonomous and potentially cost-efficient transaction log.

Third, we propose to mitigate adverse selection effects in lemon markets (Akerlof, 1970) by providing a reliable, transparent, and complete record of each marketable asset's history. In addition, our generic software design introduces a generalized transaction framework, in which the DMR use case inherits its core functionalities from the high-level framework. This way, we take practical considerations into account as the generic system design allows the extensions to other assets and ensures applicability beyond the use case of cars."

4.2.2 Related Literature

"This [sub]section provides a brief introduction to blockchain-based commercial systems, outlines the DMR use case, and identifies a research gap at the interdisciplinary intersection of the fields of information systems and economics. In consequence, [the following paragraphs introduce the issue of transaction risk in blockchain-based systems], illustrate the use case of the DMR and its practical challenges, and [highlight] the problem of adverse selection in used good markets, such as the market for used cars."

Trust-free Transaction Systems & Transaction Risk

"Transaction risk relates to the irreversibility of transactions conducted via blockchain systems (Böhme et al., 2015). In combination with decentralized timestamping and the interconnection of blocks, the irreversibility of transactions ensures the correct order of transactions and is essential to protect users from double-spending attempts and the dissemination of corrupted data by malicious agents. The resulting data immutability enables the transacting parties to trust in the correctness of the stored transactional history. In the case of erroneous transactions or fraud, the irreversible character of current protocols, such as Bitcoin or Ethereum, remains an unsolved issue and poses a prohibitive obstacle for the transaction of valuable real-world assets, such as cars and securities. All else equal this leads users to prefer alternative systems that offer mechanisms to undo faulty transactions or to retake the transacted asset by force. Overall, we take up the notion of cryptographic transaction systems introduced by Beck et al. (2016), extend the concept to the on-chain transmission of real-world assets, and formulate the following first research question:"

Research Question 3. *How can market engineers decrease the risk resulting from the irreversibility of blockchain transactions, while still providing a valid transaction log?*

Use Case - The Life Cycle of a Car in Denmark

"In the course of its product life cycle, a vehicle and its owner(s) are involved in a variety of administrative and bureaucratic processes. These processes include a variety of steps, such as a car's registration with the motor register, the payment of levies and taxes, repairs, modifications, inspections, and interactions with loan, leasing, or insurance firms. One of the most important and complicated steps is the transfer of ownership after a trade.

With Denmark being a small country, SKAT owns and oversees most of these administrative and bureaucratic processes and provides the related governmental services. More specifically, the DMR operates an IT system that handles the bureaucratic processes involved in vehicle transfers and provides a trusted record of ownership and vehicle-specific information throughout the vehicle's life cycle. As a result, the DMR database serves as a repository for all inputs and outputs from various stakeholders, such as owners, dealerships, importers, and scrap dealers, as well as government agencies, such as transport authorities, police departments, SKAT themselves, and other third parties, such as insurance companies, banks, or leasing firms.

The following steps and figure 4.3 illustrate a vehicle's life cycle in detail and highlight the involvement of SKAT, the DMR, and other stakeholders:

- *Import & initial registration:* Since there are no domestic car manufacturers in Denmark, all vehicles have to be acquired from foreign producers. Imported vehicles are registered at the DMR upon arrival and the importer has to pay levies and taxes to SKAT.
- *Allocation:* After the registration, the vehicles are transferred to dealerships, which allocate them to their new owners. As the status of ownership changes, the new owner as well as insurance information need to be reported to SKAT and stored in the DMR. Only if all requirements are met, SKAT issues a vehicle registration certificate and and grants a road approval.
- *Maintenance:* During its life cycle, a vehicle experiences a variety of maintenance procedures, such as automobile inspections, repairs, or rebuilds. To ensure road safety and to maintain a correct record of vehicle information, the DMR records these maintenance activities and any other modifications.

- *Transfer of ownership:* When a current owner wants to sell his or her vehicle and a buyer is found, the interacting parties need to settle their trade by simultaneously exchanging the vehicle and the negotiated payment amount. To minimize fraud risk, it is crucial that the DMR provides a complete and valid record on the vehicle's history and its characteristics.
- *De- and reregistration:* Following the transfer of ownership, the vehicle needs to be reregistered with SKAT and the DMR. Only if a vehicle is de- and reregistered correctly, taxes and levies are paid, and the transfer of ownership is recorded at the DMR, SKAT issues a new registration certificate legitimizing the new status of ownership and granting road approval.
- *Scrapping:* Eventually, a vehicle is worn-out or damaged and needs to be scrapped. As a result, the owner receives a scrapping certificate and the DMR deregisters the vehicle."

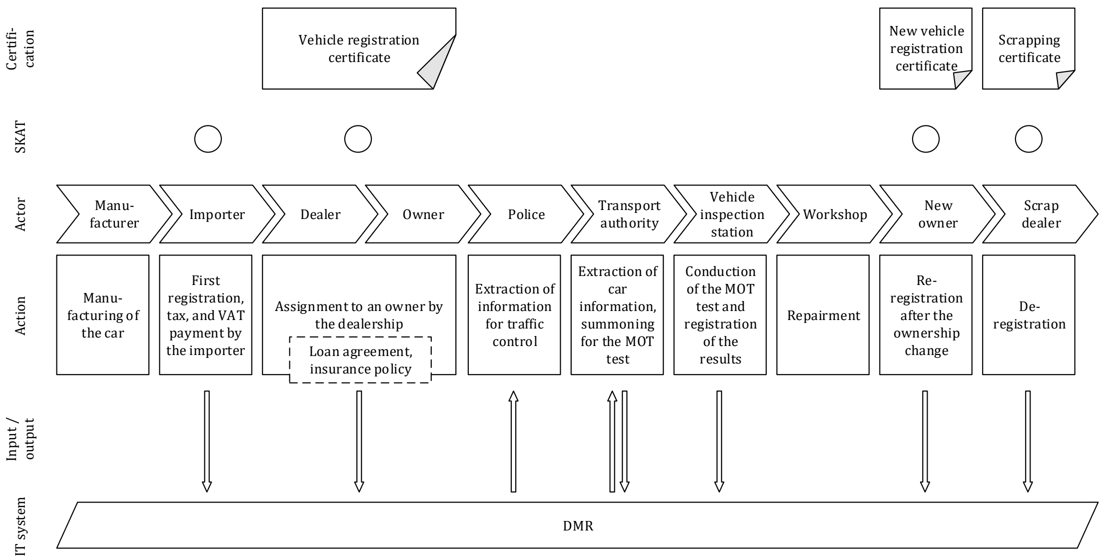


FIGURE 4.3: *The life cycle of a car in Denmark*
This figure illustrates the process steps and stakeholder involvement of a car during its life cycle (Notheisen et al., 2017).

"Along these steps, SKAT is involved at several points and faces individual challenges at each integration point, with the transfer of ownership being the most crucial one. In addition, the integration of third party services, such as financial or insurance services, and updating and maintaining the centralized DMR database produces a significant bureaucratic and organizational effort. As a result, the increasing size of the centralized DMR database leads to an increase in complexity, an increase in hardware, maintenance, and conversion costs, and a decrease in performance (Connolly and Begg, 2015; Elmasri and Navathe, 2010)."

Research Question 4. *To which extent can a blockchain-based transaction system store and represent the life-cycle of a car?*

Adverse Selection in the Market for Used Cars

"Adverse selection describes a situation, in which interacting parties attach value to the quality of a transacted object but at the same time possess different levels of information about it. One of the best-known examples for a market with adverse selection effects is Akerlof's Market for Lemons (Akerlof, 1970), where used cars of differing quality are traded between buyers and sellers.

In order to dismantle this asymmetric distribution of information, potential buyers use heuristic approaches to assess the quality of their prospective purchase and try to infer the cars' characteristics from statistical estimators based on prior experiences, markets trading similar goods, or price signals provided by sellers (Wolinsky, 1983). Despite their efforts however, the heuristic's accuracy decreases in bi- or multilateral market setups and the buyers' knowledge about the true value of a car often remains opaque and a residual uncertainty about quality cannot be resolved (Genesove, 1993). As a result, equilibrium prices reflect the average quality of all cars in the market (Wilson, 1980) and good and bad vehicles sell at the same price, while only sellers know their true characteristics. In this pooling equilibrium, the sellers of low-quality cars (i.e., lemons) earn informational rents equal to the difference between the market price and the cars' true values, and thus have an incentive to enter the market. The owners of high-quality cars on the other hand would earn negative rents as their vehicles' true values are greater than the equilibrium price, and thus withdraw form the market. Eventually, Gresham's Law comes into effect and the lemons drive out high-quality cars (Akerlof, 1970). In a continuous world, different levels of quality create a cascading effect as lower quality cars continuously drive out the marginally better ones until no demand or supply is left and the market collapses.

Reality however is less extreme and studies such as Bond (1982), Hendel and Lizzeri (2002), or Peterson and Schneider (2014) show that markets for used cars never shut down completely and that the traded volume remains substantial despite the presence of information asymmetries. One explanation for these findings is the development of counteracting institutions (Akerlof, 1970; Bond, 1982; Genesove, 1993), which aim to ensure a minimum level of quality. These institutions include the provision of guarantees, licensing and certification, or the introduction of brand names. In addition, in a long-term relationship with repeated transactions reputation-based mechanisms can function as a disciplining device (Genesove, 1993). Another explanation is the impact of efficient sorting between drivers who prefer different levels of quality (Hendel et al., 2005). However, the resulting self-selection effect only holds for non-functional parts of cars, such as a vehicle's exterior condition, and Peterson and Schneider (2014) find evidence that adverse selection effects prevail for vital parts, such as the engine or the transmission. As a third solution, Tirole (2012) proposes governmental interventions that aim to support sellers with the strongest legacy assets and at the same time cleans the market of its weakest assets. The fourth and final explanation simply describes a situation, in which the buyers are able to acquire enough information to approximate the cars quality sufficiently Bond (1982) in order to overcome the adverse selection problem. Despite their limited efficacy, all of these counteraction measures are costly, and thus might impede a market's efficiency beyond a socially optimal level (Bond, 1982). The evidence of Gavazza et al. (2014) supports this notion and indicates a negative effect of transaction costs related to information asymmetries on transaction volumes, allocation, and the welfare of lower-valuation households. Similarly, Peterson and Schneider (2014) show that adverse selection effects have a negative impact on trading volume and overall quality in the U.S. secondary market for cars.

In consequence, we follow Pagano and Jappelli (1993), Jappelli and Pagano (2002), Djankov et al. (2007), Karapetyan and Stacescu (2014) who identify a positive impact of the transmission of privately held information on market efficiency and trading volume, go beyond known concepts, and introduce a blockchain-based transaction system, that aims to resolve adverse selection by sharing information. As a distributed, publicly available, consensually agreed, and secured ledger, the blockchain facilitates the disclosure of information and impedes the provision of intentionally corrupted information. The resulting transactional database provides a valid and transparent record of each vehicle's history [and thereby improves] the ability of an uninformed buyer to approximate a car's true quality and value.

From an administrative perspective, the transaction system assumes the task of tracking changes of ownership and vehicle characteristics, improving the accuracy and transparency of the database at any given point in time. Overall, we propose to utilize the blockchain as an alternative to current institutions and a novel mechanism to publicly disclose vehicle information thereby reducing adverse selection effects in the market for used cars (Lewis, 2011)."

Research Question 5. *Which characteristics of blockchain-based transaction systems affect information asymmetries, and thus the uncertainty about quality in the market for lemons?*

4.2.3 Artifact Design

Design Decisions

To guide the creation, evaluation, and presentation of our prototypical blockchain-based transaction system, we utilize the design principles introduced in Section 4.1. Table 4.2 summarizes the mapping of our research against the DSR guidelines summarized in Subsection 4.1.1. "The resulting IT artifact is a proof-of-concept prototype that aims to replace a traditional registry system with a trust-free, decentralized, and automated alternative with a built-in mechanism to prevent unwanted transactions. Utilizing the blockchain's core features, it furthermore provides a resilient, transparent, and valid database for multiple parties, such as buyers and sellers of cars, government agencies, and other third parties that reduces information asymmetries by sharing previously private information. In order to ensure the efficacy and efficiency of our artifact, we perform a detailed requirement analysis based on the use case of the DMR and continuously reevaluate the system within each iteration of the building phase (March and Smith, 1995). Overall, we contribute to existing research of blockchain-based commercial systems by extending the knowledge on the development of a blockchain-based IT artifact, offering a new approach to address inefficiencies in public sector registries (Fairfield, 2015). In addition, we go beyond known concepts and propose a novel solution to adverse selection effects by transacting assets in a trust-free setup without a central authority or institution. "

In addition, we take the blockchain-specific design decisions introduced in Section 4.1.2 into account. Table 4.3 summarizes the related choices. Based on the resulting blockchain configuration (Xu et al., 2016, 2017), "[...] our proof-of-concept prototype utilizes the Ethereum framework introduced by Buterin (2013) and Wood (2014)."

Guideline	Contribution
Design as an artifact	"The outcome of our research is a proof-of-concept prototype that implements a blockchain-based IT artifact with built-in transaction safeguards that allow the correction of errors in the transaction process."
Problem relevance	"Our research questions respond to the mitigation of transaction risk inherent in blockchain systems (research question 3), the reduction of inefficiencies in public registry systems (research question 4), and the resolution of adverse selection risks in used good or lemon markets (research question 5)."
Design evaluation	"We evaluate and demonstrate the utility, quality, and efficacy of our prototype via structural and functional testing (Hevner et al., 2004). In addition, we execute our prototype across different scenarios of the DMR use case to test and illustrate its functionalities."
Research contributions	"The contribution of our research is threefold: First, we extend the knowledge on blockchain-based commercial systems and provide a built-in mechanism to mitigate transaction risk (Böhme et al., 2015) by allowing users to cancel incorrect transactions. Second, we adopt the concept of trust-free economic systems (Beck et al., 2016) to the use case of the DMR and introduce a novel way to replace trust-based and centralized bureaucratic registries with a trust-free, potentially cost-efficient, and autonomous transaction system. Third, we alleviate adverse selection effects and dismantle information asymmetries between buyers and sellers by sharing a transparent, reliable, and complete record of vehicle history and ownership."
Research rigor	"To ensure our research's rigor, we employ well established DSR frameworks, such as Hevner et al. (2004), Gregor and Hevner (2013), and March and Smith (1995), to guide the creation and construction of our IT artifact. In addition, we include guidelines specifically designed to support architectural and structural decisions in the development of blockchain-based systems (Xu et al., 2016; Glaser, 2017; Walsh et al., 2016)."
Design as a search process	"To discover an effective solution to the introduced research questions, we build on existing literature about blockchain-based transaction systems, such as Beck et al. (2016), Nakamoto (2008), Buterin (2013), or Wood (2014) and continuously evaluate and adapt our IT artifact throughout the development process (March and Smith, 1995; Hevner et al., 2004)."
Communication of research	"To maximize the potential impact of our research and to present our results to both, technology-oriented and management-oriented audiences likewise, we structure our work according to Gregor and Hevner (2013) and utilize the use case of the DMR to illustrate the organizational context for the artifact's development and application. To facilitate the understanding of technology-oriented audiences, we provide a detailed description of the prototype's software architecture, its implementation logic, its features, and its application context. To support management-oriented audiences, we furthermore discuss the underlying business problems as well as related economic theories. Eventually, we prove the effectiveness of our solution by discussing potentials and limitations of the prototype as well as future applications."

TABLE 4.2: *Application of the DSR guidelines to the DMR use case (Notheisen et al., 2017).*

To implement and manage a fiat currency token, we furthermore use the popular ERC-20 token standard[8]. This way, "[...] we can promote automation through transaction-triggered smart contracts [and thereby minimize] bureaucratic and organizational efforts related to the administration and maintenance of databases and registries, such as the DMR. Ethereum furthermore possesses the following desirable features: First, it provides security and resiliency through the integration of cryptographic hashing algorithms.

[8]A detailed description of the ERC-20 token standard is available in the Ethereum Wiki and on Github.

Second, due to its distributed nature, the network is able to maintain itself and there is no central point of failure. In addition, the block-based and chained data structure enables users to traverse through the entire database, retrieve every past transaction and reconstruct each vehicles history (Beck et al., 2016). In theory, this transparency provides a solution to the adverse selection effects and data inconsistency issues introduced in [Subsection 4.2.2]. In total, these features establish an environment for a trust-free transaction system that allows to move value between parties with divergent interests and information and governs the transfer of ownership by generating a complete, transparent, and secure record without a central institution."

Software Architecture & Market Design

"In order to build a powerful framework that meets the requirements described in [subsection 4.2.2], we choose an object-oriented software engineering approach and structure the underlying smart contracts hierarchically. To do so, we first define a generic marketplace structure (as shown in figure 4.4) that spans a structural framework, while the implementation of the prototype inherits its core functionalities. The generic design utilizes a two-layer approach that combines a market platform with individual goods that can be traded on this platform. Both, the platform and the traded object are represented by smart contracts, which implement different methods, functions, and variables. The marketplace contract functions as an escrow agent that organizes trading activities and defines the transaction process. The tradable contract represents the physical asset, keeps track of its current owner, and allows ownership to change after a successful trade."

To ensure the marketplace's extensibility, we [...] employ a hierarchical structure with three levels as depicted in figure 4.4: The `Marketplace` contract defines the interface and sets the minimum requirements for methods and corresponding events to achieve the basic functionalities specified above. The `StandardMarketplce` implements these methods and constitutes the basic implementation of a functional marketplace. The `IndexedMarketplace` extends the `Marketplace` with a set of convenience methods that allow the offers on the marketplace to be indexed as iterated through. This way, we segregate the interface, the core logic, and the convenience methods, [increase] the framework's robustness, [keep] it adaptable to different use cases and scenarios, and [ensure] the testability of different modules. In addition, we allow the `onTransferOwnership()` method of the `Tradable` contract to be overridden thereby allowing logic to happen during the transaction process.

Blockchain appropriateness (Wüst and Gervais, 2017)	
With our prototype, we aim to illustrate the potential of decentralized registries to record and disclose transactional information in a market setup with asymmetric information and opportunistic counterparties without a trusted third party. Using blockchain technology allows us to take these requirements into account.	
Blockchain design decisions (Xu et al., 2016)	
Decision 1: Transaction processing rate	"In 2015 the DMR conducted a total of 1,757,664 registration operations covering the registration of new vehicles by dealers, SKAT and other parties, the de- and reregistration following changes of ownership, registry updates following repairs, inspections, or modifications, and the deregistration of worn-out vehicles. At the current specification (gas limit per block, average gas cost per transaction), the Ethereum network is able to process roughly 7 to 8 vehicle transactions every 30 seconds, which equals 22,439 transactions per day. In comparison to the DMR's average daily transaction load of 4,816 operations, the Eteherum framework offers a suitable transaction rate for the infrequent transaction of cars."
Decision 2: Block selection	"To provide a reliable and consistent source of information in a public setup with conflicting agents, we choose a proof-of-work-based block selection mechanism. This approach moderates conflicting parties and prevents malicious nodes from spreading incorrect or counterfeited information."
Application design decisions (Xu et al., 2016)	
Decision 1: On- and off-chain data storage	"In order to balance the required computational power and the level of transparency, we apply a mixed on- and off-chain data storage model. To ensure a sufficient level of transparency and to enable the verification of transactions on one hand, transactional data (i.e., registration operations including repairs and automobile inspections) is stored on-chain. Personal details and other information not specific to the transaction object on the other hand will be stored off-chain in a SKAT database and can be assigned to transactions via hash-based keys."
Decision 2: Public vs. private chain	"We choose a public setup to facilitate accessibility, transparency and trustworthiness and to take the existing as well as the potential user base into account. Different privacy levels are realized through user-specific interfaces, hashing, and on- and off-chain data storage."
Decision 3: Single vs. multiple chains	"To facilitate data consistency, allow easier chain and permission management, and provide third party integration we select a single chain setup."
Decision 4: Validation oracles	"We use external validation oracles, such as SKAT, police departments, transport and road authorities, and other government agencies, as well as workshops and automobile inspectors, as trusted parties that provide and verify vehicle-specific information."
Decision 5: Permissioned vs. permissionless	"We plan to integrate our transaction system with other government services, and thus choose a permission-based setup, which requires all [users] to provide some form of governmentally approved authorization, such as a passport or ID number or a registered corporate ID, to join the network and submit transactions." One way to establish a blockchain identity is the ERC-725 standard.

TABLE 4.3: *Blockchain design of the DMR prototype (Notheisen et al., 2017).*

This way, our market platform allows the implementation of various background checks before a car is traded and grants the possibility to abort the trade by throwing the transaction, if certain conditions, such as an adequate insurance coverage or sufficient funding, are not met or one of the transacting parties does not comply to the previously agreed terms."

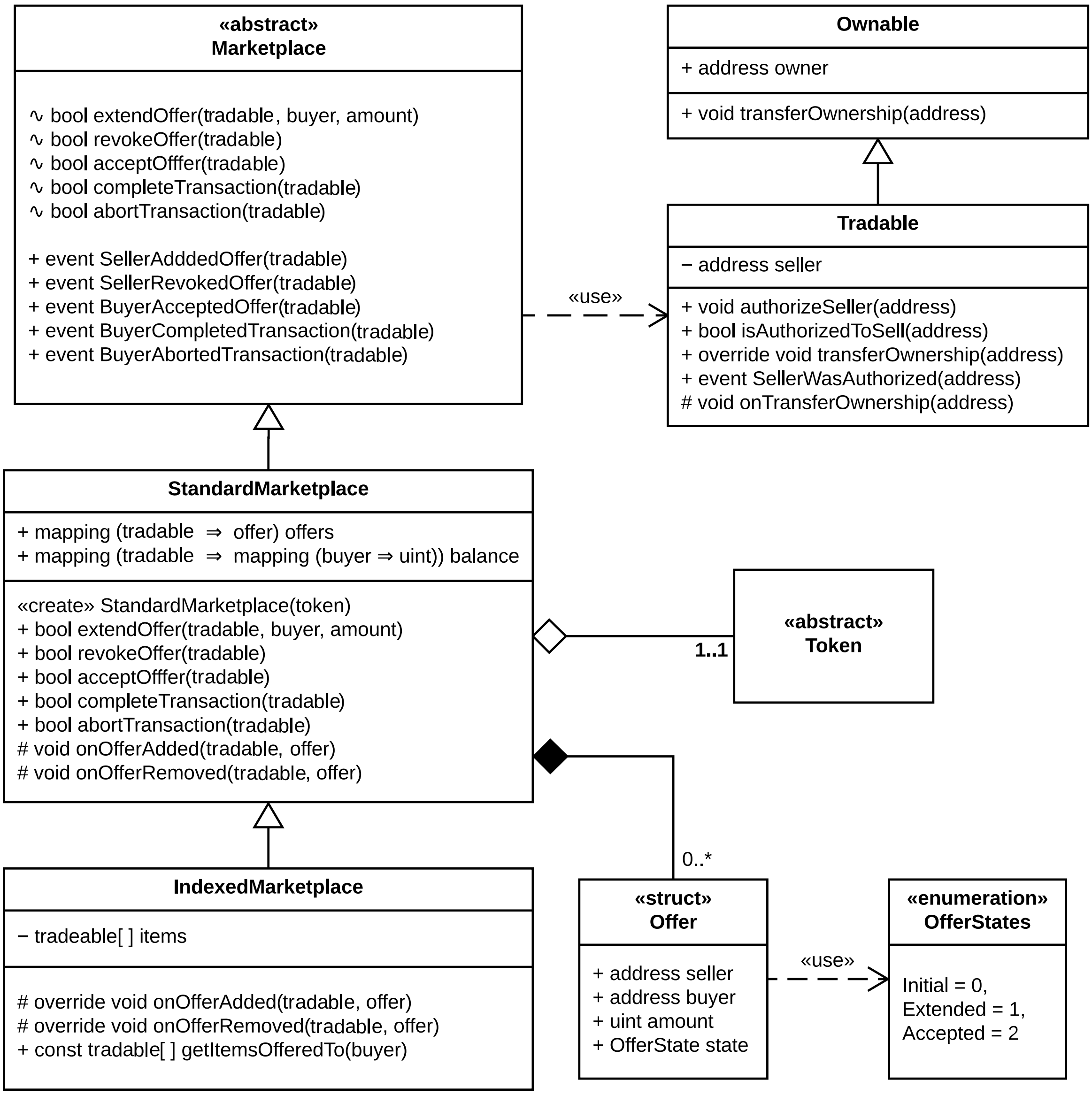


FIGURE 4.4: *Generalized software architecture of the marketplace (Notheisen et al., 2017).*

4.2.4 Artifact Features

"To develop the prototype, we use the holistic deployment framework Truffle. Truffle supports all steps of the development process including testing and deployment and [streamlines the] use smart contracts in Ethereum. [...] To implement the DMR marketplace (figure 4.5) we utilize the general marketplace structure shown in figure 4.4.

The DMR contract extends the IndexedMarketplace with the business logic relevant for the DMR, such as the ability to issue vehicles and to keep track of their ownership status afterwards. To do so, the DMR contract holds a register of the issued vehicles, their current owners, and respective license plates. The cars traded on the market are implemented by the Vehicle contract, which extends the Tradable and supplements properties required for the registration of vehicles, such as the unique vehicle identification number (VIN) and other vehicle-specific details. Instead of Ether, which is the cryptocurrency used on the Ethereum blockchain, we use an [ERC-20-based and tokenized] representation of traditional fiat currency, such as Danish Kroner, as means of payment. This way, we are able exclude any exposure to exchange rate risk. Using Danish Kroner however requires a third party, such as a central bank, a commercial bank, or a credit card company, to back or lock the value of the amount allocated to the buyer's blockchain account (Raskin and Yermack, 2016). The same holds for the seller when he or she wants to extract his return from the system."

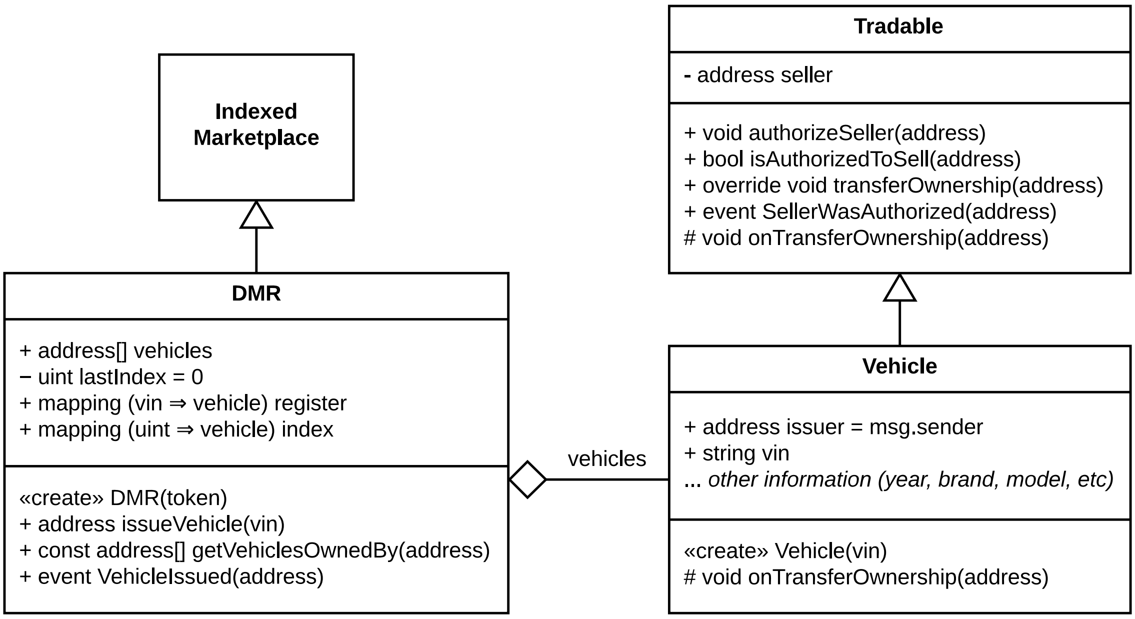


FIGURE 4.5: *Class diagram of the DMR use case (Notheisen et al., 2017).*

In order to "facilitate accessibility, we implement the prototype as web application that can be accessed via an URI from any Ethereum enabled browser, such as Mist, or by manually running a local Ethereum client while accessing the URI. Figure 4.6 shows a snapshot of the web application short before the completion of a transaction.

To improve privacy and and increase usability, we provide user-specific interfaces to different parties interacting with the system, namely buyers and sellers, government agencies, and third parties. From a practical perspective, we implement the interfaces as three different views in the web application: A car registration view, a register lookup, and a personal view, from which owned cars can be retrieved, offered, and traded.

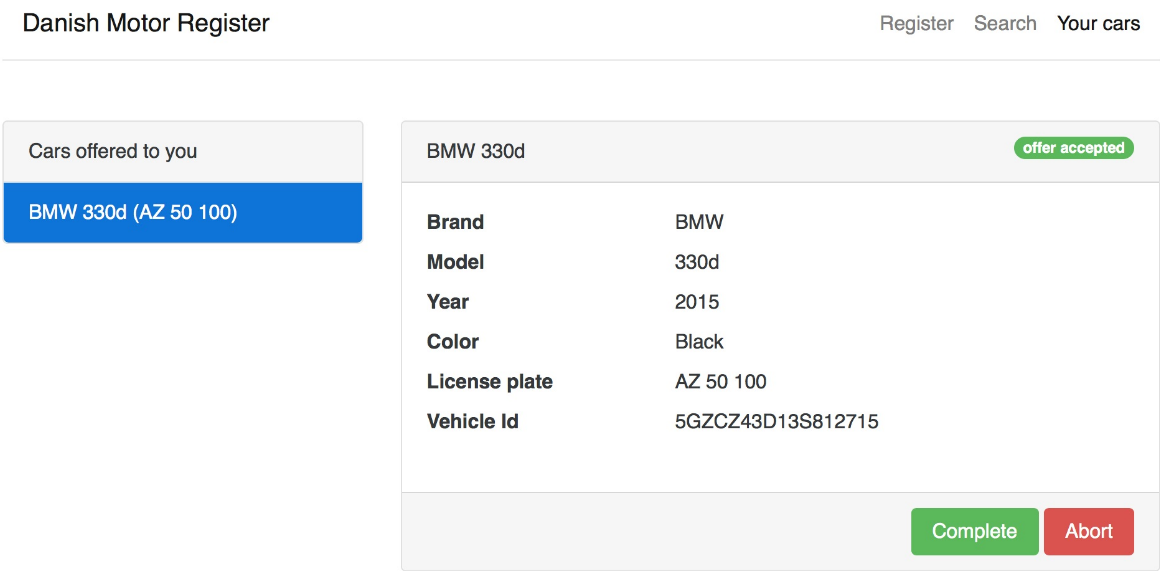


FIGURE 4.6: *Snapshot of the DMR's user interface (Notheisen et al., 2017).*

To mitigate transaction risk, we divide the transaction process into the following four steps and implement two built-in safeguard mechanisms: In the first step, we match buyers and sellers and they negotiate the terms of their trade. To reduce complexity and increase system performance, buyer-seller matching and pricing is not implemented in the prototype. Instead, buyers and sellers have to find each other and negotiate terms off-chain in the real world. In the second step, after they successfully reached an agreement, the seller can reach out to the buyer through the marketplace contract and provide an on-chain offer to sell the car by calling `extendOffer()`. To do so, he or she logs into the DMR blockchain system via the web-interface and sends an offer (`extendOffer()`) to the potential buyer by specifying the buyer's address, i.e. his public key, and the price. The public key is a hash representing the buyer's unique address or account number on the blockchain. In a real-world setup, public keys would be connected to a personal or corporate ID, enabling human individuals as well as corporate entities to buy and sell cars. After the seller has initiated the offer, the buyer has the possibility to either accept it by calling `acceptOffer()` or to do nothing, i.e. do not accept the offer.

In the case of acceptance, the buyer enters into an escrow agreement and `acceptOffer()` checks whether he or she has a sufficient amount of funds, withdraws the agreed price from his or her account, deposits it within the market, and notifies the seller about the acceptance of the offer. In the second case, the seller can revoke the offer via the `revokeOffer()` method. This is the first safeguard to prevent the provision of offers that differ from the previous off-chain agreement. In the third step, the transacting parties meet in person and exchange the physical good off-chain. The actual transfer of ownership however, has not taken place, yet. To conduct this transfer, buyer and seller have to go back onto the blockchain to complete the transaction by calling `completeTransaction()`, releasing the previously deposited funds to the seller while transferring the ownership of the asset. More specifically, `completeTransaction()` simultaneously deposits the money to the seller's account and transfers the certificate of ownership to the buyer. In line with this process, the vehicle is automatically deregistered and reregistered with the DMR.

If any problem occurs during the physical meeting, for instance if the car does not possess the previously advertised qualities, `abortTransaction()` aborts the transaction, reimburses the money to the buyer, and cancels the trade. This is the second safeguard mechanism and within this fourth and final step, each party has the means to cancel the transaction and withdraw from the agreement by calling `revokeOffer()` and `abortTransaction()` respectively. Aborting or revoking the transaction will remove the offer, transfer the funds deposited in the market back to the buyer, and stop the transfer of ownership. It is important to note, that the actual transfer of ownership of the asset and the payment comprise the final step of the two-legged transaction process and eventually settle the transaction. In both cases, the offer is deleted afterwards. As a result, both parties have the chance to abort an unwanted, unintentional, or erroneous transaction by using the transaction safeguards in the steps two and four (resaerch question 3). To illustrate the transaction process in greater detail, figure 4.7 and figure 4.8 depict the sequence of calls for a successful transaction and the different system states during the transaction process respectively. Eventually, the transaction data is immutably stored on the blockchain and publicly visible enforcing transparency (research question 5) and at the same time providing a complete and consistent record of ownership to the transacting parties, as well as SKAT and other relevant stakeholders (research question 4). In combination with the inherited transparency of the blockchain, our market design allows for a full view of issued vehicles, their current owners, as well as their history, and thus facilitates the reduction of information asymmetries in used car markets."

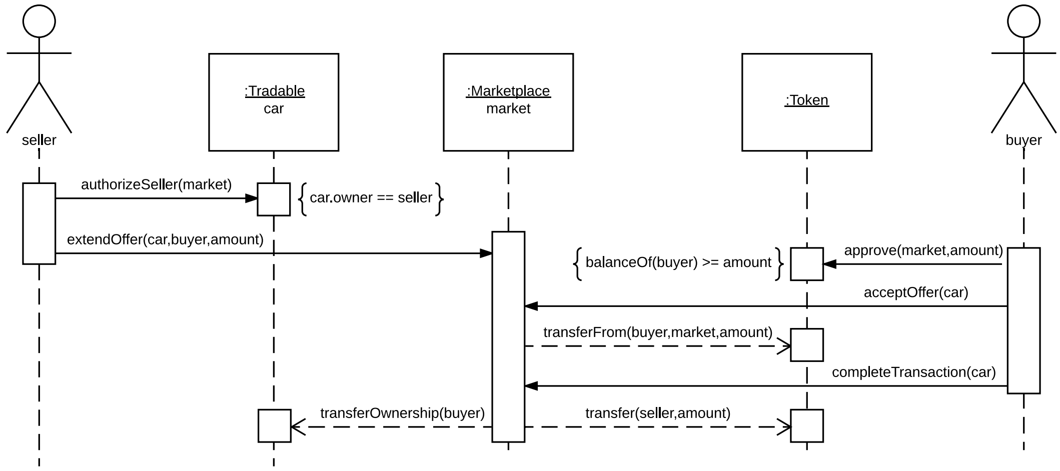


FIGURE 4.7: *Sequence of a valid transaction (Notheisen et al., 2017).*

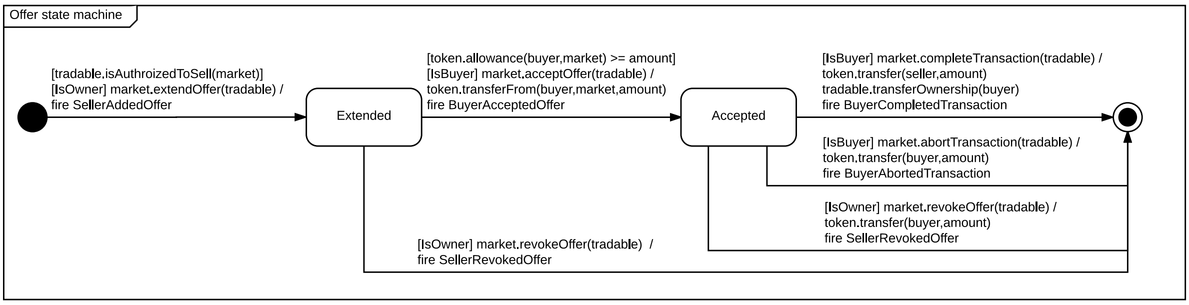


FIGURE 4.8: *Possible offer states within the transaction process (Notheisen et al., 2017).*

4.2.5 Artifact Evaluation

"The proof-of-concept prototype introduced in [Subsection 4.2.4] enables an automated and secure registration and transaction process. The system is running on Ethereum and allows users to invoke the DMR contracts to register (issue) and trade vehicles securely [on] the DMR marketplace with any other registered and authorized user. In total, we provide a solution to all three research question posed in [Subsection 4.2.2] and the use case of the DMR highlights the quality, functionality, completeness, and effectiveness of our IT artifact. Furthermore, the generalized software architecture and the market framework introduced in [Subsection 4.2.3] ensure the utility of our artifact and the provision of value beyond this specific use case. To evaluate the utility and efficacy of the prototype in greater detail, we also conduct extensive structural [...] and functional [...] tests (Hevner et al., 2004).

In the first step, we conduct various unit tests within JavaScript using the Chai Assertion Library as well as the previously introduced Truffle framework. Chai is a JavaScript library that enables the creation of unit tests and allows for both test setup and teardown before every test method. Within the structural testing, we create about 1,500 lines of code and conduct 46 unit tests in order to verify the correctness of the marketplace, the tradable, and the token. More specifically, the tests are designed to evaluate whether each public method behaves as expected when called with a correct sequence of inputs (see figure 4.7 for an example of a valid sequence of calls) and to ensure that the system behaves correctly during state changes. In the second step, the scenarios of issuing, buying, and selling cars within the use case of the DMR serve as a functional testing environment and illustrate the execution of the artifact. This way, we aim to detect any failures or potential defects in the basic marketplace, the DMR extension, and the web application. Moreover, the execution of our prototype within the testing scenarios yields average computational costs equal to 403,000 gas for a completed transaction. As a block in our setup accumulates roughly 3,140,000 gas, our system can process up to 8 transactions per block, assuming the blockchain is only utilized for the transaction of cars. If we furthermore set the average latency (i.e., block creation time) to 30 seconds, our prototype can handle up to 22,439 transactions per day[9].

Overall, the prototype addresses the transparency and data inconsistency issues related to the second hand trading of cars and illustrates how a blockchain-based transaction system approach can help to mitigate transaction risk by introducing escrow-like smart contracts. Furthermore, it allows third-party integration through observer patterns and dismantles adverse selection effects and information asymmetries through the transparent nature of the blockchain."

4.2.6 Discussion

"The IT artifact presented in [Subsection 4.2.4] introduces a novel approach to administrate registers of real-world assets by converting registration certificates into unique digital assets that are managed and maintained by the blockchain. Our system allows users to register vehicles and to trade registered vehicles securely with any other authorized user. After a transaction is completed, the traded vehicle is automatically de- and reregistered with the DMR.

[9]These processing capabilities refer the the specification of the Ethereum blockchain from August 2017.

As a result, the registry system provides a complete and correct record of each car's transactional history to potential buyers, government agencies, and other third parties without any institutional involvement. The cryptographic interconnection of the data blocks captures the timely order of past transactions and builds the foundation for data immutability, which is essential to ensure data integrity and the validity of the historical record. In combination with the decentralization of the consensus authority, the responsibility for the correctness of the transactional data shifts away from centralized institutions and towards the stakeholders that are most affected by asymmetrically distributed information. This way, our system works as a transparency device that assures the availability of a complete, valid, and public record of vehicle history and past ownership changes, thereby disclosing previously private information. More specifically, as blockchain transactions are public, potential buyers of cars are able to access the history of each vehicle, and thus can improve their assessment of the quality of a potential purchase. Moreover, no single participant within the system has to be trusted, because the entries are stored based on a consensual agreement and cannot be altered afterwards.

A clear limitation of this setup is the requirement of trusted third parties to provide vehicle-specific information following inspections, repairs, or modifications. This dependence reintroduces the potential of fraud and offers the providers of vehicle characteristics the opportunity to collude with current owners to provide wrong information. As a result, all actions outside of the transaction process cannot be fully secure and a residual risk of someone inserting corrupted information about a vehicle's characteristics remains. Although the system is not able to prevent this kind of fraud, the provision of a tamper-free historical record limits the fraudsters' ability to spread false vehicle data. Especially, if there is a certain fraction of honest nodes present in the system, traversing through the transactional history enables potential buyers and government agencies to uncover inconsistencies resulting from frauds, such as mileage manipulation. These inconsistencies could function as a signal to the buyer that indicates a low-quality vehicle. In addition, the dependence on third party information is limited to vehicle characteristics, while the record of car ownership remains unaffected, and thus still provides valuable data for the assessment of quality. Another way to handle the issue of fraud arises in the combination of blockchain technology and the Internet of Things (Zhang and Wen, 2017). In context of our use case, the Internet of Things could relieve trusted third parties from data provision duties and instead let smart cars directly report their status and changes thereof to the registry system. This way, data provision could be conducted in an automated and cryptographically secure manner (Christidis and Devetsikiotis, 2016).

A prerequisite for this approach however, is the technical ability of a vehicle to determine and report its current status to the blockchain. From a user perspective, buyers, sellers, and other parties access the system via a web application and transactions are conducted by an algorithmic process specified by smart contracts. This way, inadequate usage and misunderstandings are lowered to a minimum (Beck et al., 2016), as the direction of human behavior is governed by the deployed algorithms. In addition, the web application provides user-specific views with adequate information visualizations for each stakeholder facilitating the understanding of the transactional data. In total, these measures aim to reduce the impact of adverse selection on market efficiency by dismantling the asymmetric distribution of information between interacting parties and minimizing the buyer's uncertainty about the characteristics of the traded object.

Besides these use case-specific considerations, blockchain technology and especially the Ethereum framework are still emergent technologies, and thus face a number of technological challenges and limitations. One main issue of today's blockchains is scalability. Depending on the block's size and block creation intervals, the actual throughput - measured by the number of conducted transactions per second - is limited and the execution of a transaction can be delayed in times with high transaction loads (Gervais et al., 2016). In the context of the DMR, the focus lies on infrequent transactions of a limited number of vehicles per time interval, and thus scalability issues do not have a significant impact in this specific use case. For other use cases however, scalability issues should be taken into account. If we apply our transaction system to a larger market setup, such as the German automobile market, or a different scenario, the limited scalability, latency issues, and query delays could be a prohibitive limitation for the adoption of cryptographic transaction systems. In addition, as the distributed ledger accumulates conducted transactions it continuously grows over time, and thus occupies an increasing amount of disk space. These constraints however, are likely to be of a transient nature and might be resolved by further improvements of current and the development of new protocols as blockchain technology matures (Glaser, 2017). [Besides] technical limitations, public blockchains, such as the utilized Ethereum framework, also have negative implications for data privacy. To account for these privacy concerns, we propose an on- and off-chain storage model (Xu et al., 2016; Zyskind et al., 2015) for vehicle-specific and personal information and suggest a hash-based representation of personal and corporate IDs. In addition, market participants access the database via user-specific interfaces [...]. In combination with the permissioned blockchain setup, the requirement of an authorized ID restricts unauthorized access and ensures a minimum level of data protection.

Due to its prototypical character, the absence of real-world blockchain-based systems other than Bitcoin or other cryptocurrencies, and the variety of established IT systems, it remains challenging to assess our system's actual large-scale applicability. However, to provide a general orientation, we provide an abstract and brief distinction between centralized and distributed databases and point out the advantages of blockchain technology in the following paragraphs. In centralized databases, data is stored at one physical location and users access the stored data through an interface. As a result, centralized databases offer easy data management and maintenance, high performance, and remain scalable. On the other hand, centralization concentrates costs for setup and maintenance on the database provider, increases the risk of outages and data losses, and requires the users to trust in the governing operator (Elmasri and Navathe, 2010; Connolly and Begg, 2015). In distributed databases, the storage and processing units are kept separately, data is stored at and linked across multiple locations, and user access the database via a network. To update the nodes and to maintain the database, data needs to be replicated and duplicated across the network. Central advantages of distributed database systems are the continuous availability and increased reliability, easy data recovery, and the flexibility of modular growth. These advantages however come at the costs of a high level of complexity, an increased processing overhead, and the exposure of data integrity to inconsistencies (Elmasri and Navathe, 2010; Connolly and Begg, 2015). Blockchain-based systems combine characteristics of both systems and offer a resilient distributed database that ensures data integrity by the consensual agreement of all nodes, and hence provides a reliable database for multiple parties. Especially the openness of the transactional history to the independent scrutiny the the interacting parties and other involved stakeholders minimizes the risk of duplications, errors, and data inconsistencies. Building a registry system on a blockchain infrastructure leverages these key properties and meets the main requirements of modern registries, which include integrity, availability, accessibility, efficient reading, and immutability (Tran et al., 2017).

To provide an orientation beyond the use case of registries, we furthermore propose three prerequisites that arguably should be met for blockchain-based systems to potentially constitute an improvement over traditional approaches. First, due to its distributed nature and the integrated consensus mechanism, blockchain technology provides a conceptual approach to govern transactions between multiple parties in a public and anonymous setup without the involvement of a central party. As a result, these systems possess the ability to moderate interactions between agents with conflicting interests and motivations.

If the conflicting interests provide a strong intrinsic motivation to participate in the truth revelation process, we can also discard the idea of monetary incentives prevalent in cryptocurrencies. Second, we propose to utilize the blockchain as an approach to mitigate the exposure to asymmetrically distributed information and perceive and apply it as a toolbox to facilitate the provision, validation, and dissemination of a transactional history. Consequently, interactions without at least one party with private information cannot profit from an increase in transparency, and thus the benefits of blockchain-based systems remain limited. Third, as a distributed system blockchain technology grants multiple parties writing access to a shared database without compromising data integrity. For these benefits to take effect however, use cases need to comprise at least two conflicting parties with writing access to the system. If there is only one party with writing access, there is no need for consensus and therefore the party with the writing access simply constitutes the equivalent of a central authority. If we map these prerequisites to the use case of the DMR, we find that all three conditions are met: First, there is a conflict of interest, which arises between buyers and sellers, as sellers do not want to reveal their private information, while buyers want to learn about the true quality of the cars on the market. In addition, the multilateral market environment and the dynamic transaction process requires all parties involved to contribute data to the system."

4.2.7 Concluding Remarks

"The proof-of-concept prototype developed in this study aims to replace bureaucratic public registries with an alternative and illustrates how a blockchain-based transaction system for real-world assets might look like. In addition, it highlights how the blockchain could function as a transparency device to mitigate inefficiencies in markets with imperfect information. From a technological perspective, we provide a platform that governs the transfer of ownership of used cars and inherently provides a reliable and complete record of vehicle history to the transacting parties, government agencies, and other third parties. To implement the prototype, we apply an object-oriented software engineering approach that facilitates understanding and allows researchers and practitioners to go beyond the use case of trading cars and adopt the transaction system to other assets, transactional market setups, and registries systems.

Aside its practical relevance, our study's contribution to academic research is threefold: First, we introduce a mechanism to reduce transaction risk resulting from the irreversibility of blockchain-based transactions. Second, we replace a trust-based, centralized, and bureaucratic register with a trust-free and autonomous transactional database system, which provides a secure registration and transaction process without the need for a central governing authority. Third, we propose a novel solution concept to reduce the uncertainty about quality and the resulting adverse selection effects in lemon markets by providing a reliable, transparent, and complete record of each asset's history. To reduce complexity and to focus on the research questions at hand, we furthermore forego the integration of third party services and official processes, such as automobile inspections or permissions for rebuilds. These and other features however might be included in future versions as the prototype matures.

Apart from the noted benefits, the applied technology is still at an early development stage and faces some challenges, such as limited scalability and privacy concerns, that are not fully mastered yet. Also, users need to trust in the correctness and accuracy of the operating algorithms (Lustig and Nardi, 2015) and the provision of information about the asset by trusted third parties is still an important prerequisite. This provision however is limited to the update of vehicle-specific information following inspections, repairs, modifications, or accidents. The transaction process is conducted fully on-chain, and thus generating the transactional history does not require any third party integration. In part, this trust problem might be solved - at least in the case of cars - by the integration of the Internet of Things, wherein sensors provide the required data (Gubbi et al., 2013). Irrespective of those concerns, our prototype provides a valid first step to apply blockchain technology to the field of public registries and transaction systems and illustrates the opportunities and challenges of this approach." The impact of the increase in transparency within such a public registry is analyzed in detail in Chapter 5.

4.3 An Intermediary-free Market Mechanism

This section is partly based on the article "Trading Stocks on Blocks - Engineering Decentralized Markets". It is co-authored by Magnus Gödde and Christof Weinhardt, was presented at the 12th International Conference on Design Science Research in Information Systems and Technology (DESRIST) 2017, and was published in volume 10423 of Springer's Lecture Notes in Computer Science (LNCS). Direct citations are highlighted by double quotes.

Publication details:
Notheisen, B., Gödde, M. & Weinhardt, C.,
Trading Stocks on Blocks - Engineering Decentralized Markets,
DESRIST 2017: Designing the Digital Transformation,
Lecture Notes in Computer Science, May 2017, Volume 10243, pp. 474-478, Springer,
https://doi.org/10.1007/978-3-319-59144-5_34.

4.3.1 Introduction

"[...] In the context of markets, the combination of a distributed database, a decentralized consensus mechanism, and cryptographic security measures allows distributed system architectures and intermediary-free market designs by algorithmically enforcing agreements on the basis of predefined rules (Xu et al., 2016). In addition, the absence of centralized institutions facilitates disintermediation and allows more cost-efficient transactions (Beck et al., 2016). As a result, blockchain-based economic systems announce disruptive changes in financial markets and question the role of traditional financial institutions and market intermediaries, such as banks, exchanges, or central securities depositories. To illustrate [the design] and evaluate [the functional scope of decentralized] market platforms, we build on the growing body of literature about blockchain-based economic systems (Chapter 3) and implement a proof-of-concept prototype of a decentralized securities exchange.

Our prototype comprises a blockchain-based market platform that adopts the notion of trust-free economic systems (Greiner and Hui, 2015) and extends current knowledge on cryptographic transaction systems (Beck et al., 2016; Notheisen et al., 2017) with a crucial prerequisite for each transaction - a mechanism to connect demand and supply.

This way, we introduce a novel way to substitute traditional market institutions and intermediaries by transferring the guidance and governance of human interactions to [algorithms] borne by the blockchain's distributed network [(Lustig and Nardi, 2015)].

From a practical perspective, we provide the design and implementation of a blockchain-based market mechanism that entails the core functionality to trade stocks and constitutes a low-cost and resilient decentralized market platform. In combination with the ability of smart contracts to represent highly customizable financial assets, our prototype illustrates a new way to resolve inefficiencies, such as high search and bargaining costs, in low-volume over-the-counter markets (Duffie et al., 2005; Malinova and Park, 2017). Furthermore, token-based equity issuances provide an alternative mechanism for entrepreneurs to raise venture capital, by lowering regulatory barriers and simultaneously increasing the investors' control (Jentzsch, 2016)."

4.3.2 Related Literature

Blockchain-based Market Platforms

So far, academic literature has made little progress in developing and evaluating blockchain-powered exchanges and market platforms. Together with euroclear, the consulting firm Oliver Wyman for instance illustrates potential use cases and highlights the benefits of decentralized securities exchanges (de Velde et al., 2016). In addition, Patel (2014) presents a theoretical concept for implementation, while Clark et al. (2014) derive design principles for matching orders in a decentralized way. 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 theoretical trading model, they show that despite the risk of front-running, full transparency leads to the highest welfare, because it decreases the costs of finding liquidity.

From a practical perspective, the stuttering attempts of EtherEx and raidEX highlight that heaving a (stock) exchange on a blockchain-based system is a challenging task. Aside of legal concerns and regulatory compliance, shifting the continuous design of traditional (financial) markets - including double-sided matching and pricing, order books, and different order types - towards the discrete world of blockchain technology is essential to create a decentralized market mechanism (Clark et al., 2014; Patel, 2014).

At the same time the lack of a holistic, comprehensible, and transparent framework excludes non-technical audiences from the discussion, while the potential and implications of blockchain-based exchanges remain unclear. To address these issues, the following research question aims to shed light on the smart contract design and software architecture of blockchain-based, decentralized market mechanisms.

Research Question 6. *How can smart contracts implement a decentralized market mechanism that incorporates a double auction, keeps distributed order books, and allows traders to submit limit and market orders?*

Use Case: Decentralized Stock Exchange

The motivation to trade stocks via a blockchain is simple and similar to the motivation to develop cryptocurrencies: Blockchain technology promises a self-sufficient and transparent system with a high settlement speed and low transaction costs (Notheisen et al., 2019). In contrast, today's financial markets comprise an interlaced network of intermediaries, which make trading slow, inefficient, and potentially expensive (Harris, 2003). As a result, multiple stakeholders are involved in a transaction: Custodians manage stock ownership, brokers and investment firms forward investor's orders to exchanges. Exchanges match buy and sell orders and central counter parties take over settlement risk. Before a trade, traders acquire information about (trading) costs, the business of the traded firm (fundamental information), and a stock's price development to form an expectation about the risk and return associated with a trade. When a trader makes his or her decision to trade, he or she forwards the instruction to trade to the market. Usually this happens via several intermediaries such as brokers and superordinate banks and order flow providers. However, as a result of technological and regulatory innovation, the boundaries between intermediaries and markets blurred during the last decades. However, irrespective of their origin, market operators have to monitor and manage their risks the ensure a reliable trading environment. After a trade occurred and its trades are fixed, post-trading service providers (e.g., banks, custodians, or depositories) settle it in a two-legged process (securities $\longleftrightarrow$ cash). Figure 4.9 summarizes these steps in the value chain of securities trading and illustrates the roles of different intermediaries in the trading process.

Blockchain technology promises to streamline the trading process by making many of these stakeholders obsolete (Pinna and Ruttenberg, 2016; Notheisen et al., 2019). Pre-trade information for instance would be publicly available via the blockchain's historic record.

Custodians may be replaced by the combination of the consensus mechanism, which outsources the management of ownership to the crowd, and the distributed database, which records the resulting transfers of ownership. Brokers and order flow providers will no longer be needed as the blockchain's peer-to-peer network allows investors to directly access the exchange. In addition, matching, clearing, and settlement can be done autonomously by smart contracts. As a result, post-trade services cease to exist as clearing becomes obsolete and settlement happens in a simultaneous two-legged process. However, to evaluate these promises, we formulate the following research question:

Research Question 7. *To which extent can a blockchain-based market platform operate the value chain of securities trading and which technology features limit performance?*

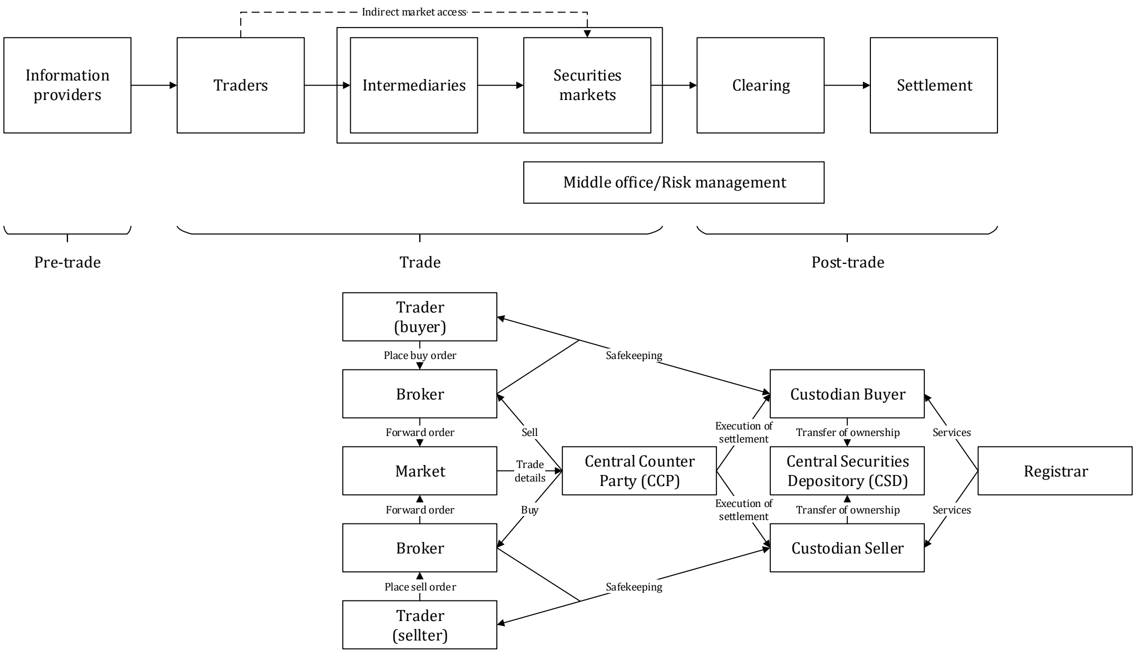


FIGURE 4.9: *Illustration of the value chain of securities trading and the trading process (based on Harris, 2003).*

4.3.3 Artifact Design

"Within the Ethereum framework (Buterin, 2013; Wood, 2014), digital assets such as currencies or stocks can be realized in the form of standardized smart contracts called tokens. From a technical perspective a token comprises a database, that enables data transactions in a distributed setup and allows the definition of arbitrary asset characteristics." To guide the implementation of the stock tokens and the surrounding market environment, we utilize the DSR and blockchain design principles introduced in Section 4.1. Tables 4.4 and 4.5 summarize the applied approaches and the resulting design choices.

Guideline	**Contribution**
Design as an artifact	The result of the research presented in this section is a proof-of-concept prototype of a blockchain-based stock exchange (IT artifact) that allows individual users to issue and trade tokenized stocks.
Problem relevance	Our prototype presents the design of a mechanism to connect demand and supply in a fully decentralized ecosystem (research question 6) and illustrates the feasibility but also highlights the limitations of decentralized stock exchanges (research question 7).
Design evaluation	To evaluate our prototype's quality and efficacy we use a laboratory-based test setting with structural and functional testing procedures. To demonstrate its utility and to test and illustrate its features, we issue various stocks and trade them on the market platform.
Research contributions	The contribution of our research is twofold: First, we complement the blockchain-based transaction system introduced in Section 4.2 with a mechanism to connect demand and supply in a fully decentralized fashion. Second, we highlight the potential of decentralized market platforms for low-volume over-the-counter markets and venture capital platforms and illustrate its shortcomings by benchmarking it against the requirement of the securities value chain.
Research rigor	To ensure scientific rigor in the creation of our IT artifact, we employ well established DSR frameworks, such as Hevner et al. (2004), Peffers et al. (2007), and March and Smith (1995). In addition, we take blochain-specific design frameworks (Xu et al., 2016; Glaser, 2017; Walsh et al., 2016) into account.
Design as a search process	To find an efficient and effective solution to research questions 6 and 7, we engineer our artifact in a continuous and iterative creation process (March and Smith, 1995; Hevner et al., 2004) that builds on existing literature about blockchain-based systems, such as Buterin (2013), or Wood (2014).
Communication of research	To maxmize our impact and hilight the multititude of application contexts, we structure our work according to Gregor and Hevner (2013) and utilize the use case of a stock exchange to illustrate the opportunities and limitation of decentralized markets. To ensure the understanding of technology-oriented readers, we illustrate the prototype's software architecture, the underlying implementation logic, and the resulting features in Subsection 4.3.4. To support management-oriented audiences, we embed our researach in a practical context in Subsection 4.3.2 and discuss central economic implications and technological limitations in Subsection 4.3.6.

TABLE 4.4: *Application of the DSR guidelines to the DEX use case.*

To implement the tokenized equity, we use the popular ERC-20[10] token standard. It enables the implementation of a standard API for tokens within smart contracts and specifies the basic functions (i.e., methods) required to issue and transfer tokens.

[10] A detailed description of the ERC-20 token standard is available in the Ethereum Wiki and on Github.

[11] These processing capabilities refer the the specification of the Ethereum blockchain from August 2017.

Blockchain appropriateness (Wüst and Gervais, 2017)	
Operating a fully decentralized market includes the determination of prices as well as updating and storing states of ownership (i.e., the system's state). An update results from a trade between at least two parties that interact with each other (multiple writers) independent of a trusted third party by design. In these interactions trade partners remain unknown (by regulation) and aim to maximize their individual gains. As a result, blockchain technology offers an appropriate toolbox to implement our prototype.	
Blockchain design decisions (Xu et al., 2016)	
Decision 1: Transaction processing rate	Executing a trade [...] costs roughly 200,000 gas. In combination with a gas limit of 4.7 million gas/block (at the time of publication), our prototype can process 24 trades per block and 2 trades per second[11]. However, modern financial markets exceed this limit and adjustments of the blockchain parameters (block creation time, block size) are required. How such an adjustment would affect market outcomes is subject to the analysis in Chapter 6.
Decision 2: Block selection	To provide reliable order books and a robust market mechanism to traders in a public setup, we utilize a proof-of-work-based block selection mechanism. This way, we aim to impede market manipulations by malicious traders.
Application design decisions (Xu et al., 2016)	
Decision 1: On- and off-chain data storage	To explore the opportunities and risks that come with a fully decentralized market mechanism, we compute and store all trade-related data on-chain.
Decision 2: Public vs. private chain	To facilitate the peer-to-peer character of our decentralized exchange, we choose a public blockchain setup. Thus, individual traders and firms can join or retract from the market independently and issue and trade equity independent of intermediaries.
Decision 3: Single vs. multiple chains	To take the different characteristics of assets (e.g., privately or publicly traded instruments, equity and debt features, or varying trading volumes) into account, we propose a multi-chain setup. However, to facilitate data consistency and improve chain and risk management we refrain from using multiple chains for one asset and limit our setup a single chain on the asset-level.
Decision 4: Validation oracles	We use external validation oracles, such as information providers or regulators, to enrich trading data with additional information about the traded assets and the issuing firms. In addition, validation oracles would allow the inclusion of reference prices.
Decision 5: Permissioned vs. permissionless	To minimize opportunistic behavior and to facilitate regulatory compliance, we require a permission to access our market platform. For trades permission is granted with a passport ID, a personal ID number, or a registered corporate ID. To issue new assets a corporate ID is required. Similar to the previous section, the ERC-725 standard offers a toolbox to implement this.

TABLE 4.5: *Blockchain design of the DEX prototype.*

In contrast to built-in crypto coins that originate directly from the blockchain protocol, the tokenized stocks on our market platform are subsequently issued on top of the protocol by third parties. In addition, ERC-20 only standardizes the basic functionality and allows the addition of convenience features such as elections or the distribution of dividends. "Eventually the token contract is stored on the blockchain and the Ethereum virtual machine executes the code fragments, while the token logic provides an immutable set of rules governing the actions of the issuers and holders of tokens without [...] a centralized third party."

To implement the underlying market place, we combine the generalized market architecture introduced in figure 4.4 in the previous section (4.2) with a decentralized market mechanism. The market mechanism implements the matching engine (see algorithm 1 in appendix B.2) and invokes an order book structure to processes the market and limit orders submitted by traders. An auction is executed every time a new order is submitted to the market. In order to prevent front running, newly submitted orders are only matched with orders that are already incorporated into the blockchain. In addition, we automatically delete orders that are not incorporated in the next block (i.e., that are not stored on the blockchain).

4.3.4 Artifact Features

"In the context of a stock exchange, a token represents the shares of one specific firm and implements storage and transfer functionalities. In addition, we allow convenience features, such as elections on annual general meetings or the distribution of dividends. In the case of venture capital investments, the total amount of funded capital could be locked into the contract and released piecewise subject to milestones in the business plan or the collective will of the investors promoting investor protection. Overall, we implement the DEX as a combination of two smart contracts, in which the exchange contract utilizes the token contract's functions to trade shares on the users' behalf. Figure 4.10 shows the full software structure of our prototype including its contracts and storage structures [...].

In the first step, a newly created token contract (`TokenStandard`) needs to be registered with the exchange contract (`DSX`) by passing the token's address to the `registerToken()` function. Upon the reception of the information, the `DSX` creates a `Market` containing the order book for the associated token. In order to make his or her shares tradeable, the token owner furthermore needs to grant the `DSX` control over some tokens, and thus determine the number of shares in the Initial Public Offering (IPO) (`deposit()`). Now the `DSX` is able to credit tokens to the accounts of investors and keeps track of stock ownership. To actually raise capital, companies need to sell their tokens (`sell()`). Figure 4.11 illustrates the steps of the funding process in greater detail. [...]. After the IPO, `sell()` and `buy()` allow investors to place market or limit orders to trade shares and implicitly performs clearing by ensuring that the seller has enough stocks and the buyer has enough money. All information associated with an order, such as `volume`, `price`, `marketId`, or the `blockNumber`, is saved in the `Order`.

Following their submission, we use the orders' unique `OrderIds` to collect all orders for a share and create a globally distributed limit order book for each token within the `Market`. Every time a new order is submitted, the `DSX` triggers a continuous double auction, that facilitates order execution based on best price matching (`match()`). Eventually, shares and funds get transferred directly between the users as matching, clearing, and settlement is unified in one joint step, and recorded by the blockchain's immutable transaction log. This log provides a history of all transactions, facilitating transparency and preventing fraud."

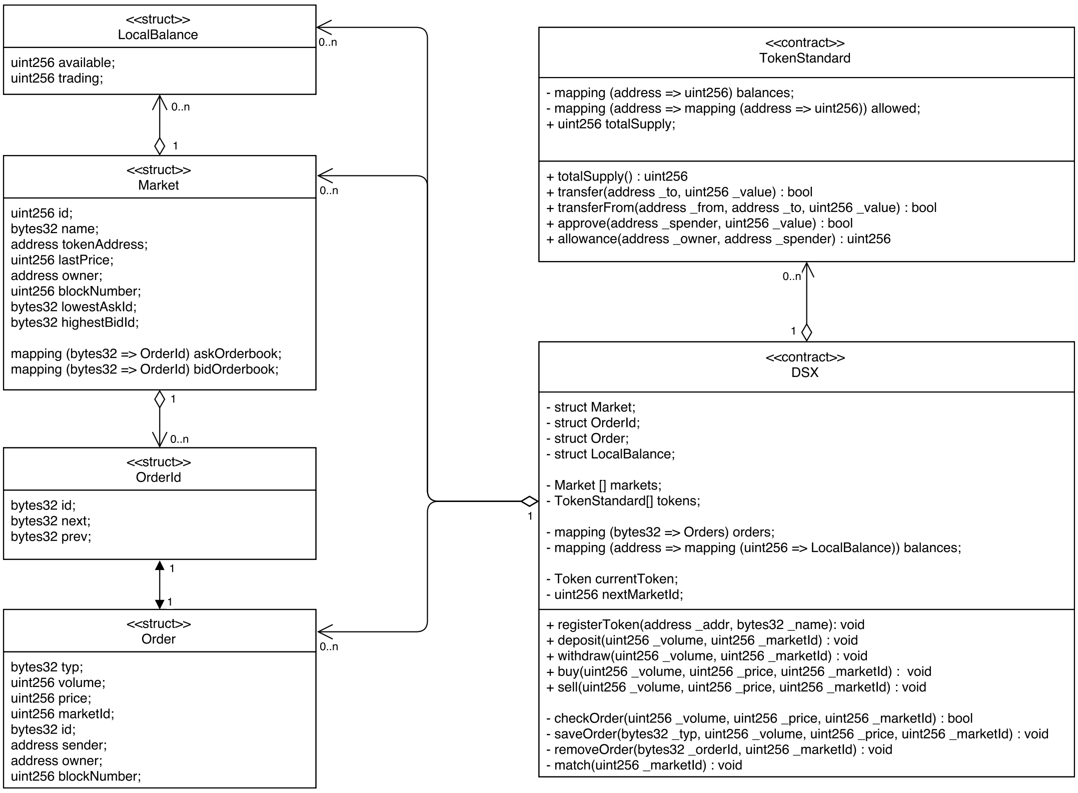


FIGURE 4.10: *Class diagram of the DEX use case (Notheisen et al., 2017)*

4.3.5 Artifact Evaluation

"To evaluate the formal correctness and the accurate functioning of the prototype, we choose a laboratory-based test setting and apply structural and functional testing procedures (Hevner et al., 2004). [More specifically], to verify the prototype's correctness, we conduct 12 unit tests using the Truffle framework and the Chai Assertian Library. [References to the specific procedures are available in appendix B].

Furthermore, the test scenarios of issuing equity and placing and executing limit and market orders to buy and sell shares, enable us to identify flaws in the software structure and yield an upper limit of two transactions per second. Eventually, these testing procedures demonstrate the validity, efficacy and formal correctness of our IT artifact and provide the foundation to [evaluate the quality of decentralized markets]."

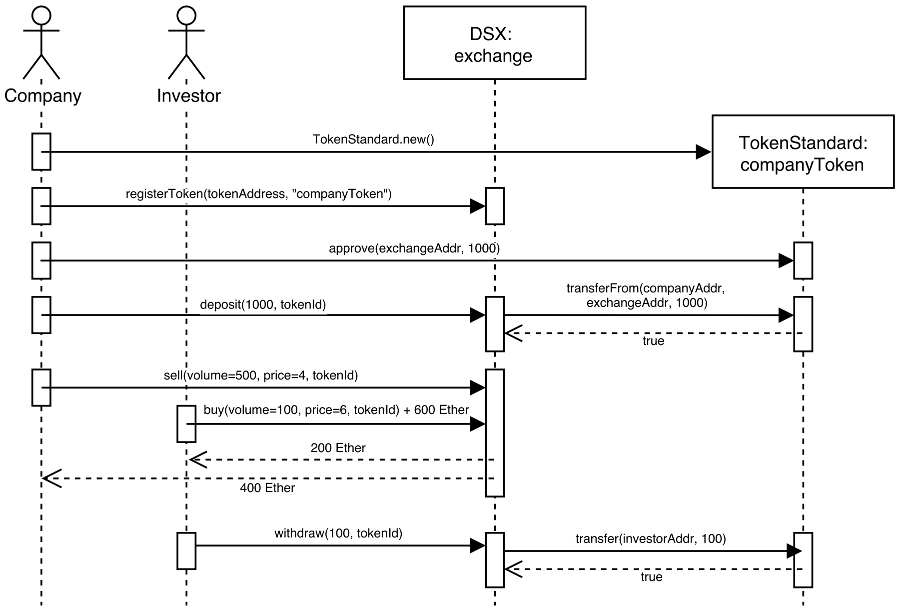


FIGURE 4.11: *Sequential illustration of the security emission process (Notheisen et al., 2017)*

4.3.6 Discussion

In total, the IT artifact presented in subsections 4.3.3 and 4.3.4 illustrates a potential design of a market environment that functions without central authorities (research question 6). More specifically, our proof-of-concept prototype allows entrepreneurs to raise capital and users to trade the resulting stocks on a secondary market. To do so, we implement a blockchain-based matching engine that matches orders decentralized, implicitly clears, and immediately settles the resulting agreements.

For entrepreneurs this offers a transparent way to bypass the hurdles of traditional IPOs, such as high costs or exaggerated regulatory requirements. Raising capital as tokenized assets is fast, cheap, and allows targeting a large audience (Ante et al., 2018). In addition, investor services, such as voting and subscription rights or dividend payouts can be formalized in the process of tokenization.

Furthermore, risky investments in start-ups can be hedged by locking in funds in the smart contract and releasing them after certain milestones are met. On the other hand, the lack of regulation may be a central motivation of opportunistic entrepreneurs to do an ICO (Amsden and Schweizer, 2018). From a resiliency and security perspective the absence of a single point of failure increases robustness towards outages and the duplication of data centers becomes obsolete. In addition, hacking the underlying smart contracts is highly impractical, as it requires control over the majority of the network's computing power.

However, the discrete, distributed, and open nature of blockchain-based systems also raises concerns with respect to the requirements of modern financial markets (research question 7). First, the dependence on fixed block creation times increases the latency of matching from milliseconds to several seconds or even minutes. In addition, it impedes the implementation of commonly applied price time precedence rules. Second, in combination with the limited size of blocks these effects increase (Notheisen et al., 2018) and furthermore limit the throughput of blockchain-based markets. A possible solution may be payment channels, a technology currently under development (Croman et al., 2016). Third, the public availability of trade information facilitates coordination among stakeholders during the ICO process (Catalini and Gans, 2018) and enables manipulative trading strategies afterwards. More specifically, the visibility of pending orders in the blockchain's memory pool enables front running (Malinova and Park, 2017), insider trading, spoofing, and other market manipulations (Weaver, 2018).

4.3.7 Concluding Remarks

"Overall, we contribute to existing research by introducing a blockchain-based market mechanism, that facilitates low-cost and intermediary-free asset transactions in an algorithmically governed and thus trust-free, easily accessible, resilient, and decentralized way. As a result, blockchain-based market platforms enable the resolution of inefficiencies in over-the-counter markets and support novel forms of venture capital. However, the blockchain is still an emergent technology, and thus exhibits some problems, such as a limited number of transactions per second or the provision of information by trusted third parties. In addition, its distributed nature prevents the implementation of time precedence rules. Keeping this in mind, our prototype is only an initial step towards decentralized market setups and economic, technological, and regulatory aspects need to be addressed in future research efforts." The quality of blockchain-based decentralized market mechanisms is subject to Chapter 6.

4.4 The Building Blocks of Decentralized Markets

In combination, the building blocks introduced and implemented in the previous sections can form the backbone of decentralized market platforms. The transaction system introduced in Section 4.2 enables interacting parties to overcome the trust frontier (see Section 3.5) with the help of fiduciary transaction safeguards. As a result, they can transact digital as well as physical assets in market environments prone of asymmetric information. In addition, the transparent, reliable, and complete record of historic transactions functions as a transparency device and supplies traders and other third parties with valuable information about the market, potential counterparties, and assets before a trade. The intermediary-free market mechanism introduced in Section 4.3 connects demand and supply by matching and executing orders in a fully decentralized fashion. As a result, market operators and other intermediaries required to connect traders to the market are replaced by the a blockchain-based infrastructure. In addition, clearing and settling a transaction becomes an integral part of the trading process. More specifically, Figure 4.12 illustrates the resulting functional scope and arranges the role of the market mechanism (4.3) and the transaction system (4.2) within a decentralized market platform.

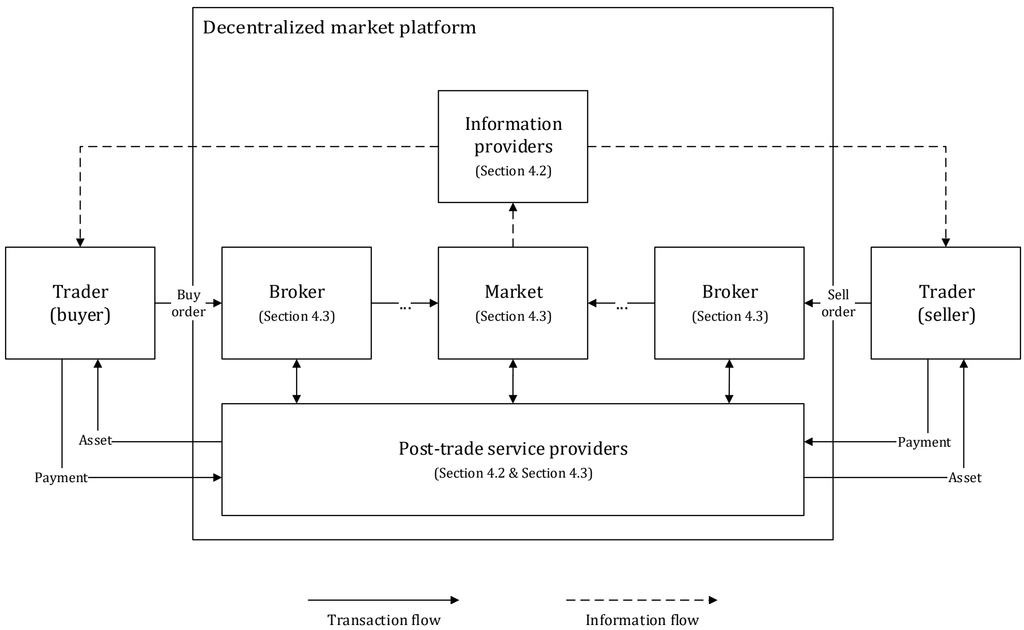


FIGURE 4.12: *Conceptual arrangement of the building blocks of decentralized markets*
To illustrate the building blocks of decentralized markets, this figure integrates the prototypes from Sections 4.2 and 4.3 and illustrates the resulting transaction and information flows.

Chapter 5

Information Asymmetries & Transparency

This chapter is based on the working paper "The Blockchain, Plums, and Lemons - Information Asymmetries & Transparency in Decentralized Markets". The paper is co-authored by Christof Weinhardt, part of the KIT working paper series in economics, and available on SSRN. It was furthermore presented at the Herrenhausen Conference 2018, FinteQC 2018, and the 7th Karlsruhe Service Summit 2018. Direct citations are highlighted by double quotes.

Manuscript details:
Notheisen, B. & Weinhardt, C.,
The Blockchain, Plums, and Lemons,
KIT Working Paper in Economics No. 130, SSRN Electronic Journal, 31 July 2018,
https://doi.org/10.5445/IR/1000092486, https://ssrn.com/abstract=3202667.

5.1 Introduction

"Despite their growing interest, researchers and practitioners still struggle to transfer the blockchain concept to the broader context of market-oriented applications. While few success stories, such as Bitcoin[12], pioneer financial markets, many initiatives fail to leverage the technology's potential efficiently.

[12]Another example is the Australian Stock Exchange's effort to replace the current post-trade system with a blockchain-based alternative. After several testing phases and stakeholder consultations, they announced in a media release that the current post-trade system "CHESS" will be replaced with a blockchain-based alternative that will take over the clearing and settling equity transactions.

One major reason for this stuttering development is the limited knowledge about the economic implications of the underlying technological concepts and their relationship with the socio-economic environment, market mechanisms, and player rationales. In consequence, we aim to shed light on the technology's capability to function in market environments with information asymmetries, quality differences, and opportunistic behavior. To do so, we examine how a core feature of blockchain-based information systems - the current, complete, and publicly available record of historic transactions (Chapter 4; Notheisen et al., 2017) - affects the behavioral patterns of market participants and the resulting impact on market outcomes.

From a technical perspective, the public record of past transactions enables the members of the blockchain network to validate the correctness of database updates within the consensus process. By auditing the past, they can evaluate the correctness of transactional data and determine whether the interacting parties possess rightful ownership of a transacted object. To facilitate overall data integrity, every user can participate in this process and has access to the historic record. In market environments with asymmetric information and quality differences, this new form of transparency does not only reduce uncertainty within interactions but also enables individual users to exploit the publicly disclosed information about peers and business partners to maximize their own gains. In this study, we determine under which circumstances such behavior occurs and how it affects a market in total. Thereby, we aim to identify factors blockchain adopters should consider before applying blockchain technology in market-oriented contexts and use cases.

To examine behavioral changes that come with a different information system configuration, we utilize a two-period lending game with incomplete information and entrepreneurs that choose effort levels (moral hazard) and differ in their disutility of effort (adverse selection). Our model comprises a loan market with a competitive banking sector that shares the market equally and a continuum of entrepreneurs, which is uniformly distributed on the interval $[0, 1]$. Entrepreneurs live for two periods, can be either good (a plum) or bad (a lemon), have access to a one-period project in each period, and apply for loans at a bank to fund these projects. At the end of period 1, the banks learn about the project outcomes of entrepreneurs and share this information via an information system. Eventually, dependent on the informativeness and access scope of the information system, banks and entrepreneurs can use this information to asses entrepreneurial quality.

In line with prior research, our findings indicate that sharing information about entrepreneurial performance mitigates the impact of adverse selection on the banking side and reduces moral hazard of plums by generating a disciplinary effect. In this study, we furthermore identify an incentive for lemons to behave opportunistically in the presence of value-adding information brokers. They can improve utility by using the information from the blockchain's public record to learn about the quality of plums and mimic them accordingly. Moreover, their opportunistic behavior is more pronounced for greater price improvements, lower quality differences, and lower quality in general. In opaque markets (i.e., markets without the analytic service of an information broker), neither plums nor lemons behave opportunistically. Irrespective of the information regime, plums and lemons are both locked-in to behavioral changes, and thus committed to inefficient equilibria in subsequent periods. While rational agents are not affected by this effect, the consequences of irrational decisions spill over to future periods. From a market perspective, mimicking lemons create a welfare gain under perfect information. However, their opportunistic behavior also violates the break-even condition of the banking sector, leads to a market collapse, and denies future generations access to credit. In total, this indicates that using blockchain-based information systems in highly competitive and transparent markets with irrational agents should be considered carefully. The same holds for implementing analytic, information-generating services on the infrastructure level (e.g. with smart contracts).

In consequence, the contribution of this study is threefold: First, we extend the growing body of research on the economics of blockchain by analyzing the effects of the blockchain's public transparency paradigm in market environments with asymmetric information. Second, we contribute to the field of banking research by examining the impact of publicly shared quality information on credit markets. And third, we add to the literature on blockchain adoption by highlighting the risks of blockchain-based transparency."

5.2 Related Literature

"This chapter relates to previous research about blockchain design and examines the economic implications of the public disclosure of information essential for the technology's functioning. In this aspect, our findings relate to the growing body of research on the economics of blockchain.

From a broader perspective, the transparency that comes with blockchain adoption also resembles features of information sharing arrangements present in modern financial markets. To take these commonalities into account, we embed our analyses within the context of information sharing arrangements in credit markets - a well-studied example of markets with asymmetric information - and extract blockchain-relevant implications from this body of research. In consequence, this section introduces the technological and economic aspects of transparency in the blockchain concept, briefly illustrates how credit information is currently shared, reviews the most important theoretical and empirical findings about information sharing arrangements, summarizes the resulting research gap, and formulates three research questions. A detailed overview of the characteristics of information sharing arrangements [...] is available in appendix A.4."

5.2.1 The Role of Transparency in the Blockchain Concept

"From a technical perspective, most blockchain systems comprise three core building blocks: A distributed database, cryptographic algorithms, and a consensus mechanism (Notheisen et al., 2017). The distributed database consists of cryptographically interconnected blocks that aggregate and store transactional data and provide a copy of the ledger to every user of the system. This distributed character of the blockchain's ledger disseminates information equally to all users of the network thereby creating a new form of transparency (Catalini and Gans, 2016). Asymmetric encryption enables users to interact with the database, allows them to specify and authorize transactions via public and private keys, and ensures the unambiguous assignment of past transactions based on their unique address in the system (public key). The decentralized consensus mechanism empowers users to consensually verify and append new transactions by securely voting on their correctness based on the historical data stored in the distributed database. More specifically, within the consensus process each participating user verifies each transaction's formal correctness by checking whether it was signed by the right entities and auditing whether the sender actually owns what he or she transacts via the historical record. In the context of Bitcoin for instance, the transparency over past transactions ensures that the sender of a new transaction owns a sufficient amount of Bitcoin to cover the sending amount (Nakamoto, 2008). In more complex interactions that comprise a two-legged transaction process, the review is not limited to the solvency of each counterparty but may include the transacted assets' attributes as well (Notheisen et al., 2017).

In the case of physical assets, transaction management furthermore requires overcoming the trust frontier between the physical and digital world via a trusted interface to prevent the incorporation of corrupted information (Hawlitschek et al., 2018).

To conduct a blockchain transaction, a user denominates a transactional object (e.g., a specific amount of money or an asset), specifies a recipient (via his or her public key), references past transactions to proof ownership, signs the transaction (with his or her own private key), and broadcasts it to the peer-to-peer network. Across the network, other users collect, verify, and aggregate broadcasted transactions and propose the resulting data blocks as database updates to their peers (Eyal, 2015)[13]. Whenever such a verified update is proposed, each participant of the consensus process checks its validity as described above before casting a vote. If a majority of the users agrees with the proposed update, the proposer appends his or her block to the blockchain, broadcasts the update to the network, and earns a reward (Nakamoto, 2008).

Building on the paradigm of public transparency, these building blocks and their functioning ensure the integrity, consistency, and correctness of data within a blockchain system and enable users to interact in the absence of a governing central authority. In markets with asymmetric information, transparency has implications that go beyond pure technological functionality and can lead to hidden information in the pre-contractual and hidden action problems in the post-contractual stage (Akerlof, 1970; Stiglitz and Weiss, 1981; Hellmann and Stiglitz, 2000). In consequence, we have to take transparency implications into account, if we aim to use blockchain technology in such environments.

On one hand, the increased transparency about asset portfolios helps traders to identify suitable counterparties thereby increasing liquidity and welfare (Malinova and Park, 2017). In repeated interactions information about past behavior facilitates the stability of reputation effects by ensuring that historical records (e.g., in form of reviews and ratings) correctly reflect actual interactions and improves the auditability of digital activity trails (Catalini and Gans, 2016). From a governance perspective, blockchain technology increases transparency over ownership, and thus alleviates opportunistic behavior of individual stakeholders (Yermack, 2017).

[13]In many blockchain systems a fraction of specialized users - often called miners - focuses on the update process, while others only send and receive transactions. For the sake of simplicity, we limit our analyses to a network of homogeneous nodes that all participate in the consensus process. Introducing different roles in the network would require the examination of user's incentives to fulfill those roles. This could be part of future research efforts as this study only aims to provide a first intuition of user rationales and welfare effects in market environments with asymmetric information (Eyal, 2015).

On the other hand, the revelation of previously private information about assets' attributes and the characteristics and behavior of interacting parties may change market dynamics and induce adverse behavior of individual users. These changes can affect market equilibria, the profits and utility of individual market participants, and eventually welfare (Bloomfield and O'Hara, 1999). As a result, it is crucial to consider technology-specific transparency effects in the decision whether and how to use blockchain technology in environments plagued by information asymmetries. More specifically, this includes understanding how the new transparency paradigm that comes with blockchain adoption affects economic interactions, market outcomes, and the welfare of an economy."

5.2.2 Lessons from Information Sharing Arrangements in Credit Markets

"The information sharing arrangements used in today's credit markets allow a first glimpse on these transparency effects and their impact. In credit markets asymmetric information and the resulting uncertainty about quality lead to inefficient allocations of capital that can cause profit reductions, welfare losses, and market failures (Stiglitz and Weiss, 1981; Hellmann and Stiglitz, 2000). For small and medium enterprises for instance, empirical evidence indicates that credit rationing is more severe for more opaque firms at the beginning of their banking relationship (Kirschenmann, 2016; Dell'Ariccia and Marquez, 2004) This effect is furthermore driven by adverse selection issues and is inversely related to firm age (Hyytinen and Väänänen, 2006). For consumer credit on the other side, Karlan and Zinman (2009) find strong evidence for moral hazard and weaker evidence for hidden information issues, while informational barriers to lender competition persist (Calem et al., 2006). To mitigate the resulting issues various institutions, such as collateral (Bester, 1987), complete contingency contracts (Sharpe, 1990), or reputation systems (Diamond, 1989) developed over time. Besides these approaches, the sharing of previously private relationship information also helps to dismantle information asymmetries and alleviate the issues outlined above (Millon and Thakor, 1985). In a similar fashion, the blockchain's distributed and complete record facilitates the sharing of information - irrespective of its actually intended use.

In practice, information sharing arrangements institutionalize the provision, scope, and disclosure of information about lenders to banks and other stakeholders. Public credit registries are centralized databases established, owned, and managed by public entities to support their supervisory duties.

As such, they provide universal coverage of loans above a specified threshold, impose participation by law, and disseminate consolidated information about an entrepreneur's riskiness to current and potential lenders and regulators. Private credit bureaus on the other hand are privately owned organizations that add significant value to credit information (Kallberg and Udell, 2003) and thereby cater to the needs of commercial lenders in their assessment of entrepreneurial risk. Participation is voluntary and based on a reciprocal agreement that offers incomplete but detailed information about loans, repayment histories, and personal backgrounds. In theory, public credit registries are set up to compensate for the lack of private arrangements (Padilla and Pagano, 2000; Jappelli and Pagano, 2002). However, in some countries both systems coexist and cater to different segments of the market (World Bank, 2013).

Theoretical predictions. Economic theory predicts that while sharing information helps to dissolve adverse selection problems and to prevent moral hazard, strategic rationales on both sides of the market are crucial factors that determine the actual effect induced by the increase in transparency. In their seminal study, Pagano and Jappelli (1993) investigate individual banks' motivation to share information and identify borrower mobility and heterogeneity, market size, and advances in information technology as positive incentives to share information. The fear of competition on the other hand impedes information sharing. In total, their model indicates that information sharing is an efficient means to mitigate adverse selection. Padilla and Pagano (1997) build on Pagano and Jappelli (1993) and find that information sharing lowers future profits by homogenizing information among banks, while raising the chances for success today. Eventually, the resulting trade-off between increasing competition on the future and higher rents today determines the banks' willingness to share information. Bouckaert and Degryse (2006) emphasize the strategic dimension of information sharing and show that incumbent lenders limit information sharing to project outcomes in order to discourage potential entrants. Consistent with this rationale, Gehrig and Stenbacka (2007) suggest that information sharing reduces informational monopoly rents earned from relationship information but also highlight that it makes poaching more profitable (Bennardo et al., 2015). However, Karapetyan and Stacescu (2014) also emphasize that this loss of informational rents induces lenders to increase their investment in the acquisition of additional information in order to regain their monopoly. From a market perspective, Bennardo et al. (2015) predict that sharing information improves coordination among lenders and thereby decreases entrepreneurs incentive to overborrow when lending from multiple banks.

As a result, interest and default rates decrease and the access to credit improves. In the case of distress however, intensified lender coordination increases default probabilities even further (Hertzberg et al., 2011).

In contrast to these studies, Padilla and Pagano (2000) focus on the entrepreneurial effects of information sharing. While sharing information about entrepreneurs raises their incentive to perform, it also creates a disciplinary effect as hazardous behavior impedes the ability to obtain credit from other sources as well. However, Padilla and Pagano (2000) also find that sharing too much information can eliminate any disciplinary effects, because entrepreneurs' true types are revealed. In consequence, lenders need to tailor the type and accuracy of information to balance the trade-off between adverse selection and moral hazard effects in order to incentive entrepreneurs to perform on their optimal level. Diamond (1989) and Vercammen (1995) examine on specific aspects of such disciplinary effects in greater detail: Diamond (1989) studies the formation and evolution of reputation effects and indicates that reputation needs time to establish. In contrast, Vercammen (1995) - who assesses the impact of credit bureau policy on entrepreneurial efforts - finds that the resulting improvement of welfare does not hold over time, because lenders become increasingly aware of entrepreneurial types as credit histories lengthen. A similar effect emerges with the increasing informativeness of consumer credit reports. More specifically, Sharma (2017) illustrates that the probability of strategic defaults is higher when the information content of credit reports is more likely to reveal entrepreneurial types.

Empirical evidence. Empirical studies aim to provide complementary evidence for these theoretical predictions and evaluate the economic impact of information sharing arrangements in a broader context. Brown and Zehnder (2010) for instance transfer the model of Pagano and Jappelli (1993) to an experimental setup and confirm their findings as more asymmetric information facilitates information sharing, while stronger competition has an impeding effect. In addition, Doblas-Madrid and Minetti (2013) utilize contract-level data from the US to study the effects predicted by Padilla and Pagano (1997) and Padilla and Pagano (2000) and find - consistent with theory - that the entry into a credit bureau reduces contract delinquencies and defaults. Similarly, Jappelli and Pagano (2002) demonstrate that lending volume is higher and credit risk lower in countries where lenders share information.

From an individual's perspective, the existence of efficient information sharing arrangements reduces firms' financing obstacles (Beck et al., 2004), as credit bureaus add significant explanatory power to failure prediction models (Kallberg and Udell, 2003).

Dierkes et al. (2013) confirm this effect channel and indicate that a prediction's accuracy increases with firm age, credit bureau experience, and the spatial distance between firm and credit bureau and decreases with firm size. With respect to private credit, Djankov et al. (2007) find that private credit bureaus are more likely in richer and public credit registries are more likely in poorer countries. Moreover, the introduction of an information sharing arrangement increases the volume of private credit in both. In total, these results support previous findings (e.g., Jappelli and Pagano, 2002; Pagano and Jappelli, 1993; Padilla and Pagano, 1997) and highlight the beneficial role of information sharing in developing countries with poor creditor rights. However, Bos et al. (2018) also identify a causal effect of negative credit information on employment and wage levels.

Brown et al. (2009) find similar effects for corporate loans and provide empirical evidence that information sharing improves the access to and lowers the cost of credit - especially for opaque ventures. However, Behr and Sonnekalb (2012) are not able to confirm these results for public credit registries but find a positive effect on loan performance. This effect is more pronounced for repeated interactions and areas with low competition, which supports the disciplinary effect predicted by Padilla and Pagano (2000). A similar ambiguity prevails for the volume effects identified in theoretical and empirical research (e.g., Padilla and Pagano, 2000; Djankov et al., 2007; Allen and Santomero, 1997). Grajzl and Laptieva (2016) find no evidence for a volume effect with respect to public credit registries whereas, private credit bureaus on the other hand are associated with an increase in lending volume. Furthermore, extending the provision of credit information to borrowers creates an awareness about financing costs and reduces credit volume and overborrowing issues (Bertrand and Morse, 2011).

In addition, there are several studies that examine the effects of information sharing arrangements from a banking perspective. Barth et al. (2009) for instance, provide strong evidence that private credit bureaus reduce lending corruption and enhance the curtailing effect of bank competition on lending corruption. Moreover, Houston et al. (2010) support Hertzberg et al. (2011)'s coordination hypothesis and indicate that information sharing decreases banks' risk-taking. This leads to positive effects on bank profitability, bank risk, the likelihood of financial crises, and economic growth. Buyukkarabacak and Valev (2012) furthermore confirm the positive effect on banking crises for both, public and private information sharing arrangements. On the other hand, Giannetti et al. (2017) underline the strategic rationales illustrated by Bouckaert and Degryse (2006) and show that banks manipulate shared credit information to protect profitable customer segments.

Blockchain implications. In total, the reviewed literature on information sharing arrangements offers several valuable insights with respect to blockchain technology: First, it helps us to understand the capability of the blockchain's record to share information. The studies of Kallberg and Udell (2003) and Dierkes et al. (2013) for instance indicate that sharing information via the blockchain's distributed and complete record of past transactions may provide an efficient tool to mitigate problems caused by pre- and post-contractual information asymmetries (Padilla and Pagano, 2000; Beck et al., 2004) and facilitate coordination among users (Bennardo et al., 2015; Hertzberg et al., 2011; Bertrand and Morse, 2011; Brown and Zehnder, 2010). However, to ensure a positive impact, it is important to fine-tune the (time) scale (Diamond, 1989; Vercammen, 1995) and (content) scope (Padilla and Pagano, 2000; Bouckaert and Degryse, 2006) of disclosed information carefully. A special challenge for instance poses the impossibility to delete past transactions, because the disciplinary effects fade with lengthening records (Vercammen, 1995). On the other hand, the blockchain's immutable and tamper-free nature prevents and thereby reduces the effects of data manipulation (Giannetti et al., 2017) - at least in the digital world (Hawlitschek et al., 2018). Second, it outlines potential channels through which a change in transparency characteristics might influence behavioral patterns and market outcomes. More specifically, using a consensually updated and shared database tightens competition (Pagano and Jappelli, 1993), dilutes informational monopolies (Padilla and Pagano, 1997, 2000; Bouckaert and Degryse, 2006), and improves market access, volume, and efficiency (Djankov et al., 2007; Brown et al., 2009). In addition, sharing previously private information on the supply side redistributes rents to the demand side (Padilla and Pagano, 1997) and creates a disciplinary effect that alleviates opportunistic behavior (Padilla and Pagano, 2000). The trade-off between those effects determines the impact on welfare, the motivation to share information, and strategic rationales on both sides of the market (Bouckaert and Degryse, 2006; Sharma, 2017)."

5.2.3 Research Gap & Research Questions

"Despite these commonalities, there is also a crucial difference between the traditional information sharing arrangements and blockchain-based information systems: Traditional arrangements built on centralized information systems provide a specific scope of information to a selected group of users. In consequence, banks have access to information about the complete market, while entrepreneurs can only access information about themselves.

The blockchain concept on the other hand does not curtail the access rights of individual users and discloses the stored information publicly. This way, blockchain-based systems ensure data integrity and facilitate the validity of database updates in the absence of a central authority. As a result, all users have the same level of information.

Thus, to fully leverage the blockchain's potential, it is crucial to understand potential side effects that come with the shift to public transparency. More specifically, in markets with asymmetric information and quality differences increasing transparency does not only reduce uncertainty but also enables opportunistic users to exploit quality information in order to maximize their individual gains. To shed light on the underlying behavioral patterns and outcomes and to identify potential risks of blockchain adoption, we formulate the following research questions:

Research Question 8. *Which participants of a market with asymmetric information are affected by the blockchain's shift towards public transparency? When and how does their behavior change?*

Within the related analyses, we investigate who changes behavior, how and why these changes occur, and evaluate the resulting outcomes. To do so, we take the perspective of both plums and lemons and examine the incentives to change behavior, the consequences that come with changes and dismantle effect channels over time. In addition, we consider different system configurations and connect individual outcomes to characteristics of the socio-economic environment. However, the effect of behavioral changes is not limited to individuals but also spills over to the market and the economy as a whole.

Research Question 9. *How do the behavioral changes of opportunistic market participants affect their counterparties, market outcomes in total, and the welfare of the economy?*

This research question covers welfare effects as well as the impact on the supply (banking) side of the market. In consequence, we examine whether the aggregated behavioral changes of individual market participants improve or impede welfare and which factors drive these effects. To analyze the markets functioning, we furthermore take a closer look at the impact of behavioral changes on the supply side (i.e., banks) of the market. Eventually, it is also important to transfer the findings from research questions 8 and 9 to a practical application context to support researchers and practitioners in their blockchain endeavors."

5.3 The Model

Economy. "There is a loan market with a competitive banking sector with $b > 1$ immortal banks and a continuum of entrepreneurs, which are uniformly distributed on the interval $[0, 1]$. Entrepreneurs live for two periods, are either plums (good) or lemons (bad), have access to one-period investment projects in each period, and apply for loans at the banks to fund these projects. They furthermore can choose a bank at the beginning of each period at zero costs. When new entrepreneurs come to a bank, the bank has no knowledge about their type. However, banks can gather information about entrepreneurial characteristics through their lending relationship (Boot and Thakor, 2000; Boot, 2000), as they observe project outcomes at the end of each period. In addition, banks share the observed default information via an information system at the end of period 1. This way they aim to reduce the information asymmetries they face when entrepreneurs switch banks and use the information acquired from the information system to approximate types (Padilla and Pagano, 2000). All actors are risk-neutral and act as rational economic agents. Figure 5.1 illustrates the sequence of actions in the economy in detail.

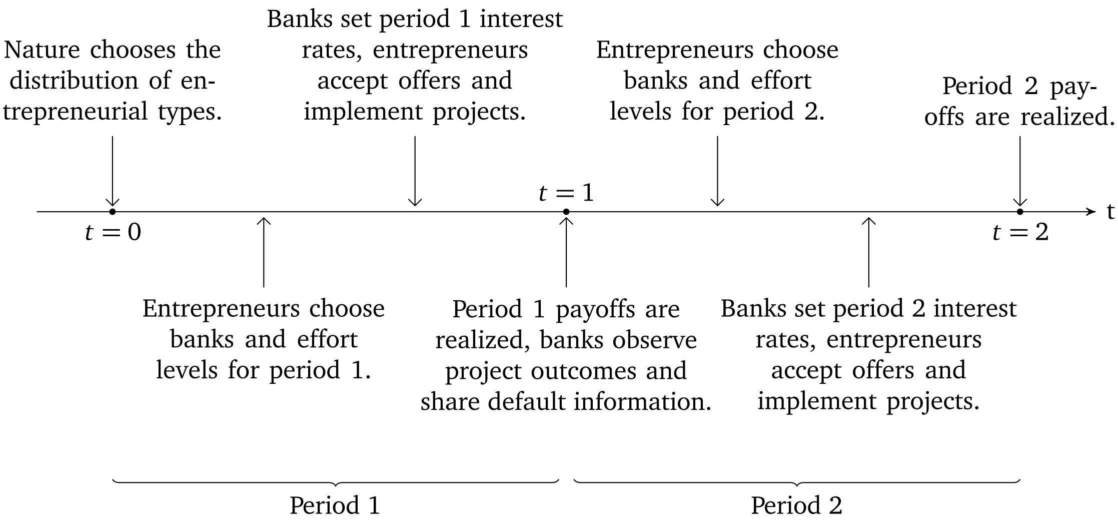


FIGURE 5.1: *Timeline of actions*

Information system. The information system functions as a means to periodically share information, stores default information over time, and makes it available to its users. This way it enables banks to assess entrepreneurs based on historic averages of past generations.

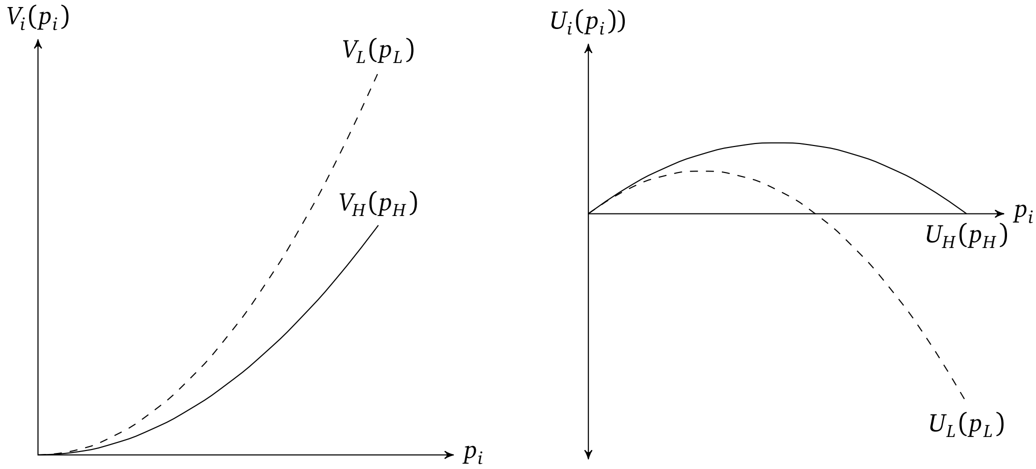
However, the accuracy of this assessment depends on the informativeness of the conveyed data. To represent this dependency in our model we define two information regimes: Imperfect and perfect information. In the imperfect information regime, the information system supplies plain default information. Under perfect information on the other hand, an information broker - for instance in form of a private credit bureau or a rating agency - adds value in form of type information to the default data. As a result of this analytic assessment, banks can identify entrepreneurial types by comparing actual period 1 efforts with historic averages. In addition, the system can either be deployed as a traditional data base or as a blockchain-based information system. In the first case, banks have full access, while entrepreneurs can only see their own performance record. In the blockchain case on the other hand, all users have access to all data.

Entrepreneurs. Entrepreneurs have no initial funds and access to a one-period investment project in each period. This project requires an initial investment of 1 at the beginning of a period and yields a positive return $R > 1$ at the end of a period, if successful. In the case of failure, it yields a return of 0 and the entrepreneur defaults. A project's probability of success $p_i \in [0, 1]$ depends on the entrepreneur's type $i \in \{H, L\}$, is monotonic in the effort exercised by an entrepreneur and creates a quadratic disutility of effort $V_i(p(i)) = a_i p_i^2$ with a cost parameter $a_L > a_H > 0$. Similar to Padilla and Pagano (1997) this allows us to interpret p as the entrepreneurs choice variable. The disutility of effort is a strictly convex function with $V' \geq 0$ and $V'' > 0$ and represents the costs an entrepreneur has to bear to achieve a specific success probability p_i. Intuitively, this reflects the idea that plums posses greater entrepreneurial skills compared to lemons. As a result, effort is always cheaper for plums but never costless for both types. More specifically, plums' greater talent $\Delta a = a_L - a_H > 0$ allows them to achieve either greater productivity levels $p_H > p_L$ at a given cost $\bar{V} = V_H(p_H) = V_L(p_L)$ or some success probability $\bar{p} \in (0, 1]$ at lower costs $V_H(\bar{p}) < V_L(\bar{p})$. In addition, the marginal costs of effort are higher for bad than for good entrepreneurs $V_L'(\bar{p}) > V_H'(\bar{p})$. For $p = 0$, the disutility of effort is equal to zero for both types ($V_L(0) = V_H(0) = 0$).

In total, entrepreneurs experience utility from successful projects and choose their individual levels of effort p_i to maximize their expected utility over both periods, while taking the effort choices of other entrepreneurs as given. They furthermore act as price takers and take the interest rates offered by the banks as given. Eventually, an individual entrepreneur's utility is equal to:

$$U_i(p_{i,1},p_{i,2}) = \underbrace{p_{i,1}(R-R_1) - V_i(p_{i,1})}_{\text{Net return period 1}} + \underbrace{p_{i,2}\big(R-E[R_2]\big) - V_i(p_{i,2})}_{\text{Expected net return period 2}}, \text{ with } i \in \{H,L\}. \tag{5.1}$$

In period 1, $p_{i,1}$ denotes effort, $V_i(p_{i,1})$ the corresponding disutility, and R_1 the repayment (principal and interest) to the bank. The same logic applies to period 2, while $E[R_2]$ represents the expected repayment given the behavior in period 1. If an entrepreneur does not get any credit, his or her expected utility is equal to zero. Figure 5.2 illustrates the 1-period cost (panel A) and utility (panel B) functions of plums and lemons respectively.



(A) *Disutility of effort*　　(B) *Utility*

FIGURE 5.2: *Entrepreneurial disutility and utility*
Functional form of the partial disutility of effort and partial utility for one period.

As illustrated in figure 5.1, entrepreneurs choose their effort levels prior to borrowing in each period, while their effort is non-observable and non-contractible[14]. As a result, interest rates cannot be conditioned on an individual entrepreneur's probability of repayment. However, interest rates will depend on the average ex-ante repayment probability of previous generations, which is accessible via the information system. In addition, project returns are observable and contractible by the lending bank[15].

[14]Practical examples include hiring a good manager, preparing a good business plan, or the potential of a project itself. For outsiders and non-experts, such as lending banks, these activities and project characteristics are hard to verify. In addition, their qualitative nature makes them hard to enforce in court (Padilla and Pagano, 2000).

[15]Contractibility of project returns ensures that in case of success the entrepreneur must repay the loan, while their observability ensures that the actual project outcome (i.e., success or default at the end of a period) is only observed by the lending bank and not any outside banks.

Eventually, the fraction of plums in the market is denoted by the uniformly distributed random variable $\theta \in (0, 1)$[16]. This distribution of plums and lemons is common knowledge. The historic average success probabilities of each type are known to the lending banks in the traditional information sharing regime and common knowledge in the blockchain regime.

Banks. Banks can raise funds for one period at a gross interest rate of $R \in (1, R]$ (principal and interest) at the beginning of each period[17], offer one-period loan contracts to the entrepreneurs, and compete in interest rates. Consequently, each bank maximizes its expected profits given the average probability of success of plums and lemons by setting the interest rates in period 1 and 2.

While providing credit, banks face adverse selection ex-ante due to the non-observable and moral hazard ex-post due to the non-contractible nature of entrepreneurial effort levels. During the initial engagement with an entrepreneur in period 1, banks can observe project outcomes and share this information with each other at the end of period 1. To mitigate the adverse selection problems in the imperfect information regime, they use the Bayes' Rule to update their beliefs based on shared default information. In the case of perfect information, they can acquire type information at zero costs. Conditional on the level of information about entrepreneurial quality, their expected profit in each period of a bank is equal to

$$E\big[\Pi_t\big] = \frac{1}{b}\Big[\theta p_{_H} R_{j,t} + (1-\theta) p_{_L} R_{j,t} - \bar{R}\Big], \text{ with } j \in \{H, L, P\} \text{ and } t \in \{1, 2\}. \tag{5.2}$$

At the beginning of period 1, banks have no information about entrepreneurial quality and compete for the whole market. As a result banks are unable to differentiate between plums and lemons, offer a pooling rate $R_{P,1}$, and share the market equally. In period 2, banks still compete in prices and share the market equally but have more information about entrepreneurs. In consequence, they offer either risk-adjusted pooling rates $R_{P,2}(0)$ and $R_{P,2}(R)$ conditioned on default under imperfect or type-specific rates $R_{H,2}$ and $R_{L,2}$ under perfect information.

[16]This ensures that there is at least one plum or lemon in the market.

[17]This assumption requires banks to pay back their funds at the end of each period and roll over to new funding at the beginning of the next period. If they cannot repay funds at the end of a period, they go bankrupt an have to quit business. As a result they set their interest rates to break even in each period independently of other previous or following periods.

Solution concept. In order to analyze the impact of the blockchain's public record, we examine the following combinations of information regimes and access scopes: While banks have either imperfect or perfect information and always have access to the information system, entrepreneurs stay uninformed with a traditional access scope. In the blockchain regime on the other hand, public access to the information system enables entrepreneurs to learn about the average success probabilities of plums and lemons. Comparing these two information regimes and access scopes allows us to examine the extent to which the quality and availability of information provokes behavioral changes of plums and lemons. To do so, we look for subgame perfect equilibria by the following rationale:

- Banks act simultaneously and maximize their profits by setting period 1 and 2 interest rates given the average historic success probabilities of plums and lemons p_H and p_L. In consequence, the vectors $(R_{P,1})$, $(R_{H,2}, R_{L,2})$, and $(R_{P,2}(0), R_{P,2}(R))$ constitute a subgame perfect equilibrium for the banking subgames in period 1 and 2 respectively.
- Entrepreneurs choose their individual effort levels $p_{i,t}$ simultaneously to maximize their expected utility over both periods, correctly anticipating the interest rates in period 1 and 2, while taking the effort levels of the other entrepreneurs as given.

Remarks. Note that while the distribution of entrepreneurial types and their average success probabilities are common knowledge among banks, the allocation of good and bad entrepreneurs to the market fractions $[0, \theta]$ and $(\theta, 1]$ needs to be observed in period 1. Intuitively speaking, banks know how many plums and lemons are in the market and the difference Δa between them but are not able to distinguish between them on an individual level. To focus on the impact of the non-discriminatory disclosure of information that comes with blockchain usage, we do not vary the scope of the information sharing arrangement. To keep the model simple, neither banks nor entrepreneurs discount profits or utility, we do not consider costs for information acquisition or sharing, and each entrepreneur's wealth is equal to zero when applying for a loan[18]. Furthermore, note that while past defaults do not have any impact on the investors' wealth level, information about past defaults does as it is recorded and shared by the lending bank. To improve accessibility, a list of variables including their scope is given in the appendix C.1."

[18]More specifically, we assume that the entrepreneurs consume the profits of successful projects immediately, and thus start with no collateral or any other capital from previous projects. In case of default, the bank forgives the debt at the end of each period as an investment project represents a separate limited liability company.

5.4 Analyses

"As stated before, a core feature that enables blockchain-based systems to function independently from central authorities is the public availability of the underlying transactional database. However, besides reducing adverse selection effects and moral hazard on the banking side, access to the blockchain's historic record also enables entrepreneurs to gather information about each others qualities. As a result, public system access allows individual entrepreneurs to direct their behavior in order to deceive banks and facilitate misjudgment. To analyze whether and how this potential for deception might affect markets' functioning and outcomes, we establish the banking perspective in the first subsection (5.4.1). In Section 5.4.2, we build on the resulting interest rates to investigate the motivation of switching and staying plums and lemons to mimic their respective counterparts given different information system configurations. Eventually, Section 5.4.3 combines both perspectives and examines the welfare effects of the increased transparency that comes with blockchain adoption on a market level. Appendix C provides proofs of propositions 1 to 12 (C.2) and supportive calculus for the profits and the utility of banks and entrepreneurs (C.3)".

5.4.1 Banking Perspective

"To establish the market environment for entrepreneurs, we characterize the banking equilibrium first. To find the equilibrium rates charged in a partly competitive market with shared default information, we build on the approaches of Padilla and Pagano (1997) and Padilla and Pagano (2000) and use backward induction, while taking entrepreneurial effort levels and quality differences as given. To simplify our analyses, we assume that the entrepreneurial effort levels p_H and p_L are exogenously given and that $p_H > p_L$.

The banks set period 1 and period 2 interest rates to break even given their cost of capital $\bar{R}$ and entrepreneurial efforts p_H and p_L, while competition erodes monopoly rents. At the beginning of period 2, entrepreneurs can switch banks and banks use the information about period 1 to assess entrepreneurial quality and charge risk-adjusted interest rates in period 2. In the case of imperfect information (i.e., default information), the information system allows the banks to separate defaulters and non-defaulters and Bayesian learning leads to two pooling equilibria. For perfect information on the other hand, banks can acquire type information based on period 1 performance to separate plums and lemons perfectly. In period 1, the absence of information leads to a uniform pooling rate.

Assessment of Entrepreneurs with Imperfect Information

Suppose that the banks share the market equally in period 1, each bank observes project outcomes at the end of period 1, and shares default information consequently. At the beginning of period 2, each bank accesses the information system and utilizes the default information to offer entrepreneurs a pooling rate conditional on period 1 project outcomes. More specifically, the bank uses Bayes' rule, to approximate whether a customer is good or bad conditional on period 1 default and given the distribution of types and their average success probabilities. Figure 5.3 illustrates the resulting probability structure.

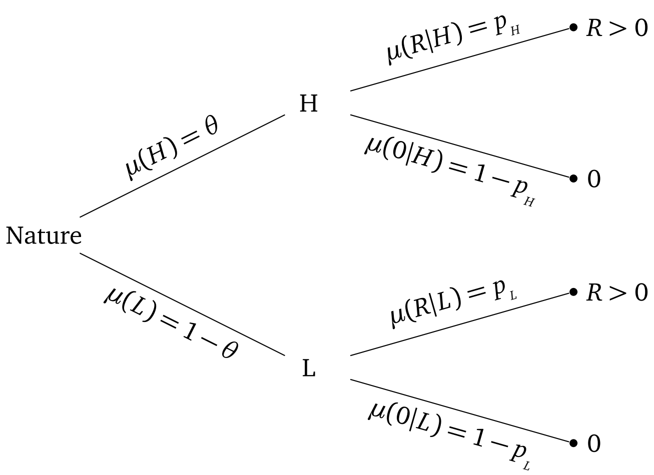


FIGURE 5.3: *Structure of a priori success probabilities of plums and lemons*

Based on this structure, $\mu(H|R)$ denotes a bank's posterior belief at the beginning of period 2 that an entrepreneur who was successful in period 1 is a plum. Conversely, $\mu(H|0)$ is the posterior probability of being a plum conditional on failure in period 1. The posterior probabilities for lemons follow the same idea. Using Bayes' theorem, the posterior success probabilities of plums and lemons are equal to equations 5.3, 5.4, 5.5, and 5.6 conditional on success and default in period 1. Moreover, the updated beliefs can be interpreted as the probability that a bank identifies plums and lemons correctly given period 1 project outcomes.

$$\mu(H|R) = \frac{\mu(R|H)\mu(H)}{\mu(R)} = \frac{p_H\theta}{\theta p_H + (1-\theta)p_L}, \tag{5.3}$$

$$\mu(L|R) = 1 - \mu(H|R) = \frac{p_L(1-\theta)}{\theta p_H + (1-\theta)p_L}, \tag{5.4}$$

$$\mu(H|0) = \frac{\mu(0|H)\mu(H)}{\mu(0)} = \frac{(1-p_H)\theta}{\theta(1-p_H) + (1-\theta)(1-p_L)}, \tag{5.5}$$

$$\mu(L|0) = 1 - \mu(H|0) = \frac{(1-p_L)(1-\theta)}{\theta(1-p_H) + (1-\theta)(1-p_L)}. \tag{5.6}$$

Proposition 1 implements this notion and formalizes the banks' perception of project risk in period 2. Intuitively speaking, this means that in a market with both types and lending not all plums will be successful and not all lemons will default, while the probability for success (default) is higher for plums (lemons). As a result, default information is helpful to approximate effort levels but not as good as having perfect information.

Proposition 1. *Sharing default information at the end of period 1 enables banks to approximate the quality of entrepreneurs but still bears the risk of an incorrect assessment. As a result, banks regard defaulted entrepreneurs as riskier, underestimate the success probabilities of defaulters, and overestimate the one of non-defaulters on average.*

$$p_H > \mu(H|R)p_H + \mu(L|R)p_L > \theta p_H + (1-\theta)p_L > \mu(H|0)p_H + \mu(L|0)p_L > p_L.$$

Period 2 Interest Rates

Imperfect information. To determine the interest rates offered in period 2, the banks utilize the default information from the information system to adjust their beliefs about plums and lemons. In consequence, they weight the success probabilities of defaulters with $\mu(H|0)$ and $\mu(L|0)$ and the success probabilities of non-defaulters with $\mu(H|R)$ and $\mu(L|R)$ and a bank's expected period 2 profits are equal to:

$$
\begin{aligned}
E\big[\Pi_2\big] = \frac{1}{b}\Big[& \underbrace{\big(\theta p_{_H} + (1-\theta)p_{_L}\big)}_{\text{Fraction non-defaulters}} \underbrace{\big(\mu(H|R)p_{_H} + \mu(L|R)p_{_L}\big)R_{P,2}(R)}_{\text{Expected profit non-defaulters}} \\
& + \underbrace{\big(\theta(1-p_{_H}) + (1-\theta)(1-p_{_L})\big)}_{\text{Fraction defaulters}} \underbrace{\big(\mu(H|0)p_{_H} + \mu(L|0)p_{_L}\big)R_{P,2}(0)}_{\text{Expected profit defaulters}} - \bar{R}\Big].
\end{aligned}
\tag{5.7}
$$

Competitive pressure ensures that expected profits are equal to 0 and each bank offers the following pooling rate to defaulters:

$$
R_{P,2}(0) = \begin{cases} \frac{\bar{R}}{\mu(H|0)p_{_H}+\mu(L|0)p_{_L}}, & \text{if } p_i' \leq p_i \leq p_i'', \\ R, & \text{if } \frac{\bar{R}}{R} \leq p_i < p_i'(0) \text{ or } p_i'' < p_i \leq 1, \\ \text{no lending}, & \text{otherwise.} \end{cases}
\tag{5.8}
$$

In equation 5.8, p_i' and p_i'' represent the minimum success probabilities that solve the quadratic break-even condition $\big(\mu(H|0)p_{_H} + \mu(L|0)p_{_L}\big)R_{P,2}(0) - \bar{R} \overset{!}{=} 0$ when both types exercise positive effort levels ($p_{_H} > p_{_L} > 0$). For success probabilities outside of these intervals, the pooling rate would exceed the expected return to successful entrepreneurs, and thus the banks cannot charge more than the project return R.

The same logic applies to successful entrepreneurs, and thus the interest rate offered to them is equal to

$$
R_{P,2}(R) = \begin{cases} \frac{\bar{R}}{\mu(H|R)p_{_H}+\mu(L|R)p_{_L}}, & \text{if } p_i'' \leq p_i \leq p_i'', \\ R, & \text{if } \frac{\bar{R}}{R} \leq p_i < p_i' \text{ or } p_i'' < p_i \leq 1, \\ \text{no lending}, & \text{otherwise.} \end{cases}
\tag{5.9}
$$

p_i' and p_i'' solve the bank's break-even condition for successful entrepreneurs $\big(\mu(H|R)p_{_H} + \mu(L|R)p_{_L}\big)R_{P,2}(R) - \bar{R} \overset{!}{=} 0$. Again, banks cannot charge more than the full project return R for values of p_i outside the optimal intervals. In both cases, default and success, no lending occurs for effort levels below $\frac{\bar{R}}{R}$. This also includes situations, where only one type exerts positive effort and the other exerts no effort at all (i.e. $p_{_H} = 0$ or $p_{_L} = 0$).

If one bank would undercut its rivals and charge interest rates below $R_{P,2}(0)$ or $R_{P,2}(R)$ it would win the competition but make a loss on average. More specifically, undercutting $R_{P,2}(0)$ would draw all defaulters and undercutting $R_{P,2}(R)$ all successful entrepreneurs. However, neither of these rates complies with the bank's break-even condition, as they both would underestimate the actual distribution of plums and lemons among defaulters and non-defaulters. For interest rates greater than $R_{P,2}(0)$ or $R_{P,2}(R)$, no entrepreneur would agree to lend and the offering bank would not be able to repay its funding and simply go out of business. In total, banks do not earn any rents on entrepreneurs as the expected gains on plums are offset by the expected losses generated by lemons mixed in the pools of defaulters and non-defaulters.

Perfect information. In contrast to imperfect information, an information system with a value-adding information broker allows each bank learn about the types of entrepreneurs before offering interest rates in period 2. This type information enables them to separate plums and lemons and charge perfectly discriminatory prices conditional on the type assessment in period 1. In consequence, period 2 profits in the perfect information regime add up to

$$E\left[\Pi_2\right] = \frac{1}{b}\Big[\underbrace{\theta p_{_H} R_{H,2}}_{\text{Expected profit plums}} + \underbrace{(1-\theta) p_{_L} R_{L,2}}_{\text{Expected profit lemons}} - \bar{R} \Big]. \tag{5.10}$$

Solving the linear break-even condition $\theta(p_{_H} R_{H,2} - \bar{R}) \stackrel{!}{=} 0$ yields the interest rate offered to plums 5.11, while competition prevents efficient undercutting or the extraction of informational rents.

$$R_{H,2} = \begin{cases} \frac{\bar{R}}{p_H}, & \text{if } p_{_H} \geq \frac{\bar{R}}{R}, \\ \text{no lending}, & \text{otherwise.} \end{cases} \tag{5.11}$$

Consistent with the approach for plums, we find the type-specific interest rate offered to lemons by solving the break-even condition $(1-\theta)(p_{_L} R_{L,2} - \bar{R}) \stackrel{!}{=} 0$ for $R_{L,2}$.

$$R_{L,2} = \begin{cases} \frac{\bar{R}}{p_L}, & \text{if } p_{_L} \geq \frac{\bar{R}}{R}, \\ \text{no lending}, & \text{otherwise.} \end{cases} \tag{5.12}$$

Similar to imperfect information, lending at a rate better (i.e., lower) than $R_{H,2}$ or $R_{L,2}$ would allow a bank to win the competition for plums or lemons while serving them at a loss. Charging an interest rate higher than R (i.e., more than a project creates) on the other hand would push entrepreneurs out of the market, and thus no lending would occur at all. As a result banks earn zero profits on both types.

Period 1 Interest Rates

In period 1, a new generation of entrepreneurs enters the market and engages in a business relationship with the banks for the first time. As a result, banks do not posses any knowledge about individual characteristics of entrepreneurs and and thus offer an uniform pooling rate to plums and lemons to compensate this lack of information. This leads to the following expected profits for period 1:

$$E\big[\Pi_1\big] = \frac{1}{b}\Big[\big(\theta p_{H} + (1-\theta)p_{L}\big)R_{P,1} - \bar{R}\Big]. \tag{5.13}$$

Again, competition erodes monopoly rents, enforces zero profits for all banks, and leads to

$$R_{P,1} = \begin{cases} \frac{\bar{R}}{\theta p_H + (1-\theta)p_L}, & \text{if } p_{H} + p_{L}\frac{(1-\theta)}{\theta} \geq \frac{\bar{R}}{\theta R}, \\ \text{no lending}, & \text{otherwise.} \end{cases} \tag{5.14}$$

where the lower bounds for p_{H} and p_{L} formalize the bank's break-even thresholds for all combinations of entrepreneurial efforts (i.e., $p_{i} \in [0,1]$, $i \in \{H, L\}$). As indicated above, charging a rate higher than $R_{P,1}$ would allow competing banks to undercut profitably, while offering a rate below $R_{P,1}$ would create a loss on average. In addition, for lending to occur, the period 1 interest must not exceed the total return R entrepreneurs can extract from projects in the case of success. With respect to their funding, banks have to pay back their investors at the end of each period and roll over their funding. As a result, they have to break even in each period, and thus cannot take a loss in period 1 in order to win the competition for plums in period 2. Furthermore, period 1 interests between banks are equal in equilibrium, and thus banks share the market equally while making zero profits. More specifically, banks earn a profit on plums, which is offset by the loss incurred from lending to lemons.

Proposition 2. *In equilibrium, interest rates vary with the information available to the banks and rates under perfect information bracket less transparent regimes. In addition, banks can never charge more than the project return without risking a market collapse.*

$$\bar{R} \leq R_{H,2} \leq R_{P,2}(R) \leq R_{P,1} \leq R_{P,2}(0) \leq R_{L,2} \leq R.\text{"}$$

5.4.2 Entrepreneurial Perspective

"In contrast to the assumption in Section 5.4.1, entrepreneurial success is not exogenous but determined by the effort an individual entrepreneur invests in his or her project. As a result, effort choices arise endogenously and depend on the disutility a specific level of effort creates, the interest rates charged by the banks, and project returns. As a result, we characterize the equilibrium efforts of plums and lemons in this section and examine how the public transparency that comes with the use of a blockchain-based information system affects individual choices.

For our comparative analyses, we distinguish between the choices of uninformed and informed entrepreneurs given imperfect and perfect information: Uninformed entrepreneurs maximize their total utility without any information about their peers. This baseline setup represents the characteristics of an information system with a traditional access scope. Informed entrepreneurs on the other hand, can costlessly acquire information about the average success probabilities of plums and lemons from past generations. This setup formalizes the characteristics of a blockchain-based information system, which does not discriminate between users and disseminates (historic) information equally among banks, plums, and lemons. This knowledge allows entrepreneurs to mimic their respective counterparts in period 1 in order to change the banks' perception, and thus interest rates in period 2. Note that the ability to mimic does not depend on the presence of an information broker as entrepreneurs know their own type. Instead, they simply compute the average success probabilities from the default information of past generations to guide their behavior and set period 1 efforts. As a result, the potential behavioral changes are solely driven by the information system's access scope and not its informativeness.

In the following subsections, we derive the equilibrium effort levels and the resulting utility of individual entrepreneurs given imperfect and perfect information on the banking side and a limited and full access scope on the entrepreneurial side. In addition, we utilize comparative statics to investigate, how changing behavior in period 1 affects effort levels in period 2 and under which system configurations (information regimes/access scopes) utility improves. Figure 5.4 summarizes the underlying scenarios, highlights the level of information on each side of the market, and indicates the rationale for the following comparative analysis.

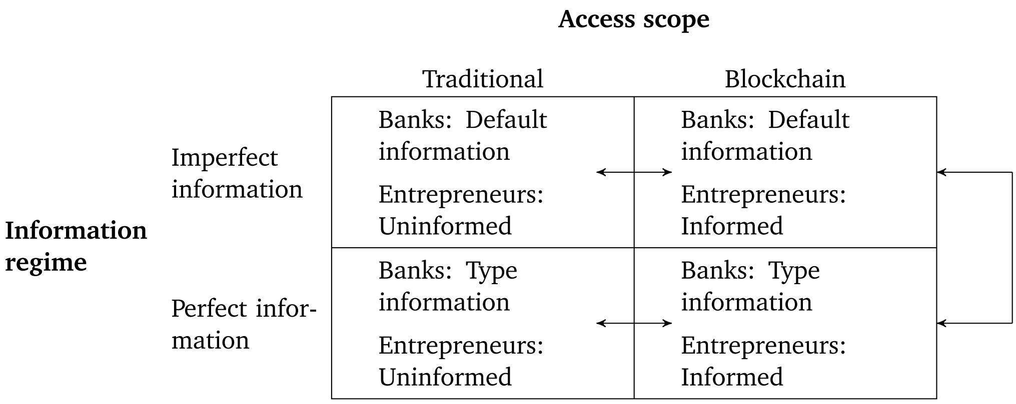


FIGURE 5.4: *Information system configurations and analytic scenarios*
This matrix illustrates the scope of our comparative analysis and summarizes how the information regime and access scope vary with the system's configuration. Arrows indicate comparative analyses.

Uninformed Entrepreneurs

Effort choices under imperfect information. In the imperfect information regime, banks cannot distinguish between plums and lemons but try to approximate entrepreneurial quality based on the observed and shared default information from period 1. As a result, banks offer the pooling rates $R_{P,2}(0)$ and $R_{P,2}(R)$ conditional on period 1 project outcomes. Both, plums and lemons, incorporate this in their individual rationale and the utility over two periods is equal to equation 5.15, where $\Delta R = R_{P,2}(0) - R_{P,2}(R)$ represents the price improvement that results from project success in period 1.

$$
\begin{aligned}
U_i(p_{i,1}, p_{i,2}) &= \underbrace{p_{i,1}(R - R_{P,1}) - a_i p_{i,1}^2}_{\text{Period 1 utility}} + \underbrace{p_{i,2}(R - E[R_{P,2}]) - a_i p_{i,2}^2}_{\text{Period 2 utility}} \\
&= p_{i,1}(R - R_{P,1}) - a_i p_{i,1}^2 + p_{i,2}(R + p_{i,1}\Delta R - R_{P,2}(0)) - a_i p_{i,2}^2.
\end{aligned}
\tag{5.15}
$$

In addition, entrepreneurs do not posses any knowledge about the success probabilities of their peers. As a result, they have no means to guide behavioral changes and choose their efforts to maximize total utility. In consequence, deriving and solving the first order condition for period 1 and period 2 respectively yields the following effort choices:

$$(5.16) \qquad p^U_{i,1} = \frac{R - R_{P,1} + \frac{\Delta R}{2a_i}\big(R - R_{P,2}(0)\big)}{2a_i - \frac{(\Delta R)^2}{2a_i}}, \qquad p^U_{i,2} = \frac{R + p_{i,1}\Delta R - R_{P,2}(0)}{2a_i}.$$

Note that $p^U_{i,t}$ takes the value of 1, if the prospect of high net returns in period 2 would push effort beyond 100% and the value of 0 if no lending occurs[19]. Figure 5.5 picks up the rationale of entrepreneurs outlined in equations 5.15 and 5.16 by illustrating marginal costs ($MC_{i,t}$), revenues ($MR_{i,t}$), and the resulting equilibrium effort levels of plums and lemons in periods 1 and 2[20]. It also highlights that plums always choose higher effort levels than lemons as success is cheaper for them. The magnitude of this difference depends on the quality difference $\Delta a > 0$ between both types. In addition, the prospect of a lower price in period 2 incentivizes entrepreneurs to invest more effort than in period 1.

Proposition 3. *In the imperfect information equilibrium, uninformed plums always exert more effort than uninformed lemons and* $p^U_{H,t} > p^U_{L,t}$ $\forall t \in \{1,2\}$. *In addition, both types decrease effort levels in period 2 and* $p^U_{i,1} > p^U_{i,2}$ $\forall i \in \{H, L\}$.

Effort choices under perfect information. In the perfect information regime, an information broker evaluates period 1 performance of entrepreneurs and thereby allows banks to separate plums and lemons and offer type-specific interest rates to them. In consequence, their behavior in period 1 qualifies entrepreneurs to lend at either $R_{H,2}$ or $R_{L,2} \geq R_{H,2}$ in period 2 and total utility is equal to

$$(5.17) \qquad U_i\big(p_{i,1}, p_{i,2}\big) = \underbrace{p_{i,1}\big(R - R_{P,1}\big) - a_i p^2_{i,1}}_{\text{Period 1 utility}} + \underbrace{p_{i,2}\big(R - R_{i,2}\big) - a_i p^2_{i,2}}_{\text{Period 2 utility}}.$$

[19]No lending occurs in cases, whenever $p^U_{i,t}$ is too low to allow the banks to break even.

[20]The linearity of marginal costs and revenues, and thus the uniqueness of equilibria arises from the quadratic nature of the disutility of effort chosen for this study. Note that more cost functions with a higher degree or other functional forms may lead to multiple equilibria. However, we are confident that for this initial study a simple cost function suffices and leave model setups with more complex or more general functional forms to future research.

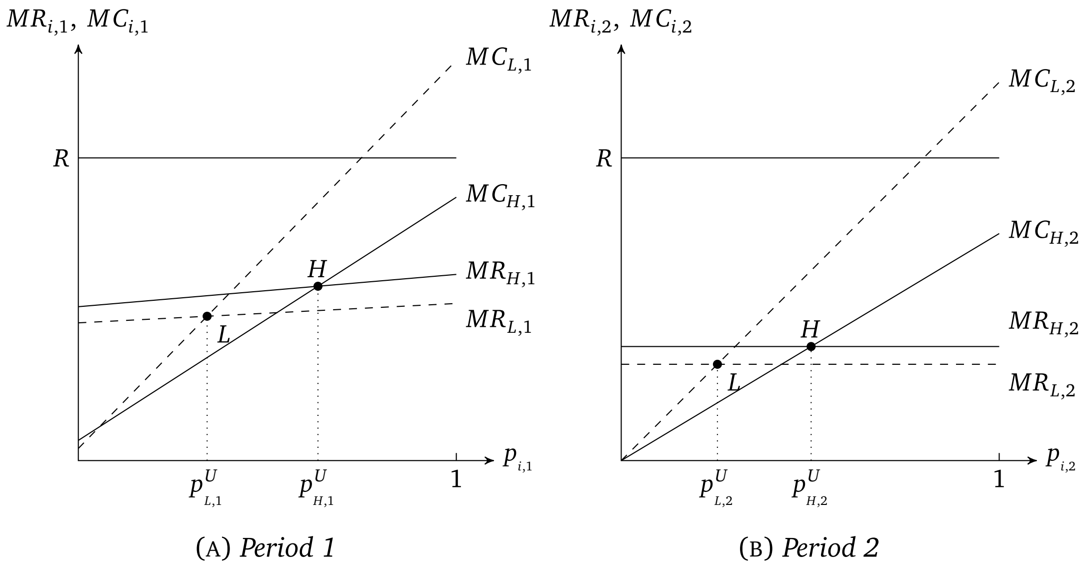


FIGURE 5.5: *Effort choices of uninformed entrepreneurs under imperfect information*
The loci $MR_{i,t}$ depict the marginal return to effort for each type $i \in \{H, L\}$ and period $t \in \{1, 2\}$. Similarly $MC_{i,t}$ illustrates the type- and time-specific marginal disutility (i.e., cost) of effort. Solid lines represent plums and dashed lines lemons. The intersection points H and L define equilibria for plums and lemons, respectively. The horizontal line at R represents the social return to effort in each period.

However, without access to the information system entrepreneurs do not have any information how to behave in period 1, in order to qualify for a lower rate. In consequence, they anticipate interest rates offered in period 2 correctly and in compliance with their type and maximize total utility accordingly. Similar to the imperfect information regime, deriving the resulting first order conditions for both periods and solving them for $p_{i,1}$ and $p_{i,2}$ respectively yields the equilibrium choices for plums and lemons:

$$p^U_{i,1} = \frac{R - R_{P,1}}{2a_i}, \qquad p^U_{i,2} = \frac{R - R_{i,2}}{2a_i}. \tag{5.18}$$

Again, $p^U_{i,t}$ assumes the value of 0 without lending and 1 if net returns are too high. Figure 5.6 illustrates the equilibrium effort choices of plums and lemons in periods 1 and 2 and highlights differences between types and periods. While entrepreneurs are pooled in period 1, the separating equilibrium in period 2 enhances the impact of quality differences and induces plums to increase and lemons to lower their period 2 effort. More specifically, offering discriminatory interest rates disables the stochastic price effect and thereby prevents entrepreneurs from indirectly profiting from higher efforts in period 1.

Proposition 4. *Under perfect information, plums always exert greater equilibrium effort than lemons and* $p^U_{H,t} > p^U_{L,t}$ $\forall t \in \{1,2\}$. *In addition, the separation in period 2 prevents plums from decreasing* ($p^U_{H,2} \geq p^U_{H,1}$) *and lemons from increasing* ($p^U_{H,2} \leq p^U_{H,1}$) *effort levels.*

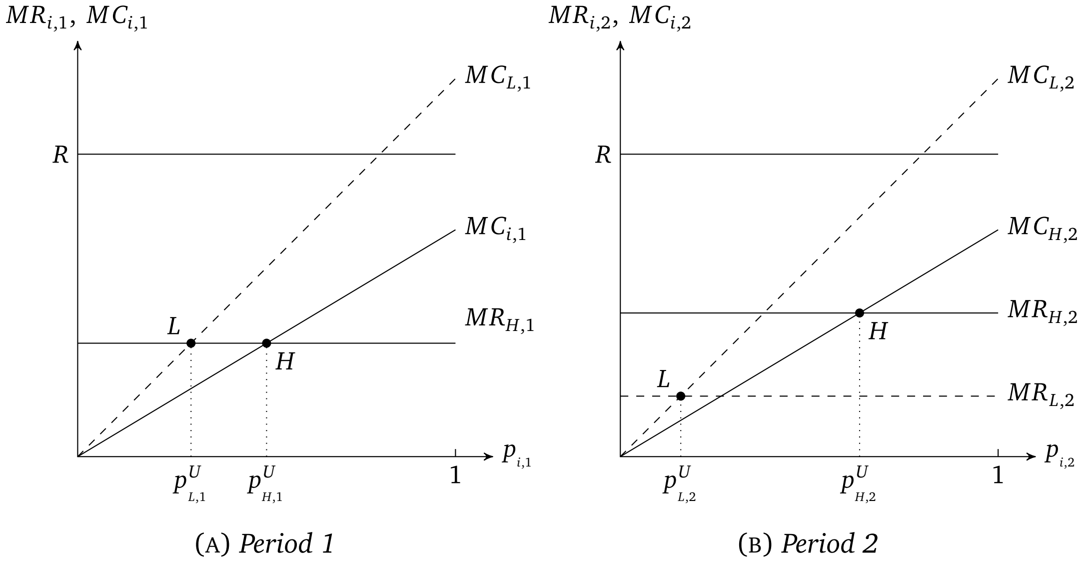


FIGURE 5.6: *Effort choices of uninformed entrepreneurs under perfect information*
The loci $MR_{i,t}$ depict the marginal return to effort for each type $i \in \{H, L\}$ and period $t \in \{1, 2\}$. Similarly $MC_{i,t}$ illustrates the type- and time-specific marginal disutility (i.e., cost) of effort. Solid lines represent plums and dashed lines lemons. The intersection points H and L define equilibria for plums and lemons, respectively. The horizontal line at R represents the social return to effort in each period.

Informed Entrepreneurs

In contrast to uninformed entrepreneurs, informed plums and lemons have access to information about the average success probabilities of previous generations stored in the historic record of the blockchain-based information system. This information allows them to direct their behavior in period 1 and mimic the respective other type $-i$ in order to deceive the bank they are lending from. Formally, we implement this notion by setting period 1 effort levels of informed entrepreneurs to period 1 choices of the respective other type from the uninformed scenario. This way a lemon can look like a plum at the end of period 1 and vice versa.

To investigate whether such behavior occurs, we examine its potential impact on utility in period 1 ($\Delta U_{i,1}$) and period 2 ($\Delta U_{i,2}$). In period 1, mimicking always creates a utility loss, because it requires a shift away from the optimal choices identified in Section 5.4.2. In consequence, period 2 gains have to outweigh this period 1 loss for a given set of effort choices ($p_{i,1}, p_{i,2}$) to make mimicking profitable. Eventually, the total change in utility $\Delta U_i = \sum_{t\in\{1,2\}} \Delta U_{i,t}$ quantifies this net impact of mimicking over time. If total utility increases, mimicking is a dominant strategy. In addition to the motivation to mimic, we dismantle utility effects into their components and identify changes in the realized return to effort, the related cost, and period 2 prices as effect channels.

Recall that the ability to mimic does not depend on the information regime. However, perfect and imperfect information still affect the banking equilibrium (i.e., interest rates), and thus indirectly affect mimicking. Also note that setting period 1 efforts to a fixed value limits the choice of entrepreneurs to the effort exerted in period 2. To find these period 2 choices, we apply the first order condition to entrepreneurial utility and solve it for $p_{i,2}$.

Effort choices under imperfect information. Under imperfect information, banks have to rely on default information to approximate the characteristics of plums and lemons. As a result, they offer the pooling rates $R_{P,2}(0)$ and $R_{P,2}(R)$ conditional on period 1 project outcomes. From an entrepreneurial perspective, the uncertainty on the banking side creates a stochastic price effect ΔP that translates the impact of behavioral changes from period 1 to period 2. Consequently, utility over two periods is equal to

$$
\begin{aligned}
U_i\big(p^U_{-i,1}, p_{i,2}\big) &= \underbrace{p^U_{-i,1}\big(R - R_{P,1}\big) - a_i (p^U_{-i,1})^2}_{\text{Period 1 utility}} + \underbrace{p_{i,2}\big(R - E[R_{P,2}]\big) - a_i p^2_{i,2}}_{\text{Period 2 utility}} \\
&= p^U_{-i,1}\big(R - R_{P,1}\big) - a_i (p^U_{-i,1})^2 + p_{i,2}\big(R + \underbrace{p^U_{-i,1}\Delta R}_{\Delta P} - R_{P,2}(0)\big) - a_i p^2_{i,2}.
\end{aligned} \tag{5.19}
$$

In addition, access to the information system supplies them with behavioral information about plums and lemons and thereby enables mimicking in period 1 by setting period 1 efforts to $p^I_{i,1} := p^U_{-i,1}$. Solving the resulting first order condition with fixed period 1 efforts yields the period effort choices of mimicking entrepreneurs:

$$
p^I_{i,2}(p^U_{-i,1}) = \frac{R + p^U_{-i,1}\Delta R - R_{P,2}(0)}{2a_i}. \tag{5.20}
$$

Again, $p^I_{i,2}$ takes the value 0 without lending and is capped at 1. In period 1, the imbalance between the realized return and the corresponding costs, created by changing efforts, pushes entrepreneurs out of their equilibrium as $MR_{i,1}(p^U_{-i,1}) \neq MC_{i,1}(p^U_{-i,1})$. Moreover, changing period 1 efforts shifts entrepreneurs to a new equilibrium in period 2, where realized returns and costs change according to the new effort choice $p^I_{i,2}(p^U_{-i,1})$. However, this new equilibrium is still influenced by the behavioral change in period 1, as the inter-temporal stochastic price effect indirectly affects the direction and strength of effort changes to period 2. In conjunction with proposition 3 this indicates that plums continue to lower their effort levels in period 2 after behaving like lemons in period 1. The same logic applies to lemons but with an inverse direction as they raise their efforts to mimic plums.

Proposition 5. *When entrepreneurs commit to mimicking under imperfect information and set $p^I_{i,1} := p^U_{-i,1}$, they are locked-in to exert inefficiently low (plums) or high (lemons) effort levels $p^I_{H,2} < p^U_{H,2}$ and $p^I_{L,2} > p^U_{L,2}$ in period 2 as well.*

To examine the impact on utility, we take a closer look at utility changes in periods 1 and 2. For plums, utility in period 1 decreases as the deviation from equilibrium effort to $p^I_{H,1} = p^U_{L,1} < p^U_{H,1}$ (proposition 3) creates an imbalance between marginal costs and returns $MR_{i,1}(p^U_{-i,1}) < MC_{i,1}(p^U_{-i,1})$. As a result, the positive cost effect that comes with lower efforts cannot offset the associated negative return effect. In period 2, plums are furthermore locked-in to their inefficient behavior in period 1 via the price effect and the utility loss spills over to period 2 ($\Delta U_{H,2} < 0$). In total, the utility losses in periods 1 and 2 sum up to $\Delta U_H < 0$ and indicate that mimicking does not provide any benefits to plums.

For lemons, the analysis is a bit more complex: While deviation from equilibrium also leads to utility losses $\Delta U_{L,1} < 0$ in period 1[21], increasing efforts $p^I_{L,1} > p^U_{L,1}$ shifts them to a lower expected interest rate in period 2 (proposition 5). Moreover, the costs for reaching this new equilibrium are borne in period 1, and a utility gain $\Delta U_{L,2} > 0$ occurs in period 2. More specifically, the price effect outweighs the increasing costs associated with higher efforts. However, in total these gains cannot outweigh the loss in period 1, and thus the net utility change $\Delta U_L = \Delta U^U_{L,1} + \Delta U^U_{L,2}$ remains negative as period 1 costs dominate. In consequence, lemons do not profit from changing their behavior in period 1 either.

Proposition 6. *Mimicking does not constitute a dominant strategy under imperfect information as it leads to equilibria with inferior utility $U_i\big(p^U_{-i,1}, p^I_{i,2}\big) < U_i\big(p^U_{i,1}, p^U_{i,2}\big)\ \forall i \in \{H, L\}$.*

[21] In contrast to plums, the increasing efforts of lemons lead to inefficient high productivity levels, where $MR_{i,1}(p^U_{-i,1}) > MC_{i,1}(p^U_{-i,1})$.

As result, proposition 6 indicates that the introduction of a blockchain-based information system does not induce entrepreneurs to deviate from their equilibrium efforts without the analytic service of an information broker. Moreover, if they would exhibit deceptive behavior in period 1 they are locked-in to their inefficient choice and their utility would decrease even further. Figure 5.7 illustrates the behavioral changes of plums and lemons in period 1, their impact on period 2 efforts, the related trade-offs, and the utility gains and losses in an exemplary manner.

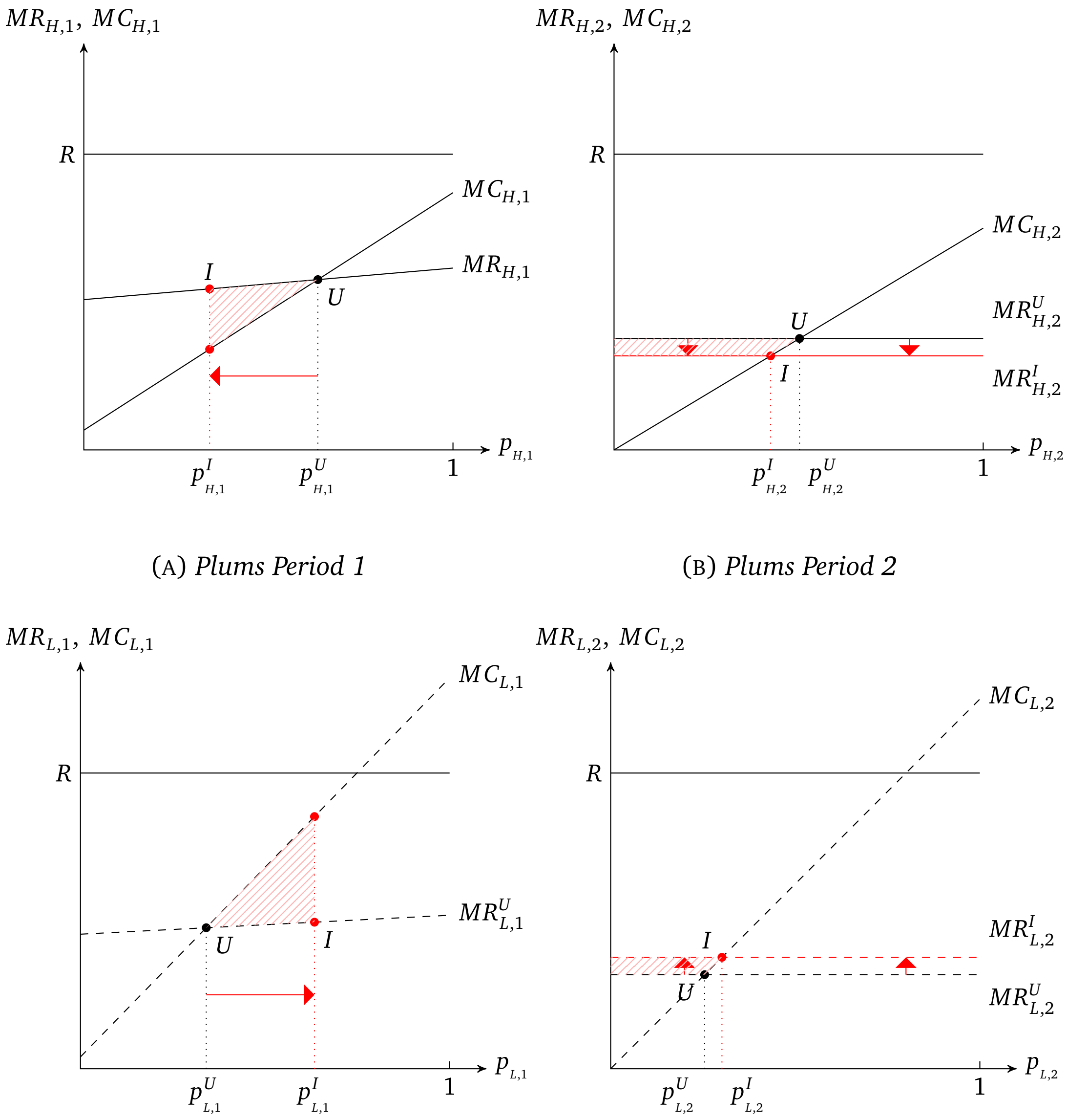
Effort choices under perfect information. Under perfect information, the banks can distinguish between plums and lemons and are able to offer type-specific interest rates $R_{H,2} \leq R_{L,2}$ in period 2. As a result, behavioral changes in period 1 create a deterministic price effect ΔP in period 2 and total utility is equal to

$$U_i\left(p^U_{-i,1}, p_{i,2}\right) = \underbrace{p^U_{-i,1}\left(R - R_{P,1}\right) - a_i(p^U_{-i,1})^2}_{\text{Period 1 utility}} + \underbrace{p_{i,2}\overbrace{\left(R - R_{-i,2}\right)}^{\Delta P} - a_i p^2_{i,2}}_{\text{Period 2 utility}}. \tag{5.21}$$

Moreover, the extended access scope of the information system enables plums to learn about the average success probabilities of their respective counterparts and eventually mimic them. In consequence, fixing period 1 efforts to $p^I_{i,1} := p^U_{-i,1}$ and solving the resulting first order condition for $p_{i,2}$ yields the period 2 choices mimicking entrepreneurs (5.22).

$$p^I_{i,2} = \frac{R - R_{-i,2}}{2a_i}. \tag{5.22}$$

Like before, $p^I_{i,2}$ takes the value of 0 without lending and cannot be higher than 1. However, the deviation from the uninformed equilibrium in period 1 creates an imbalance between returns and costs as $MR_{i,1}(p^U_{-i,1}) \neq MC_{i,1}(p^U_{-i,1})$ and leads to new period 2 equilibria for both types. In these equilibria, banks charge either $R_{H,2}$ or $R_{L,2}$ to entrepreneurs who pretended to be plums or lemons in period 1. As a result, decreasing period 1 efforts to $p^U_{L,1}$ crushes plums' and increasing period 1 efforts to $p^U_{H,1}$ boosts lemons' net returns in period 2. Similar to the imperfect information regime, this indicates that mimicking in period 1 is followed by a behavioral change with the same direction in period 2.



(A) *Plums Period 1*

(B) *Plums Period 2*

(C) *Lemons Period 1*

(D) *Lemons Period 2*

FIGURE 5.7: *Effort choices of informed entrepreneurs under imperfect information*
The loci $MR_{i,t}$ depict the marginal return to effort for each type $i \in \{H, L\}$, period $t \in \{1, 2\}$. Similarly $MC_{i,t}$ illustrates the type- and time-specific marginal disutility (cost) of effort. Solid lines represent plums and dashed lines lemons. If marginal returns or costs change with the information regime we indicate this difference with U for uninformed and I for informed entrepreneurs. Otherwise, no indication is given. Behavioral changes that come with the blockchain regime in period 1 and the resulting impact in period 2 are marked in red. More specifically, the utility changes $\Delta U^j_{i,t}$ of plums and lemons are illustrated by a filling with a red pattern, while red arrows indicate the direction of changes and corresponding effects. In period 1, the intersection point U defines the equilibrium before blockchain usage, whereas I represents the adjusted behavior of mimicking entrepreneurs. Similarly, in period 2 U highlights the equilibrium efforts before blockchain usage and I the equilibrium outcomes that result from deceptive behavior in period 1. The horizontal line at R represents the social return to effort in each period.

Proposition 7. *Consistent with the imperfect information regime, entrepreneurs who commit to mimicking under perfect information and set* $p^I_{i,1} := p^U_{-i,1}$*, are locked-in to their behavior and furthermore decrease (plums) or increase (lemons) period 2 effort. In consequence,* $p^I_{H,2} < p^U_{H,2}$ *and* $p^I_{L,2} > p^U_{L,2}$.

From a utility perspective, plums still experience a utility loss $\Delta U_{H,1} < 0$ when they lower period 1 effort to an inefficiently low return level $MR_{i,1}(p^U_{-i,1}) < MC_{i,1}(p^U_{-i,1})$. The same holds true in period 2, where the inefficient behavior from period 1 spills over to period 2 via an increased interest rate $R_{L,2} \leq R_{H,2}$ and creates an additional utility loss $\Delta U_{H,2} < 0$. In total, this finding is consistent with the prediction for imperfect information and highlights that plums are not able to derive any utility gains from mimicking - independent of the information regime.

Proposition 8. *Under perfect information, mimicking does not constitute a dominant strategy for plums as it leads to an equilibrium with inferior utility* $U_H\big(p^I_{H,1}, p^I_{H,2}\big) < U_H\big(p^U_{H,1}, p^U_{H,2}\big)$.

Similar to plums, lemons also make a suboptimal choice in period 1 ($MR_{L,1}(p^U_{H,1}) > MC_{L,1}(p^U_{H,1})$) and loose utility as a result ($\Delta U_{L,1} < 0$). However, the deterministic nature of the inter-temporal price effect allows them to maximize their gains from mimicking. More specifically, in combination with the resulting return effect, the price effect outweighs the costs associated with higher efforts and creates a utility gain in period 2 ($\Delta U_{L,2} > 0$). Eventually, the utility gains in period 2 are strong enough to offset the costs of mimicking from period 1 and total utility increases $\Delta U_L > 0$.

Proposition 9. *In contrast to plums, the historic performance information disclosed by a blockchain-based system enables informed lemons to reach a new equilibrium with* $U_L\big(p^I_{L,1}, p^I_{H,2}\big) > U_L\big(p^U_{L,1}, p^U_{L,2}\big)$. *In consequence, mimicking is a dominant strategy under imperfect information.*

Moreover, the resulting net utility gain depends on the difference between the relative interest rate improvement (relative price effect) and the increase in the disutility of effort it entails (relative cost effect).

$$\Delta U_L = \underbrace{\frac{(R-R_{P,1})^2}{4a_L}\Bigg(\underbrace{\frac{(R_{L,2}-R_{H,2})(2R-R_{H,2}-R_{L,2})}{(R-R_{P,1})^2}}_{\text{Relative price effect}} - \underbrace{\frac{(a_L-a_H)^2}{a_H^2}}_{\text{Relative cost effect}}\Bigg)}_{\text{Net utility gain}} > 0. \tag{5.23}$$

In total, this indicates that the introduction of a blockchain-based information system only induces lemons to mimic plums if banks can be deceived (i.e., when they have type information). Plums on the other hand, do not experience any benefits from additional information. In addition, mimicking entrepreneurs are locked-in to their inefficient choice - irrespective of their type. Figure 5.8 summarizes these findings and illustrates the behavioral changes of plums and lemons in period 1, their impact on period 2 efforts, and indicates the utility gains and losses incurred in both periods."

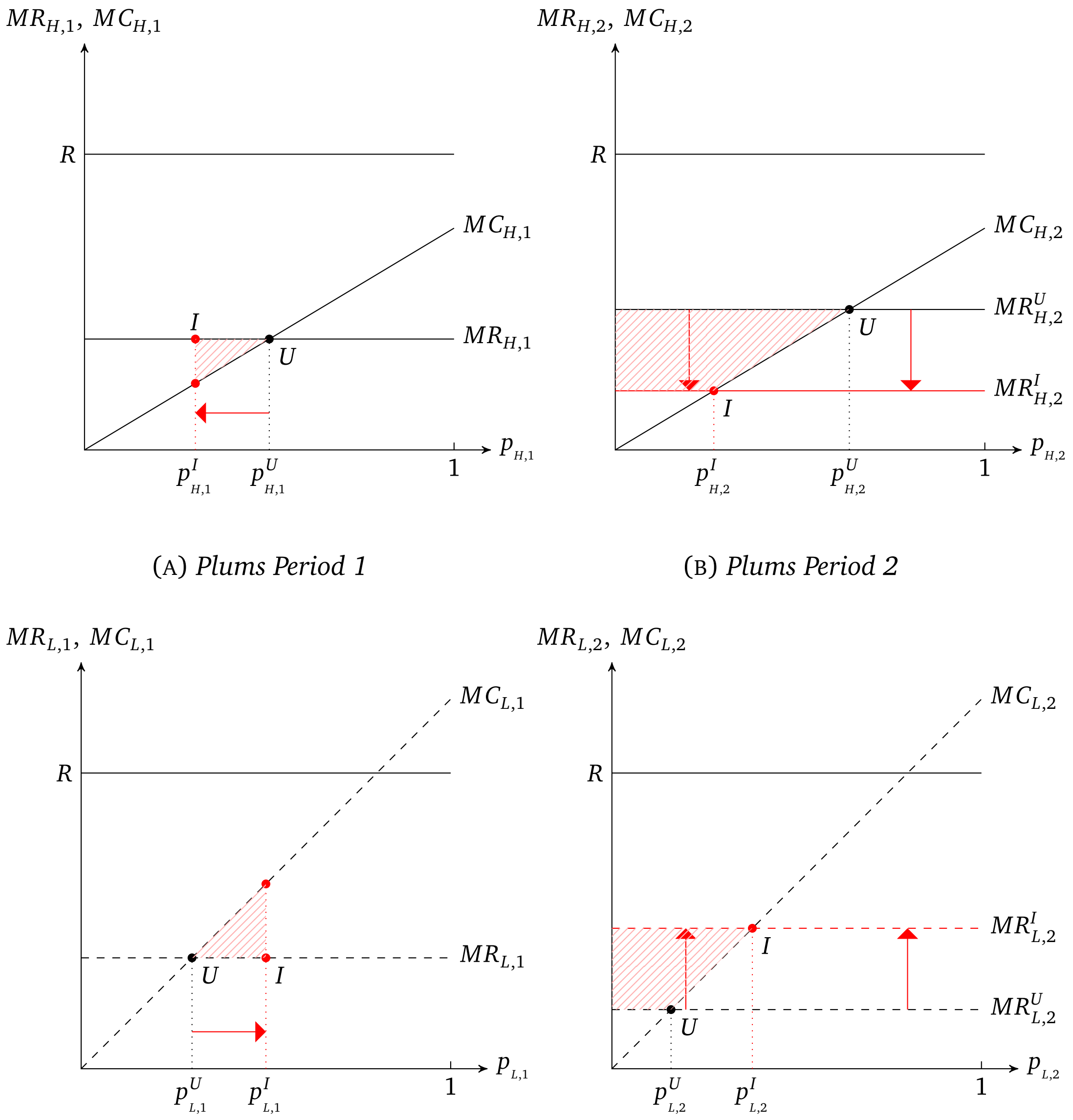
5.4.3 Market Perspective

"Section 5.4.2 highlights that entrepreneurs - or more specifically lemons - only have an incentive to mimic their counterparts when banks can observe type information. Plums on the other hand have no incentive to do so, irrespective of the information regime. In consequence, we focus on the perfect information regime in our welfare analysis. Moreover, we set the interest rates offered and consequently charged by banks as exogenously given, while their order is defined by proposition 2. This ensures the validity of our comparative analysis and formalizes the notion that banks use the information from past generations to determine the interest rates offered to the current one. In addition, banks act as mediators between the capital market and entrepreneurs, and thus do not generate welfare directly. Taking these considerations into account, we define total welfare as the aggregate utility (Lange, 1942) of all mimicking lemons and unmodified plums:

$$\begin{aligned}W\Big(p^U_{H,1}, p^U_{H,2}, p^I_{L,1}, p^I_{L,2}\Big) &= \underbrace{\theta\big[\underbrace{p^U_{H,1}R - \bar{R} - V_H(p^U_{H,1})}_{\text{Period 1}} + \underbrace{p^U_{H,2}R - \bar{R} - V_H(p^U_{H,2})}_{\text{Period 2}}\big]}_{\text{Welfare from plums}} \\ &\quad + \underbrace{(1-\theta)\big[\underbrace{p^I_{L,1}R - \bar{R} - V_L(p^I_{L,1})}_{\text{Period 1}} + \underbrace{p^I_{L,2}R - \bar{R} - V_L(p^I_{L,2})}_{\text{Period 2}}\big]}_{\text{Welfare from lemons}}\end{aligned} \tag{5.24}$$

To evaluate the welfare effects of blockchain adoption, we compare equation 5.24 with the welfare generated by uninformed entrepreneurs while holding the information regime fixed (perfect information). The resulting welfare change ΔW is defined as the difference between welfare in the informed scenario and completely uninformed entrepreneurs.

$$\Delta W = W(p^U_{H,1}, p^U_{H,2}, p^I_{L,1}, p^I_{L,2}) - W(p^U_{H,1}, p^U_{H,2}, p^U_{L,1}, p^U_{L,2}) = (1-\theta)\Delta U_L. \tag{5.25}$$



(A) *Plums Period 1*

(B) *Plums Period 2*

(C) *Lemons Period 1*

(D) *Lemons Period 2*

FIGURE 5.8: *Effort choices of informed entrepreneurs under perfect information*

The loci $MR_{i,t}$ depict the marginal return to effort for each type $i \in \{H, L\}$, period $t \in \{1, 2\}$. Similarly $MC_{i,t}$ illustrates the type- and time-specific marginal disutility (cost) of effort. Solid lines represent plums and dashed lines lemons. If marginal returns or costs change with the information regime we indicate this difference with U for uninformed and I for informed entrepreneurs. Otherwise, no indication is given. Behavioral changes that come with the blockchain regime in period 1 and the resulting impact in period 2 are marked in red. More specifically, the utility changes $\Delta U^j_{i,t}$ of plums and lemons are illustrated by a filling with a red pattern, while red arrows indicate the direction of changes and corresponding effects. In period 1, the intersection point U defines the equilibrium before blockchain usage, whereas I represents the adjusted behavior of mimicking entrepreneurs. Similarly, in period 2 U highlights the equilibrium efforts before blockchain usage and I the equilibrium outcomes that result from deceptive behavior in period 1. The horizontal line at R represents the social return to effort in each period.

Eventually, ΔW depends on the share of lemons in the market $(1-\theta)$ and is driven by the utility gains they experience from mimicking (equation 5.23). The utility of plums does not affect welfare, because they do not change their behavior. In addition, there is no welfare effect on the banking side, as banks earn zero profits in their role as mediators and their costs of capital are constant and equal to $\bar{R}$.

Proposition 10. *Driven by the utility gains of mimicking lemons, the introduction of a blockchain-based information system increases the total welfare of our economy as $\Delta W > 0$.*

However, this entrepreneurial perspective on welfare does not consider the special role of banks and how they are affected by the behavioral changes of informed lemons. As mediators between the capital market and entrepreneurs, they manage entrepreneurial risks and distribute funds to plums and lemons in each period. To do so, they assess entrepreneurial quality, pool and separate risk accordingly, and offer credit conditional on their assessment, while perfect competition enforces the zero profit constraint. In consequence, they build their assessment on the historic information acquired from the information system and offer risk-adjusted interest rates to break-even given the average success probabilities learned from past generations. In the current generation, the introduction of a blockchain-based information system supplies entrepreneurs with additional information that induces lemons to change their behavior. As a result, the actual effort levels exerted in period 1 and 2 do not comply with the break-even conditions $E[\Pi_1] \stackrel{!}{=} 0$ and $E[\Pi_2] \stackrel{!}{=} 0$ anymore. In the period 1 pooling equilibrium this is not harmful as efforts of lemons increase ($p^I_{L,1} > p^U_{L,2}$) and thus the realized profit $\Pi^I_1 > 0$. In period 2 however, the realized profit $\Pi^U_2 < 0$ as mimicking lemons wrongfully qualify for $R_{H,2}$ and the quality difference $\Delta a > 0$ prevents risk-adequate effort levels.

Proposition 11. *While the behavioral change of lemons improves welfare for the current generation, it also hurts the zero-profit constraint of the lending banks in period 2 as $p^U_{H,2} > p^I_{L,2}$. As result banks are not able to roll over funding at the end of period 2, go bankrupt, and future generations of entrepreneurs are cut off the capital market.*

Note that in all other scenarios, the introduction of a blockchain-based information system does not affect welfare as there is no incentive for rational agents to adapt their behavior given additional quality information.

However, when entrepreneurs are prone to irrational behavior - as it is often the case in retail markets[22] - deviation from the uniformed equilibrium can harm welfare significantly ceteris paribus. For mimicking plums this is always the case, because they have to lower effort levels in period 1 to mimic lemons (proposition 3 and 4) and the resulting lock-in effects (proposition 5 and 7) push them to equilibria with lower utility in both periods (proposition 6 and 8). In addition, banks are not able to break even on them anymore, go bankrupt at the end of period 1, and the market collapses. Lemons on the other hand always experience a utility gain in period 2, because they receive a better price when mimicking plums in period 1. Under imperfect information however, this gain does not outweigh the costs of mimicking created in period 1 and total utility decreases (proposition 6). While raising effort levels in period 1 is beneficial for banks, the same rationale as in proposition 11 drives them into banruptcy in period 2. Possible reasons for irrational behavior include the misinterpretation (i.e., wrong assessment) of historic data, the limited ability of entrepreneurs to access and process the information from the blockchain-based information system, or simply flawed strategic rationales."

5.5 Discussion

"However, the analysis in Section 5.4 does not consider long term effects that may arise with a longer lifespan of individual generations or overlapping generations. Figure 5.9 illustrates these model variations and forms a foundation for the following discussion of related effects.

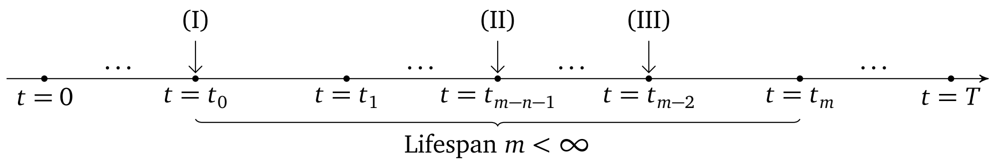
In the case of a longer lifespan, generations live for $m \in (2, \infty)$ periods instead of two. As a result, lemons can choose to change their behavior and mimic plums at the beginning of each period. Panel A of figure 5.9 illustrates a generation with a m period lifespan and highlights potential timings for opportunistic behavior. If they decide to mimic before the first period, they can improve loan conditions in period 2 but cut themselves off the capital market for all subsequent periods (I). A behavioral change before some intermediate period $m-n-1$ where $2 < n < m$ creates a positive utility in each period including $m-n-1$ and an additional utility improvement in period $m-n$ (II). However, as a a result of the market collapse at the end of period $m-n$, entrepreneurs are not able to implement any more projects and utility is equal to zero for the rest of their life.

[22] There is a multitude of studies that show the existence of irrational behavior empirically (Poteshman and Serbin, 2003; Shapira and Venezia, 2001) and analyze the underlying biases and effects (Patel et al., 1991; Subrahmanyam, 2007).

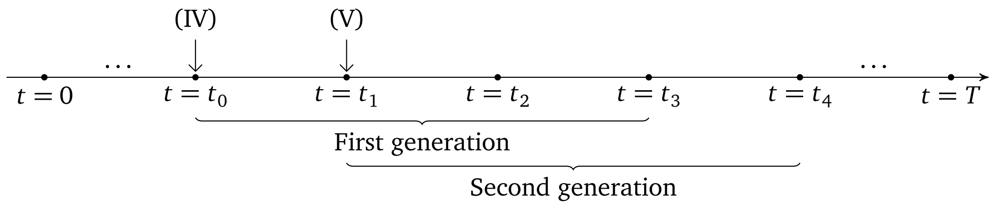
If lemons deceive banks in penultimate period $m-2$, they can fund and implement a project in each period and increase their utility in the last period (III). In addition, they are not affected by the market collapse at the end of period m and the following generations have to suffer the consequences. Equation 5.26 summarizes the total utility generated in each case (I - III). Moreover, from $t_2 < t_{m-n-1} < t_m$ directly follows that betraying in the penultimate period $m-2$ is the best strategy to maximize utility, if we assume that interest rates are constant over time.

$$\underbrace{\sum_{t=t_1}^{t_2} U_{L,t} + \Delta U_L}_{\text{(I)}} < \underbrace{\sum_{t=t_1}^{t_{m-n-1}} U_{L,t} + \Delta U_L}_{\text{(II)}} < \underbrace{\sum_{t=t_1}^{t_m} U_{L,t} + \Delta U_L}_{\text{(III)}} . \tag{5.26}$$

Proposition 12. *If the lifespan of a generation increases to $m < \infty$, mimicking in the penultimate period $m-2$ is a dominant strategy for lemons.*



(A) *Generations with a longer lifespan*



(B) *Overlapping generations*

FIGURE 5.9: *Model variations*

This figure illustrates the timelines of actions of opportunistic lemons with a lifespan of $m < \infty$ periods as well as lemons with overlapping generations. In addition, $2 < n < m$. Different cases of opportunistic behavior are highlighted with arrows and superscripts (I) to (V).

To discuss to effects of overlapping generations, we assume that each generation lives for three periods and a new generation arrives at the market in every period. Panel B illustrates resulting population structure for two generations. Each generation has the chance to mimic the respective other type within their own generation in each period. However, according to proposition 12, lemons do not mimic plums between $t = t_0$ and $t = t_1$ (IV).

Instead, they increase their effort levels between t_1 and t_2 to extract the utility gain ΔU_L at the end of the third and last period of their life (V). As a result, the market collapses at $t = t_3$ and the second generation is not able to get funding for the third and last project. If the lemons of the second generation are aware of this behavioral pattern, it is optimal for them to deceive banks and mimic plums between t_1 and t_2 (i.e., the first period of their life) as well (V). The resulting utility is equal to $U_{L,t_2} + U_{L,t_3} + \Delta U_L$, which is greater than $U_{L,t_2} + U_{L,t_3}$. Note that this notion of overlapping generations does not consider interconnections between generations, such as ancestry or heritage. In addition, we do not consider changing average success probabilities as a result of the behavioral changes of the first generation.

Proposition 13. *If entrepreneurial generations overlap each other, the first generation of lemons that reaches the last period of their life triggers a cascade of opportunistic behavior. As a result, all subsequent generations that still overlap with the first one will mimic in the same period.*

In addition, there are some other minor model variations and limitations, we will discuss briefly here. First, repeating the two-period lending game with an infinite number of generations does not affect our findings in the long run. The market collapses, when one generation of lemons decides to mimic plums and consequently all subsequent generations loose access to the capital market. It is also important to note that the first generation is not able to deceive, because there is no information to guide their behavioral change stored in the information system at $t = 0$. Second, in Section 5.3 we assumed that neither banks nor entrepreneurs discount profits or utility. Introducing a positive discount rate on the entrepreneurial side would emphasize the timing of utility changes as today's utility becomes more valuable than tomorrow's. In consequence, the costs of mimicking in period 1 would increase, while its gains in period 2, and thus ΔU_L would decrease. Third, relaxing competition in the banking sector - for instance via relationship information - would allow banks to extract rents from an informational monopoly, and thereby increase their ability to compensate violations of their break-even condition. Similarly, a risk averse banking sector would incorporate a safety cushion in the break-even condition, and thus become more robust towards opportunistic behavior. Finally, good entrepreneurs do not drop out of the market, because they remain unaffected by the behavior of lemons and always experience positive utility when implementing a project - if their effort levels are high enough to get a funding. In a dynamic world however, this may change as banks adapt their behavior to take the consequences of misbehaving lemons into account."

5.6 Concluding Remarks

"In total, the analyses in Section 5.4 and the extensions discussed in Section 5.5 help us to derive several lessons for blockchain ventures in research and practice. First and foremost, they relate to research question 8 and indicate that the public disclosure of quality information can give rise to opportunistic behavior. More specifically, we find that lemons can increase their utility by behaving opportunistically, when information brokers, such as credit bureaus or rating agencies, enhance the informativeness of the stored and shared data. In such market environments, increasing period 1 efforts gives lemons access to better prices in period 2. To determine which effort levels qualify them as plums, they use the information from the blockchain's public record to learn about the average quality of plums and lemons and adapt their behavior accordingly. The resulting utility gain is more pronounced for greater price improvements, lower quality differences, and lower quality in general. In contrast, we do not find any incentives for plums to behave opportunistically. Moreover, their decreasing utility over both periods is in line with prior research such as Padilla and Pagano (2000) and outlines the disciplinary effect increasing transparency can have. In opaque markets, banks pool plums and lemons conditional in period 1 project outcomes and neither type has an incentive to behave opportunistically.

Irrespective of the information regime, we furthermore observe lock-in effects across all analytic scenarios and entrepreneurial types. As a result, plums (lemons) who lower (increase) their efforts in the first period will do the same in the subsequent one. The severity of this effect is driven by the transparency of a market as well as price and quality differences and reinforces the consequences of opportunistic behavior in period 1. While extraneous for rational agents, erroneous decisions made by irrational agents can spill over to period 2 and harm utility permanently as entrepreneurs are committed to their inefficient choice from period 1.

From the market perspective taken in research question 9, the opportunistic behavior of lemons creates a welfare gain within their own generation. This gain depends on the share of lemons $(1-\theta)$ and is driven by their utility gains of mimicking. However, the resulting unjustified access to better loan conditions harms the break-even condition of banks and prevents them from breaking even. As a result, the banks are not able to roll over funding, the supply side of the market collapses, and future generations are cut off from funding. In all other scenarios, the combination of irrational behavior of entrepreneurs and the following lock-in effects would harm welfare through a negative utility, while the market still collapses.

Eventually, the findings hold across various model variations, while generations with a longer lifespan experience an endgame effect and opportunistic behavior cascades through overlapping generations. In addition, we are confident that they hold implications that go beyond the market for credit and apply to other lemon markets, such as the used car or the insurance market, as well.

With respect to practical considerations, these findings indicate that blockchain adoption can lead to market collapses in markets with a high level of transparency and intense competition. To mitigate these issues, blockchain designers could refrain from using smart contracts to implement value-adding services and analytic applications on the infrastructure level. In addition, using blockchain-based systems in environments prone to irrational behavior - such as retail markets - can harm welfare and impede a market's functioning permanently.

In aggregate, we contribute to three research streams: First, we contribute to the growing body of literature on the economics of blockchain by shedding light on the impact of the blockchain's public transparency paradigm on behavioral patterns in markets exposed asymmetric information. Second, we contribute to the field of banking research by examining the effect of the disclosure of quality information to the broad public. As a result, our findings hold implications for the design of information sharing arrangements as well open-banking initiatives and transparency regulations (Gomber et al., 2018; Gozman et al., 2018; Anagnostopoulos, 2018). Third, we contribute to the body of blockchain adoption literature by highlighting the risks of market-oriented application contexts.

However, this initial study is limited in various ways and calls for a multitude of model extensions: First and foremost, we limit our analyses to comparative statics and believe that considering dynamic interactions between banks and entrepreneurs could add another interesting dimensions to our results. We also set the cost for information sharing and acquisition - and thus the information system itself - to zero for both sides of the market. While adding a constant cost factor on both sides of the market would simply shift interest rates to a higher and utility to a lower level, modelling the actual costs of a blockchain-based systems is more complex. In addition, we do not consider switching costs, refrain from using a generalized functional form of the disutility of effort, and exclude evolution of wealth on the entrepreneurial side and the role relationship information and opportunistic behavior on the banking side. These aspects are interesting and relevant extensions to consider in the context of public transparency and provide great opportunities for future research."

Chapter 6

The Quality of Decentralized Markets

This chapter is based on the working paper "Trading Stocks on Blocks - The Quality of Decentralized Markets". The paper is co-authored by Vincenzo Marino, Daniel Englert, and Christof Weinhardt, part of the KIT working paper series in economics, and available on SSRN. It was furthermore presented at FinteQC 2018 and CCConf 2018. Direct citations are highlighted by double quotes.

Manuscript details:
Notheisen, B., Marino, V., Englert, D., & Weinhardt, C.,
Trading Stocks on Blocks - The Quality of Decentralized Markets,
KIT Working Paper in Economics No. 129, SSRN Electronic Journal, 18 January 2019,
https://doi.org/10.5445/IR/1000092485, https://ssrn.com/abstract=3318181.

6.1 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), Notheisen et al. (2017), and Daian et al. (2019) begin to explore trader behavior, market design, and technological issues.

However, while practical approaches promise fair and transparent trading (Daian et al., 2019), 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 exchange 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 et al. (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 the 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 et al., 2017; Hawlitschek et al., 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 the 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."

6.2 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 6.5, 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."

6.2.1 The Concept of Blockchain-based Markets

"In financial markets, the potential of decentralized applications goes beyond the tokenization of assets and crypto assets (Catalini and Gans, 2018; Peterson, 2018) and include transparent transaction systems (Notheisen et al., 2017), efficient settlement systems (Mills et al., 2016; Chiu and Koeppl, 2018), and decentralized stock markets (Lee, 2016; Jessel and Marshall, 2016; Notheisen et al., 2017; Workie and Jain, 2017). As a result, blockchain technology promises improvements in corporate governance, transparency, and liquidity (Catalini and Gans, 2016; 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 technology's block-based nature limits the transaction throughput and shifts trading from continuous to discrete time (Section 4.3; Notheisen et al., 2017).

In consequence, the first practical decentralization efforts focus on the clearing and settlement processes instead of market mechanisms. In 2015 for instance, the Australian stock exchange ASX commenced to settle equity transactions with a blockchain-based system[23] in the near future. In recent years, we furthermore observe a growing number of DEX concepts and market platforms that trade a variety of assets. These DEXs operate continuous limit order books in a decentralized fashion, while smart contracts assume the role of traditional market operators (Daian et al., 2019).

Augur and Gnosis for instance, aim to decentralize prediction markets[24] 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 A.4 in appendix A.5 provides a brief overview of selected ventures.

[23]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.

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

Academic literature, on the other side, has only started to explore the increasingly popular phenomenon of DEXs[25] Patel (2014), for instance, presents a theoretical implementation concept, while Clark et al. (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 by decreasing the costs of finding liquidity. Daian et al. (2019) furthermore show that malicious users use arbitrage bots to exploit the distributed and discrete nature of DEXs to frontrun. Notheisen et al. (2017) 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 the transaction throughput of a blockchain-based exchange, and thus affect the way new orders are processed. In the following, we define 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 et al., 2016). In Ethereum, the size of a block is also affected by the gas limit and currently between 20 and 30 kilobytes (Buterin, 2013). 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[26]. However, in blockchain-based markets, the impact of the underlying blockchain configuration goes beyond scalability but also affects market outcomes."

[25]Besides DEXs, recent research about decentralized markets centers on financial intermediation and search and bargaining costs in over-the-counter markets. For assets traded on multiple exchanges for instance, Malamud and Rostek (2017) find that decentralization improves the allocation of risk to traders and increases price impact. Albin and Foley (1992) simulate bilateral trades (i.e., the communication of trade intentions and bargaining efforts) among geographically dispersed agents and find a positive relationship between decentralization and the allocation of resources. The resulting outcomes depend on information and communication costs (Albin and Foley, 1992) and heterogeneity among traders' valuations intensifies the price impact of search frictions (Hugonnier et al., 2014). From a market perspective, intermediation is costly (Babus and Hu, 2017) but alleviates search frictions (Li and Schürhoff, 2019) and improves information diffusion (Babus and Kondor, 2018). However, to our knowledge the studies in this field focus mostly on trader characteristics and macroeconomic effects. Thus, the implications for the microstructure of blockchain-based markets are limited.

[26]For information on average BSs we refer to blockchain.com for Bitcoin and etherscan.io for Ethereum.

6.2.2 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 6.1. 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 operator 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, a market'S 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 Röell, 1996). In addition, platform characteristics and market outcomes are shaped by external factors, such as regulatory constraints, the current state of technology, and competition.

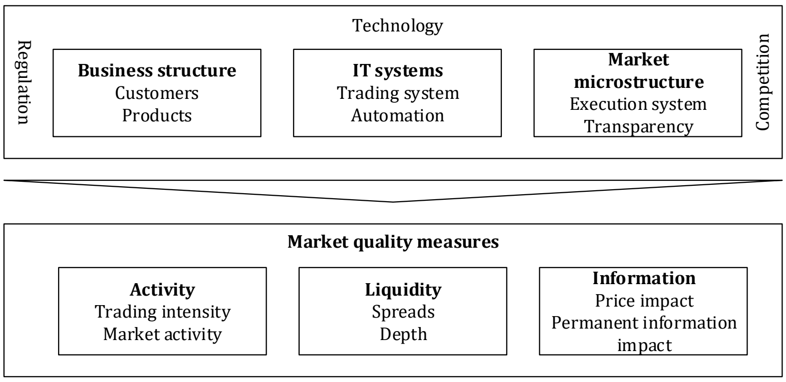


FIGURE 6.1: *Market quality framework*
This figure illustrates the market quality framework introduced by Zhang et al. (2011) and presents the three dimensions of market quality as well as their determinants .

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 et al., 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, 2003). 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, the required order-level data may be hard to obtain (Hasbrouck, 1991b). In contrast, volume- or quantity-based measures such as Amihud (2002)'s illiquidity measure or the order book imbalance (Cao et al., 2009; Brogaard et al., 2014) provide a more coarse but robust and readily available means to study market quality developments.

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 et al., 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 6.4.1."

6.2.3 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 blockchain-based 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 et al., 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 et al., 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 Röell, 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 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 et al., 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 high frequency traders. 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."

6.2.4 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 DEXs, 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 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 10. *How do the size and frequency of database updates (i.e., blocks) impact the activity, liquidity, and price formation on blockchain-based markets?*

By answering this research question, we aim to evaluate the potential of intermediary-free market setups, assess their quality characteristics, and identify facilitating and impeding factors as well as 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."

6.3 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[27] 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 6.5."

6.3.1 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.

[27] 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.

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 the remaining orders. 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, and the limit price. Based on this sample, we finally adjust trade prices, quantities, and limits by stock splits that occurred during the observation period[28]. 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[29]. 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.

[28]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.

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

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 for each stock i.

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 6.1 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 DEX 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[30].

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 6.1. The minimum and maximum configurations also consider shifts by one standard deviation (column 4 in table 6.1). As a result, we calibrate the minimum, medium, and maximum BS for stock i's market by equation 6.1, where $\bar{x}_i$ denotes the average number of trades per day and σ_i the corresponding standard deviation.

[30]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.

$$\text{(6.1)} \quad \begin{aligned} \text{BS}_i^{min}(\text{BCT}) &= max\left\{\left\lceil \frac{\bar{x}_i - \sigma_i}{14 \cdot \frac{60}{\text{BCT}}} \right\rceil, 2\right\}, \\ \text{BS}_i^{med}(\text{BCT}) &= max\left\{\left\lceil \frac{\bar{x}_i}{14 \cdot \frac{60}{\text{BCT}}} \right\rceil, 2\right\}, \\ \text{BS}_i^{max}(\text{BCT}) &= max\left\{\left\lceil \frac{\bar{x}_i + \sigma_i}{14 \cdot \frac{60}{\text{BCT}}} \right\rceil, 2\right\}. \end{aligned}$$

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 6.1 report the BS of all 9 configurations and 30 stocks.

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 table 6.1, and feed the resulting market mechanism with the input sample from the previous subsection. In consequence, the replication of market outcomes is guided by the following steps:

First, the pre-processed time-stamped buy and sell orders from the input sample are submitted to the market, while order books collect them in ascending order (time). Based on this list, the first order of a day triggers 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.

(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 Börse 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 6.1: *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. Columns 5 to 13 report the BS for all 9 blockchain configurations based on equation 6.1.

Second, 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 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.

Finally, 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[31]. 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 with unexecuted orders, while fully executed orders are removed. Figure 6.2 summarizes these steps and highlights the integration of the BS and the BCT parameters within the replication of market outcomes.

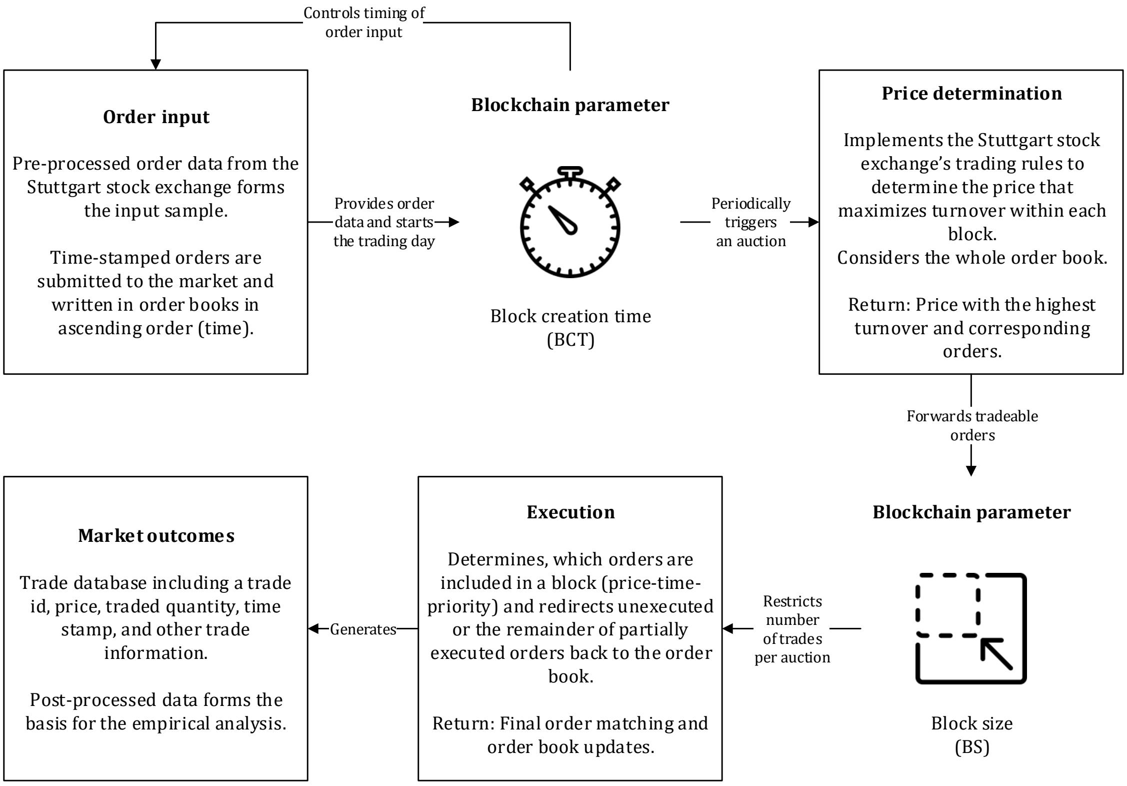


FIGURE 6.2: *Process steps to replicate market outcomes*

The following paragraphs introduce the price determination, the following execution, and the resulting market outcomes in detail. In addition, appendix B.3 illustrates the software structure of the market mechanism in detail.

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

Price Determination. Stuttgart's exchange 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 B.2 in appendix B.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 6.1, 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.

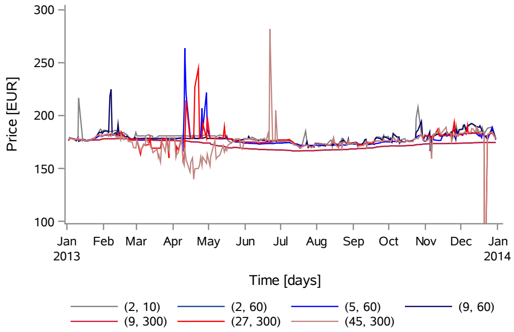
In addition, we iterate through all possible combinations of bid and ask orders within a block to find the order matching with the highest turnover[32]. To ensure price-time priority during this process, we fill the blocks with the most recent orders that maximize the price. Eventually, the execution 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 6.3 depicts the daily average trade prices and total volumes throughout 2013 in an 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. 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[33]. 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 follows in Section 6.5.

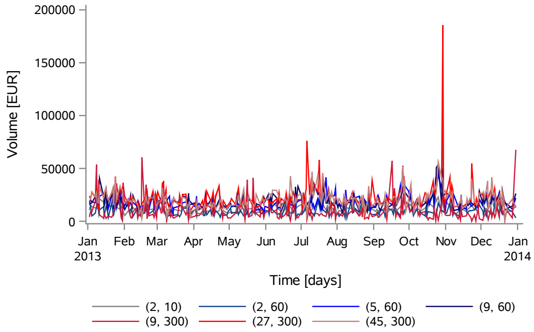
Furthermore, we can observe a constant price between September and December in Deutsche Börse's $(Min, 10)$ configuration. This effect is caused by a relatively large ask limit order with a quantity of 18,700 (compared to an average of 275) and a limit of 50 EUR, which is partially executed over time. 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 has to erode the surplus, until the price can be determined by other limit orders again. In total, these issues highlight the need to post-process the replicated data.

[32] 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).

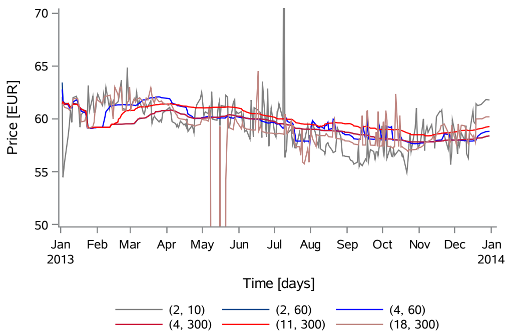
[33] We are aware that exchanges use circuit breakers and reference prices to prevent such effects. However, for the sake of simplicity and computational efficiency of the replication, we deal with these issues outside of the market mechanism by post-processing the market outcomes (see Section 6.3.1).



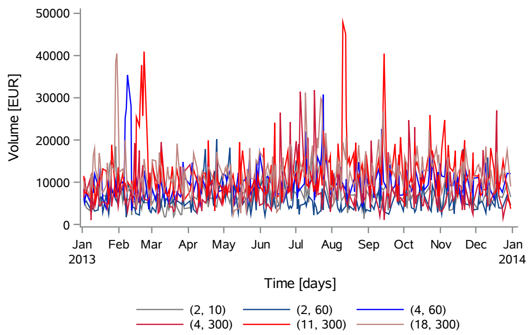
(A) *VW AG - Trade prices*



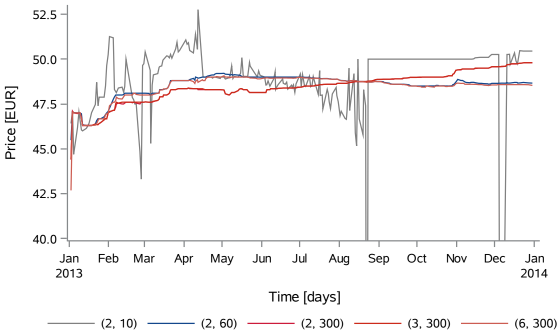
(B) *VW AG - Trading volumes*



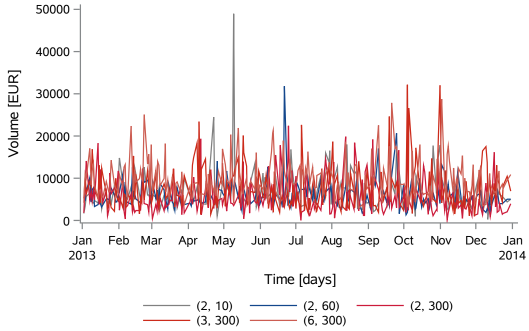
(C) *SAP SE - Trade prices*



(D) *SAP SE - Trading volumes*



(E) *Deutsche Börse AG - Trade prices*



(F) *Deutsche Börse AG - Trading volumes*

FIGURE 6.3: *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.

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 6.5, 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 and replicate the impact of circuit breakers (Subrahmanyam, 1994), while preserving price variations. In addition, if the first order of a day was submitted late, this could lead to block creations shortly after midnight in 300 minute configurations. To correct these time stamps, we set them to 11.59 p.m. of the previous day."

6.3.2 Summary Statistics

"Eventually, the data generation process described in the previous subsection (6.3.1) 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 trading activity at Stuttgart and covers a period from January 1, 2013 to December 31, 2017. During this period 12.5 million real-world submissions result in 12 million replicated executions with a turnover of EUR 122 billion. Eventually, the final data panel comprises 302,493 stock-day-[34] and 4,546,605 stock-block-configurations. 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 6.2 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[35]. 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.

[34] Note that this is below 332,370 (= $1,231$ days $*$ 30 DAX stocks $*$ 9 configurations) days, since some shares are not traded daily.

[35] 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 6.2: *Summary Statistics*

This table summarizes the trade data from Stuttgart (column 2), the replicated market outcomes (columns 3 to 11), and the resulting aggregated data panel (columns 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 6.1). 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.

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 6.1, column 13)."

6.4 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 6.4.1 and embed them into our empirical strategy in Subsection 6.4.2."

6.4.1 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 and summarize them in appendix A.6.

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.

Trade count. The TC is defined as the daily number of trades and measures the execution frequency within a market. Equation 6.2 formalizes this definition, while $n_{i,d,s}$ denotes the number of trades on day d for stock i under configuration s.

$$TC_{i,d,s} = n_{i,d,s}. \tag{6.2}$$

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

$$TO_{i,d,s} = \sum_{j=1}^{TC_{i,d,s}} Price_{i,d,s,j} \cdot Quantity^{T}_{i,d,s,j}, \tag{6.3}$$

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. To avoid a misleading interpretation, we consider both the TO and 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:

$$ATS_{i,b,s} = \frac{\sum_{j=1}^{TC_{i,b,s}} Quantity^{T}_{i,b,s,j}}{TC_{i,b,s}}. \tag{6.4}$$

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

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 are 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 illiquid 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 et al., 2011). In consequence, we follow Amihud (2002) and define DILLIQ as

$$DILLIQ_{i,d,s} = \frac{|Return_{i,d,s}|}{TO_{i,d,s}}. \tag{6.5}$$

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 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)[36] 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 ($Quantity^{S}_{i,b,s,j}$):

$$RQP_{i,b,s} = \frac{\sum_{j=1}^{TC_{i,b,s}} Quantity^{R}_{i,b,s,j}}{\sum_{j=1}^{TC_{i,b,s}} Quantity^{S}_{i,b,s,j}}. \tag{6.6}$$

In equation 6.6, 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 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, values closer to 1 indicate 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 6.4 summarizes the interpretation of the RQP.

[36] 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.

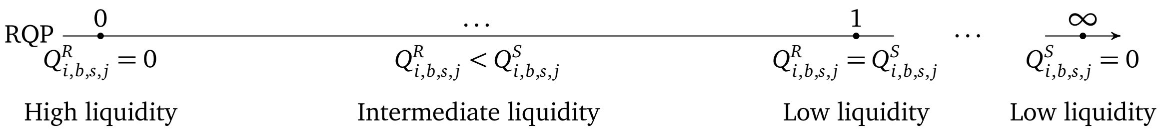


FIGURE 6.4: *Interpretation remaining quantity proportion (RQP)*
This figure illustrates the interpretation of the RQP. A high value implies low and a low value implies high liquidity. More specifically, if less of the ordered quantity remains after an execution, the ability to trade is higher and vice 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.*

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

$$BI_{i,b,s} = BD_{i,b,s} \cdot \ln\left(\frac{Price_{i,b,s}}{Price_{i,b-1,s}}\right). \tag{6.7}$$

$Price_{i,b,s}$ 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 to capture volatility effects that come with different blockchain configurations (see figure 6.3)."

6.4.2 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 6.3.1 and summarized in table 6.2. 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 6.4.1 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 6.8 provides the full specification of our empirical model:

$$\begin{aligned}
MQM_{i,t,s} = \alpha &+ \beta_1 BS_{i,s} + \beta_2 BCT_{i,s} + \beta_3 BS_{i,s} BCT_{i,s} \\
&+ \beta_4 VG_i + \beta_5 VG_i BS_{i,s} + \beta_6 VG_i BCT_{i,s} \\
&+ \beta_7 OQ_{i,t,s} + \beta_8 OQ_{i,t,s} BS_{i,s} + \beta_9 OQ_{i,t,s} BCT_{i,s} \\
&+ \beta_{10} LnReturn_{i,t,s} + \beta_{11} SDPrice_{i,t,s} + \beta_{12} LnSize_i \\
&+ \vec{\gamma} S + \vec{\delta} T + \vec{\omega} D + \varepsilon_{i,t,s}
\end{aligned} \tag{6.8}$$

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 6.8 (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 their interaction (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 leads to 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[37]. 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[38]. Eventually, model 6 comprises all variables, controls, and fixed effects, and thus is equal to equation 6.8.

Across models 1 to 6, we control for stock, year, and intraday fixed effects through the terms $\vec{\gamma}S$, $\vec{\delta}T$, $\vec{\omega}D$.[39] 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 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."

[37]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 D.1 in appendix D.1 provides details on the resulting classification.

[38]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.

[39]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 6.3.1). Accordingly, the regression parameters $\vec{\gamma}$, and $\vec{\delta}$, $\vec{\omega}$ are vectors with 30, 5, and 24 dimensions, respectively.

6.5 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 6.4.1 and analyze each quality dimension in a separate subsection. Hence, Subsection 6.5.1 evaluates market activity (TC, TO, and ATS), Subsection 6.5.2 presents our findings on liquidity (DILLIQ and RQP), and Subsection 6.5.3 investigates price formation (BI). In addition, we ensure the robustness of our findings in Subsection 6.5.4, 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."

6.5.1 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.

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 6.3 summarizes the regression outputs for models 1 to 8.

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 6.3: *Regressions trade count (TC)*

*This table presents β coefficients of models 1 to 8 (see Section 6.4.2) 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.*

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 data, partial executions may cause 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 6.5.4.

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, statistically significant, and implies a weak contrarian effect on the number of trades per day across all models. 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.

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 6.4: *Regressions turnover (TO)*

*This table presents β coefficients of models 1 to 8 (see Section 6.4.2) 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.*

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, we examine the individual effects of the BS and the BCT first (model 1 and 2) and 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 6.4, the BS has a positive, significant (0.1% level), and economically large effect on the TO of a stock. More precisely, the full specification 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. Consequently, the negative impact of enhanced BCTs seems 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 6.3, 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.

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 6.5 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 findings on the TC, 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 6.5.4. 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 medium to 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, this effect 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.

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 6.5: *Regressions average trade size (ATS)*

*This table presents β coefficients of models 1 to 8 (see Section 6.4.2) 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.*

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 leads to 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."

6.5.2 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 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 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.

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 6.6 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 after adding quality controls in models 6 to 8. In addition, the interaction with the OQ is neither 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.

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 6.6: *Regressions daily Amihud illiquidity measure (DILLIQ)*
*This table presents β coefficients of models 1 to 8 (see Section 6.4.2) 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.*

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 6.7 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 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. 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, liquidity 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 6.7 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 6.7."

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 6.7: *Regressions remaining quantity proportion (RQP)*

*This table presents β coefficients of models 1 to 8 (see Section 6.4.2) 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.*

6.5.3 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 introduce and discuss these findings in detail in the following paragraphs.

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 6.3. 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 6.5.4. Table 6.8 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 contradicts previous findings on the relationship between trading volumes and volatility (Jones et al., 1994; Darrat et al., 2003).

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 6.3 and appendix D.2 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.

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 6.8: *Regressions absolute block impact (ABI)*

*This table presents β coefficients of models 1 to 8 (see Section 6.4.2) 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.*

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."

6.5.4 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, modify the input sample, take order book imbalances as independent variable into account, examine the impact of BDs on prices, and disentangle the effects of BCT changes. The underlying motivation and analyses are described in the following subsections.

Number of Blocks

In the first robustness test, we focus on confounding effects that may arise from different block frequencies across our data sample. 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 higher 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, the results of the regressions are reported in table D.3 in appendix D.3.

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 D.4 in appendix D.3 presents the results of the regressions. 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 Subsection 6.5.1 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 6.3. 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 6.8.

In total, we do not find any contradicting evidence and can confirm most of the findings from Subsection 6.5.1. 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.

Additional Controls

The aim of the third robustness analysis is to verify our interpretation and to disentangle the effects of partial executions and order book imbalances on market activity. More specifically, we hypothesize in Subsection 6.5.1 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 6.8) with the RQP as an independent variable (see Section 6.4.1) to verify this hypothesis. Table D.5 in appendix D.3 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 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 D.5 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 6.5, a smaller BS and a shorter BCT may increase the average amount of shares per trade. In total, table D.5 in appendix D.3 highlights the role of order book imbalances and underlines that parts of the activity effects presented in Subsection 6.5.1 may be driven by partial executions.

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 6.2. 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 a 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 D.5 in appendix D.3 confirm our findings from Subsection 6.5.3. 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.

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 6.9 summarizes the results and shows that the time effects identified in this section indeed depend on the change of BCTs[40]. 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."

[40]In addition, figure D.4 in appendix D.3 provides complementary illustrations by the means of boxplots.

△ **MQM**	△ TC		△ TO		△ ATS		△ DILLIQ $\cdot 10^6$		△ RQP		△ 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 6.9: *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 yields the same 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.*

6.6 Discussion

"While our findings highlight the impact of the blockchain configuration on decentralized markets' activity, liquidity, and price formation, they are bound by several limitations. In this section, we discuss our results by illustrating the limitations of the order data, the data generation process, the applied 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 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. 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 exchange 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 et al., 2017; Malinova and Park, 2017; Daian et al., 2019) or other manipulative strategies, such as spoofing (Viana, 2018; Daian et al., 2019).

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 consistently significant at the 0.1% level, indicating a basic explanatory contribution of our analyses.

Eventually, our study may suffer from the p-value problem that comes with the size of our data panel. According to Lin et al. (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 a first approximation on how the blockchain's discrete data structure and update procedure may affect market outcomes. In consequence, we hope to offer initial guidance to the engineers of decentralized markets and support them in their endeavors to build, evaluate, and improve their trading platforms."

6.7 Concluding Remarks

"In total, this study provides a first analytic assessment of the quality of decentralized (stock) markets by examining the impact of central blockchain parameters on a market's activity, liquidity, and information processing capability. To examine the influence of different block sizes and block creation times, 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 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. On the other hand, the effect of lower block creation times 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, the analyses of the influence of blockchain configurations on price formation indicates that the price impact of a new block is stronger for bigger and faster blocks. Therefore, blockchain configurations that maximize market activity 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 leads 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 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 modeling, 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 character of blockchain-based markets on one hand, while ensuring a sufficient level of privacy on the other hand (Gencer et al., 2017). Nevertheless, we are confident to provide a fertile ground to researchers and initial guidance to practitioners with this study."

Chapter 7

Conclusion & Outlook

Blockchain technology enables market engineers to create fully decentralized market platforms that allow users to interact in the absence of central authorities and intermediaries. Driven by the promise of cost savings and the prospect of efficiency gains, organizations boost their blockchain activities and explore a multitude of market-oriented applications. However, as an infrastructure technology, the blockchain determines platform characteristics, influences user behavior, and affects market outcomes. In consequence, a thorough understanding of the technology and its impact is crucial to facilitate effective adoption and mitigate adverse side effects. This thesis constitutes a first step towards the assessment of blockchain-based, decentralized markets and illustrates their elements (Chapter 3), demonstrates their feasibility (Chapter 4), and analyzes the impact of central blockchain characteristics (Chapters 5 and 6). The following sections summarize the resulting contributions, discuss the implications, and outline opportunities for future research.

7.1 Contributions

The main contribution of this thesis is threefold and comprises a conceptual, technology, and economic level: First, on the conceptual level, Chapter 3 combines a structured literature review with Weinhardt and Gimpel (2007)'s interdisciplinary market engineering framework to create and extend the blockchain engineering framework. In particular, it addresses the following two research questions:

Research Question 1. *Which pivotal elements and layers define blockchain-based market platforms?*

Research Question 2. *To which extent can the blockchain implement the multi-faceted nature of trust prevalent on the peer-to-peer platforms of today's sharing economy?*

The resulting framework contributes to the rapidly expanding body of blockchain research in IS and adjacent fields and arranges the elements of blockchain-based systems within a market context, highlights the pivotal role of trust, and establishes a common language for researchers and practitioners. Thereby, it offers a toolbox to support the construction of blockchain-based platforms, structure research efforts, communicate findings, and to position a particular work in relation to other studies. In total, the blockchain engineering framework comprises five layers – the environment layer, the infrastructure layer, the application layer, the agent layer, and the behavioral layer. These layers incorporate social, legal, and economic constraints, the hard- and software of the blockchain infrastructure, the micro and business structure of the market platform, and the action spaces and actual behavior of users (research question 1). However, the behavioral and technological conceptualizations of trust differ substantially. In the behavioral layer, trust is perceived as a complex and interlaced construct with a multitude of stakeholders, targets, and dimensions. On the other side, the trust-free character of blockchain-based systems emerges from the infrastructure layer and focuses on technological details, while neglecting the actual behavior of interacting users. The resulting trust frontier separates the application and the behavioral layer and overcoming it is paramount to realize fully decentralized markets (research question 2).

Second, Chapter 4 focuses on the technology level and utilizes two proof-of-concept prototypes to illustrate and evaluate the blockchain's capability to implement the building blocks of decentralized markets. The first prototype introduces a transparent transaction system that enables interacting parties to transfer physical assets of varying quality (i.e., cars) in market environments prone to asymmetrically distributed information. Research questions 3 to 5 formulate related challenges, guide the artifact's development, and ask for economic implications.

Research Question 3. *How can market engineers decrease the risk resulting from the irreversibility of blockchain transactions, while still providing a valid transaction log?*

Research Question 4. *To which extent can a blockchain-based transaction system store and represent the life-cycle of a car?*

Research Question 5. *Which characteristics of blockchain-based transaction systems affect information asymmetries, and thus the uncertainty about quality in the market for lemons?*

The resulting IT artifact contributes to both the growing body of blockchain design literature and the interdisciplinary analysis of blockchain-based economic systems. Practically, it offers an alternative to bureaucratic, trust-based, and centralized registry systems that enables the transaction of physical assets by providing a valid, transparent, and consistent record to traders, authorities, and other third parties. More specifically, Section 4.2 introduces a fiduciary safeguard mechanism to reduce the transaction risk arising from the blockchain's immutable nature (research question 3). Second, it utilizes the use case of a vehicle register to illustrate and assess the challenges and limitations of fully decentralized registry systems (research question 4). Third, it connects the prototypes technological nature to its economic application context by leveraging the blockchain's publicly available record to alleviate the negative effects of information asymmetries in lemon markets. In addition, the generalized software design of the market framework takes practical considerations into account, facilitates extensions, and ensures its adoption beyond the use case of trading cars.

The second prototype utilizes this extensibility, focuses on the microstructure aspects, and implements a blockchain-based market mechanism. Consequently, research questions 6 and 7 ask:

Research Question 6. *How can smart contracts implement a decentralized market mechanism that incorporates a double auction, keeps distributed order books, and allows traders to submit limit and market orders?*

Research Question 7. *To which extent can a blockchain-based market platform operate the value chain of securities trading and which technology features limit performance?*

Similar to the first prototype, Section 4.3 offers both academic and practical insights. Academically, it contributes to interdisciplinary blockchain design literature as well as economically driven IS research. Practically, it illustrates and evaluates a blockchain-based market mechanism that empowers users to trade stocks in a fully decentralized fashion. More specifically, the market mechanism implements a matching engine and invokes an order book structure to processes the market and limit orders submitted by traders (research question 6). As a result, intermediaries and centralized market operators are rendered obsolete, while clearing and settling a transaction becomes an integral part of the trading process (research question 7). In combination with highly customizable assets, this facilitates cheap and efficient platforms and offers an alternative channel for venture capital investments. On the other side, the prototype also highlights the distorting and restricting effect of the blockchain's discrete nature.

Third, the economic level investigates the impact of distinctive blockchain characteristics identified on the technology level (Chapter 4) on behavioral patterns and market outcomes. Chapter 5 focuses on the blockchain's public transparency paradigm and utilizes game theory to examine its effect on the behavior of different types of users, market outcomes, and welfare:

Research Question 8. *Which participants of a market with asymmetric information are affected by the blockchain's shift towards public transparency? When and how does their behavior change?*

Research Question 9. *How do the behavioral changes of opportunistic market participants affect their counterparties, market outcomes in total, and the welfare of the economy?*

Guided by these research questions, the contribution of Chapter 5 is threefold: First, it extends the growing body of research on the economics of blockchain by analyzing the effects of the blockchain's public transparency paradigm in market environments with asymmetric information. Second, it contributes to the field of banking research by examining the impact of the disclosure of quality information to the broad public. And third, it adds to the interdisciplinary blockchain adoption and IS literature by highlighting the risks of blockchain-based transparency. In line with prior research about information sharing arrangements, the related findings indicate that the blockchain's record mitigates the impact of adverse selection effects and reduces moral hazard by disciplining entrepreneurs. On the other side, there is evidence that lemons can increase their utility by behaving opportunistically, when information brokers enhance the informativeness of the stored and shared data. This effect seems more pronounced for greater price improvements, lower quality differences, and lower quality in general. In opaque markets, neither plums nor lemons behave opportunistically. Irrespective of the information regime, there are lock-in effects across all types and scenarios. Thus, the consequences of irrational decisions spill over to future periods (research question 8). From a market perspective, opportunistic lemons create a welfare gain within their own generation. However, their behavior also violates the break-even condition of the banking sector, leads to a market collapse, and denies future generations the access to credit (research question 9). In total, these findings highlight that blockchain adoption in market environments exposed to irrational behavior and intense competition should be considered carefully (research question **??**).

Finally, Chapter 6 examines the impact of the blockchain's discrete, block-based data structure and update procedure on the quality of decentralized markets. The related analysis considers the size and frequency of new data blocks, covers three quality dimension (activity, liquidity, and information), and comprises the empirical assessment of quality effects, the identification of quality drivers and trade-offs, and the discussion of practical implications. Research question 10 condenses these aspects as follows:

Research Question 10. *How do the size and frequency of database updates (i.e., blocks) impact the activity, liquidity, and price formation on blockchain-based markets?*

Answering this question contributes to three streams of research: First, it adds to the growing body of interdisciplinary blockchain research by providing an initial technology-agnostic assessment of the relationship between blockchain design parameters and market quality. Second, it paves the way for empirical research on decentralized markets by highlighting interesting starting points. Third, it resembles the scale and scope of modern financial markets, and thus offers initial guidance to the engineers decentralized markets. In total, the empirical analyses of Chapter 6 indicate that increasing the capacity of data blocks improves activity, while higher block frequencies impose a trade-off between higher turnovers and lower trade sizes. In addition, they suggest 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 positive effect of the update size and frequency on a block's price impact highlights that faster and bigger blocks are no silver bullet to scale decentralized markets and may facilitate volatility.

7.2 Future Research

The Role of Trust in Real-World Applications

While the blockchain can be considered as trust-free within the boundaries of a closed ecosystem (Chapter 4), the actual impact of the underlying technology on trust is rarely addressed in academic literature (Chapter 3). "Although first academic attempts to investigate the potential of blockchain technology in replacing trusted third parties are made (Bogner et al., 2016; Sun et al., 2016), the success of such attempts is rather limited and primarily focuses on the context of online interaction and transaction transparency (Huckle et al., 2016).

Actual connections of the blockchain with the physical world are hardly addressed [...]. A noteworthy exception is a recent paper by Pazaitis et al. (2017), who approach the issue of 'trusted interactions on top of the trustless blockchain technology' by the introduction of a so-called proof-of-value concept. [This concept highlights] the value of a (human) contribution to [verify interactions in] a sharing ecosystem. Following this promising work, future research should address the design of trusted interfaces to support the successful implementation of blockchain-based [...] platforms – not only for online, but also for offline interactions. Overcoming the trust frontier without the necessity of trusted third parties will be a major challenge for future work and may provide platform operators with a business opportunity. Moreover, to better understand consumers' perception of blockchain-based platforms, particularly with regard to the formation of trust, future research should address the conceptualization and development of adequate measurement instruments for trust in blockchain-based algorithms" (Hawlitschek et al., 2018, p. 60). An important first step in this endeavor is to explore how the blockchain as a technological environment affects the concepts, dimensions, and targets of trust from a user perspective.

Information Asymmetries & Transparency - Model Extensions

While the theory-driven analyses in Chapter 5 offer initial insights on the economic effects of public transparency, the abstract nature of the model neglects central characteristics of real markets. To take these limitations into account, multiple model extensions and relaxations come to mind: First and foremost, the analyses are limited to comparative statics. Considering dynamic interactions between market participants would add a crucial dimensions and allow the examination of behavioral actions and reactions. Second, the cost for acquiring and sharing - and thus the operation of the blockchain-based information system at hand - are set to zero for both sides of the market. In consequence, modelling the actual costs and incentives to take more active roles that come with different design decisions constitutes a noteworthy and interesting extension. Third, the current model does not take the switching costs of entrepreneurs into account, refrains from generalizing the disutility of effort, and excludes the impact of entrepreneurial wealth. On the banking side, the role of relationship information is not considered, while opportunistic behavior is not possible. Relaxing these assumptions would contribute to a more realistic assessment of the blockchain's public transparency paradigm and provides opportunities for future research.

Native Decentralized Trading Data

Despite the growing number of fully decentralized exchanges, trading data from these market places is still scarce. Consequently, Chapter 6 utilizes order data from the Stuttgart stock exchange to compute trades on a DEX. While this approach resembles the scale and scope of actual financial markets, it may lead to biased results: First and foremost, while the data generation process approximates the behavior traders in a fully decentralized market environment, it still builds on Stuttgart's market model and orders submitted to it. On the other side, the decisions of traders on a decentralized platform are affected by the blockchain's discrete and transparent nature and may deviate substantially. Second, the utilized quality measures are adapted from established market quality literature, and thus their interpretability remains limited. As a result, directions for future research comprise the examination of native decentralized trading data, the study of related behavioral changes, and the development of tailored quality measures. From an economic perspective, this includes modelling, measuring, and analyzing behavioral patterns, assessing the implications for traders and the market, the identification of manipulative strategies, and the development of countermeasures. From a technical perspective, the tension between the preservation of the market platforms' decentralized and trust-free character and the provision of a sufficient level of privacy constitutes a challenge.

Technology Selection & Blockchain Adoption

Despite the technology's disruptive potential and their efforts, many organizations struggle to orientate in the rapidly growing and increasingly complex market for blockchain solutions (Friedlmaier et al., 2018). Thus, "finding the right technology for [a specific application] constitutes a challenging task that needs to incorporate the constantly evolving blockchain landscape and the functional [and organizational] requirements of a use case [and its stakeholders] alike. While IS research offers a variety of taxonomies and frameworks, such as Glaser and Bezzenberger (2015) or Notheisen et al. (2017), that help to structure [blockchain knowledge], many organizations still fail to connect these abstract concepts to [their] specific requirements [...]" (Notheisen et al., 2019, p. 4615). To resolve this issue, Notheisen et al. (2019) combine established methods to develop taxonomies with a requirements perspective and introduce a new technology assessment tool. To illustrate the tool's application and efficacy, they furthermore apply their method to the use case of blockchain-based securities post-trading.

Appendix A

Related Literature

A.1 List of Publications

(1) Title	(2) Authors	(3) Year	(4) Outlet	(5) Type	(6) Thesis
Blockchain as Platform	Glaser, F., Hawlitschek, F. & Notheisen, B.	2019	Business Transformation through Blockchain. Vol. 1	Book chapter	✓ 2.1.2
Breaking Down the Blockchain Hype – Towards a Blockchain Market Engineering Approach	Notheisen, B., Hawlitschek, F. & Weinhardt, C.	2017	25th European Conference on Information Systems (ECIS)	Conference proceedings	✓ 3
The limits of trust-free systems: A literature review on blockchain technology and trust in the sharing economy	Hawlitschek, F., Notheisen, B. & Teubner, T.	2018	Electronic commerce research and applications	Journal article	✓ 3.5
Trust-free Systems in the Trust Age? A Review on Blockchain and Trust in the Sharing Economy	Hawlitschek, F., Notheisen, B., Mertens, C., Teubner, T. & Weinhardt, C.	2017	17th International Conference on Group Decision and Negotiation (GDN)	Conference proceedings	✓ 3.5.1
Trading Real-World Assets on Blockchain An Application of Trust-Free Transaction Systems in the Market for Lemons	Notheisen, B., Cholewa, J. B. & Shanmugam, A. P.	2017	Business & Information Systems Engineering	Journal article	✓ 4.2
Trading Stocks on Blocks - Engineering Decentralized Markets	Notheisen, B., Gödde, M. & Weinhardt, C.	2017	12th International Conference on DESRIST, Springer Lecture Notes in Computer Science (No. 10243)	Conference proceedings	✓ 4.3
The Blockchain, Plums, and Lemons	Notheisen, B. & Weinhardt, C.	2018	KIT Working Paper Series in Economics (No. 130)	Working paper	✓ 5
Trading Stocks on Blocks - The Quality of Decentralized Markets	Notheisen, B., Marino, V., Englert, D. & Weinhardt, C.	2019	KIT Working Paper Series in Economics (No. 129)	Working paper	✓ 6
Requirement-driven Taxonomy Development – A Classification of Blockchain Technologies for Securities Post-Trading	Notheisen, B., Willrich, S., Diez, M. & Weinhardt, C.	2019	52nd Hawaii International Conference on System Sciences (HICSS)	Conference proceedings	✓ 7.2
Retail Investor Behavior, Exchanges, and Financial Market Innovation: Insights from the 4th European Retail Investment Conference (ERIC)	Burghof, H.-P., Fecker, A., Koch, C. & Notheisen, B.	2017	Creadit and capital markets	Journal article	
A blockchain-based smart grid: towards sustainable local energy markets	Mengelkamp, E., Notheisen, B., Beer, C., Dauer, D. & Weinhardt, C.	2017	Computer science - research and development	Journal article	
Register 4.0 - vom Potenzial blockchainbasierter Publizität für den Mobiliarkredit	Gorlow, V., Notheisen, B. & Simmchen, C.	2017	Recht 4.0 - Innovationen aus den rechtswissenschaftlichen Laboren, DSRI Herbstakademie	Conference proceedings	

TABLE A.1: *List of publications*

This table comprises a list of publications of the thesis author. Columns 1 to 4 provide titles, (co-)authors, years, and outlets. In addition, column 5 differentiates between peer-reviewed journal articles and conferences proceedings, edited book chapters, and unpublished working papers presented at refereed conferences. Column 6 indicates inclusion in the thesis at hand and refers to the corresponding chapter or section.

A.2 Consensus Mechanisms

(1) Consensus Mechanism	(2) Security	(3) Latency	(4) Volume	(5) Anonymity	(6) Application	(7) References
Computation-based proofs						
Proof of Work	Moderate	High	Low	High	Bitcoin, Ethereum	Nakamoto (2008), Buterin (2013)
Time-based proofs						
Proof of stake	Moderate	High	Low	-	Ethereum (Serenity)	Walsh et al. (2016), King and Nadal (2012)
Proof of activity	Moderate	High	Low	-	Decred	Bentov et al. (2014), Tschorsch and Scheuermann (2016)
Permission-based proofs						
Probabilistic voting	Low	Low	Moderate	-	Ripple	Schwartz et al. (2014)
Federated Byzantine Agreement	Moderate	Low	Moderate	Low	Stellar	Mazieres (2015)
Proof of authority	High	Low	-	Low	Microsoft Azure	Angelis et al. (2018)
Memory-based proofs						
Proof of capacity	-	Moderate	-	-	Spacemint	Dziembowski et al. (2015)
Proof of retrievability	-	High	-	High	Permacoin	Miller et al. (2014)
Communication-based proofs						
Proof of bandwidth	High	High	High	Moderate	TorCoin	Debus (2017), Ghosh et al. (2014)
Dependent-based proofs						
Proof of publication	Low	-	-	-	CommitCoin	Todd (2014)
Proof of burn	Low	Low	-	High	Slimcoin	Debus (2017)

TABLE A.2: *Overview consensus mechanisms*
This table summarizes the characteristics of selected consensus mechanisms and classifies them into computational-based, time-based, permission-based, memory-based, communication-based, and dependent-based approaches. Column 1 comprises the name and class of a mechanism, column 2 its security, and columns 3 to 7 latency, transaction volume, user's level of anonymity, actual applications, and references for further information, respectively. Security, latency, volume, and anonymity is either 'High', 'Moderate' and 'Low'. If no information could be found, the respective cell are left empty'. Cachin and Vukolic (2017) and Mingxiao et al. (2017) provide more extensive reviews.

A.3 Concept Matrix Interdisciplinary Blockchain Literature

	Blockchain technology	**Trust-free economic systems**	**Bitcoin & cryptocurrencies**	**Financial service innovation & FinTech**
Beck et al. (2016)		x		
Brenig et al. (2016)	x			
Dhillon (2016)			x	
Frey et al. (2016)	x			
Geng (2016)				x
Ingram and Morisse (2016)			x	
Wörner et al. (2016)	x			
Baiyere and Salmela (2015)				x
Brenig et al. (2015)			x	
Connolly and Begg (2015)			x	
Dahlberg et al. (2015)				x
Glaser and Bezzenberger (2015)	x			
Greiner and Hui (2015)		x		
Hur et al. (2015)			x	
Ingram et al. (2015)			x	
Kazan et al. (2015)			x	
Lustig and Nardi (2015)		x		
Mai et al. (2015)			x	
Morisse (2015)			x	
Fürstenau and Kliewer (2014)			x	
Glaser et al. (2014)			x	
Kazan and Damsgaard (2014)				x
Kazan et al. (2014)				x
Liebenau et al. (2014)				x
Moser et al. (2013)			x	
Hjelholt and Damsgaard (2012)				x
Puschmann et al. (2012)				x

TABLE A.3: *Concept matrix blockchain in IS*
This table shows the IS studies identified in the review of Notheisen et al. (2017) and assigns them to the concepts of Blockchain technology, Trust-free economic systems, Bitcoin & cryptocurrencies, and Financial service innovation & FinTech.

A.4 Information Sharing Arrangements in Practice

Sharing information helps to mitigate problems associated with asymmetric information and improves market efficiency. In practice, information sharing takes place via centralized institutions that set and govern the rules of the information exchange. In credit markets - the analytic environment we arrange this study in - information sharing arrangements are either set up by superior institutions as public credit registries or form endogenously as private credit bureaus. This section illustrates their features and highlights differences.

	Public credit registries	**Private credit bureaus**
Purpose	• Support the state's role as a supervisor of financial institutions • Collect information on standing borrowers and make it available to the actual and potential lenders (i.e., the reporting financial institutions) and regulators • Usually no provision of value-added services • Focus on banking supervision	• Cater to the information requirements of commercial lenders • Provide value-added services, such as credit scores, collection services • Collect comprehensive data to asses and monitor the creditworthiness of individual clients • Exchange of information among banks and financial institutions
	• Theoretical substitutes: Public credit registers are set up to compensate for the lack of private information sharing arrangements, having been created mostly where no private credit bureaus existed • Practice: Private and public credit reporting systems of coexist and cater to different segments of the credit market	
Ownership & Operation	• Public entities created by national government authorities and managed by central banks, supervision agencies, or other regulatory authorities • Single entity per (national) market	• Set up, owned, and managed by commercial enterprises or non-profit organizations • Borrowers have the right to inspect data and request deletions or corrections • Potentially competing multinational operations

	Public Credit Registries	**Private Credit Bureaus**
Coverage	• Loans made by regulated financial institutions • All loans above the reporting threshold must be registered • Compulsory participation imposed by regulation based on rules dictated by law • Resulting from their national regulatory origin, public credit registries cover only intranational loans and struggle with the international integration of capital markets	• Detailed information on small business loans, consumer credit, and trade credit provided by financial and non-financial lenders • Gather and process information on firms and individuals from multiple sources, including credit markets, lenders, and suppliers • Voluntary participation based on the principle of reciprocity and rules based on contractual agreements • In most jurisdictions data storage is limited to a certain amount of time (e.g., European Commission, 2018)
Data	• Information about the type, terms, and structure of outstanding loans • Personal & identifying information	• Information about the type, terms, and structure of individual loans, repayment histories and performance of individual standing borrowers • Integration of hard, soft (Liberti and Petersen, 2018), black, and white information from additional sources such as public records, demographic databases or lawsuits
Summary	Universal coverage of loans above a specified threshold, which mainly consists of credit data and is disseminated in consolidated form as the total loan exposure of a borrower	Incomplete but detailed coverage of individual loans, which is merged with credit data and other data to enable a comprehensive assessment of individual borrowers
References	Pagano and Jappelli (1993); Padilla and Pagano (2000); Jappelli and Pagano (2002); Djankov et al. (2007); World Bank (2011, 2013)	

A.5 Decentralized Markets in Practice

(1) Name	(2) Transaction object	(3) Functional scope	(4) Technology	(5) 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 crypto currencies and crypto tokens	Waves platform	https://wavesplatform.com (✓, ✓)

TABLE A.4: *Overview of decentralized exchanges*

Overview of selected blockchain-based market platforms including the name of the venture (1), the type of transaction object (2), the functional scope implemented in a decentralized fashion (3), the utilized (blockchain) technology (4), and a reference to additional information (5). Checkmarks in column 5 indicate the availability of whitepapers and contain embedded links to them.

A.6 Overview 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 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 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 interpret.	ATS does not provide information on the trade frequency.
daily Amihud illiquidity measure (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 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 A.5: *Overview market quality measures*
All measures are calculated for each stock i, each blockchain configuration s, and each block b or day d, respectively.

Appendix B

Software & Algorithms

B.1 Prototypes

To facilitate comprehensibility of the findings from chapter 4, this appendix provides Gitlab references to the prototypes' smart contracts and testing procedures. Tables B.1, B.2, and B.3 provide an overview, brief descriptions, and hyperlinks.

File path & directory	Description	Link
.../ Section 4.2 - A Transparent Transaction System	Prototype implementation	https://goo.gl/Tt1USk
.../ Section 4.3 - An Intermediary-free Market Mechanism	Prototype implementation	https://goo.gl/m1yNT3

TABLE B.1: *Repository overview*

File path & code file	Description	Link
.../ 4.2 .../ contracts	**Implemented smart contracts**	**https://goo.gl/aeAC6C**
.../ 4.2 .../ .../ DMR.sol	Market place and registry for cars	https://goo.gl/kz6QgP
.../ 4.2 .../ .../ HumanStandardToken.sol	Token-based user account	https://goo.gl/iLYCZ3
.../ 4.2 .../ .../ IndexedMarketplace.sol	Generalized market place with safeguards	https://goo.gl/TU7T6o
.../ 4.2 .../ .../ Marketplace.sol	Functional scope of a market place	https://goo.gl/CS3icA
.../ 4.2 .../ .../ Migrations.sol	Final transaction settlement	https://goo.gl/aGDuLP
.../ 4.2 .../ .../ Owned.sol	Functional scope of a transactional object	https://goo.gl/5qsHj6
.../ 4.2 .../ .../ StandardMarketplace.sol	Generalized market place	https://goo.gl/mNVQgJ
.../ 4.2 .../ .../ StandardToken.sol	Generalized token	https://goo.gl/wtQde1
.../ 4.2 .../ .../ Token.sol	Functional scope of a token (ERC-20)	https://goo.gl/cYq37G
.../ 4.2 .../ .../ Tradeable.sol	Generalized transactional object	https://goo.gl/7gr9Ss
.../ 4.2 .../ .../ Vehicle.sol	Transactional object with vehicle characteristics	https://goo.gl/zcHZFf
.../ 4.2 .../ test	**Testing procedures**	**https://goo.gl/vE743w**
.../ 4.2 .../ .../ DMR.js	Test car registry	https://goo.gl/xHuczD
.../ 4.2 .../ .../ HumanStandardToken.js	Token-based cash management	https://goo.gl/EcVEpm
.../ 4.2 .../ .../ StandardMarketplace.js	Test generalized market place	https://goo.gl/YZjzxp
.../ 4.2 .../ .../ Tradeable.js	Test transactional object	https://goo.gl/3i8zxb

TABLE B.2: *Directory overview "Section 4.2 - A Transparent Transaction System"*

File path & code file	Description	Link
.../ 4.3 .../ contracts	**Implemented smart contracts**	**https://goo.gl/1pM2QE**
.../ 4.3 .../ .../ ConvertLib.sol	Conversion	https://goo.gl/1XXL5A
.../ 4.3 .../ .../ DSX.sol	Market place and mechanism	https://goo.gl/znZCwm
.../ 4.3 .../ .../ Migrations.sol	Final transaction settlement	https://goo.gl/UY7KxY
.../ 4.3 .../ .../ Token.sol	Tokenized security	https://goo.gl/UbNPqG
.../ 4.3 .../ test	**Testing procedures**	**https://goo.gl/1b4cBq**
.../ 4.2 .../ .../ DSXspec.js	Testing procedures IPO and trading	https://goo.gl/tB2wmf

TABLE B.3: *Directory overview "Section 4.3 - An Intermediary-free Market Mechanism"*

B.2 Decentralized Matching Engine

Algorithm 1: Decentralized matching engine

```
Data: Buy orders, Sell orders, market ID
Result: Void
BidOrderID := HighestBidOrderID
AskOrderID := HighestAskOrderID
while (orderbook[BidOrderID].price ≥ orderbook[AskOrderID].price and
  orderbook[BidOrderID].blockNumber ≠ orderbook[AskOrderID].blockNumber) do
    if (orderbook[BidOrderID].amount = 0 or orderbook[AskOrderID].amount = 0) then
        return
    end
    if (orderbook[BidOrderID].amount ≥ orderbook[AskOrderID].amount) then
        fill := orderbook[AskOrderID].amount
        orderbook[BidOrderID].amount − = fill
        available token balance buyer + = fill
        trading token balance seller − = fill
        send money to seller(fill · orderbook[AskOrderID].price
        send money to buyer(fill · (orderbook[BidOrderID].price − orderbook[AskOrderID].price))
        if (orderbook[BidOrderID].amount > orderbook[AskOrderID].amount) then
            OldAskOrderID = AskOrderID
            AskOrderID = get next cheapest ask order()
            remove order(OldAskOrderID)
        else
            OldAskOrderID = AskOrderID
            OldBidOrderID = BidOrderID
            AskOrderID = get next cheapest ask order()
            BidOrderID = get next highest bid order()
            remove order(OldAskOrderID)
            remove order(OldBidOrderID)
        end
    else
        fill := orderbook[BidOrderID].amount
        orderbook[AskOrderID].amount − = fill
        available token balance buyer + = fill
        trading token balance seller − = fill
        send money to seller(fill · orderbook[AskOrderID].price)
        send money to buyer(fill · (orderbook[BidOrderID].price − orderbook[AskOrderID].price))
        OldBidOrderID = BidOrderID
        BidOrderID = get next highest bid order()
        remove order(OldBidOrderID)
    end
end
```

B.3 Replicated Market Mechanism

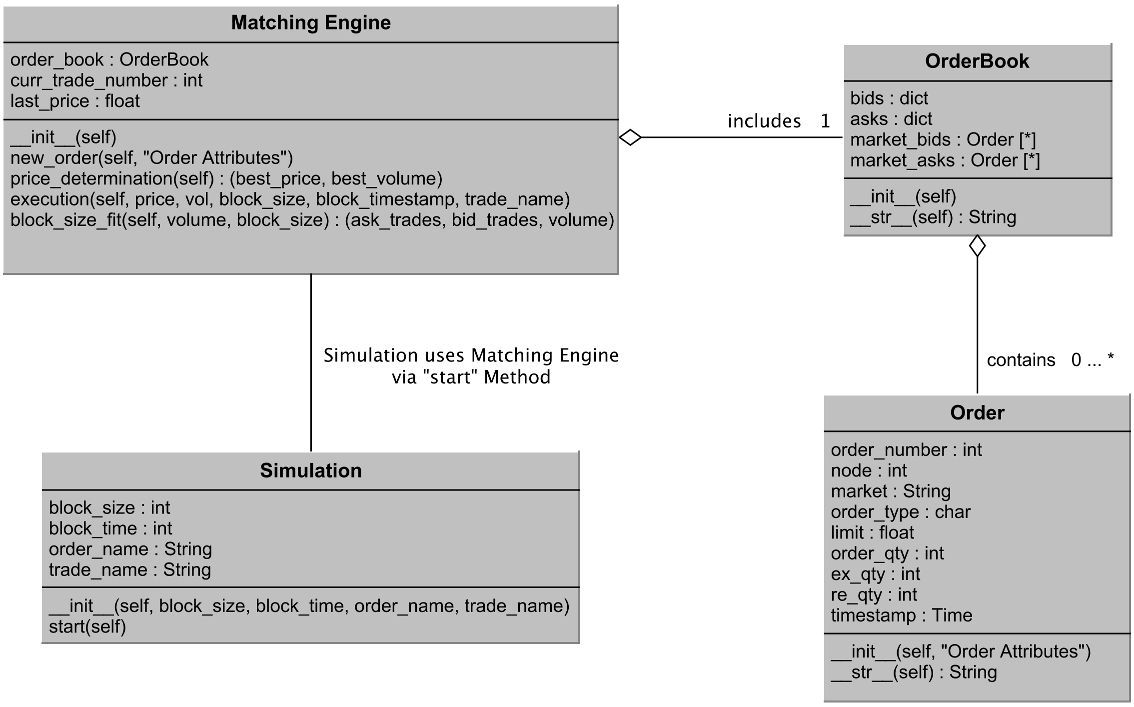


FIGURE B.1: *Class diagram replicated market mechanism*

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 B.4: *Data structure market outcomes*

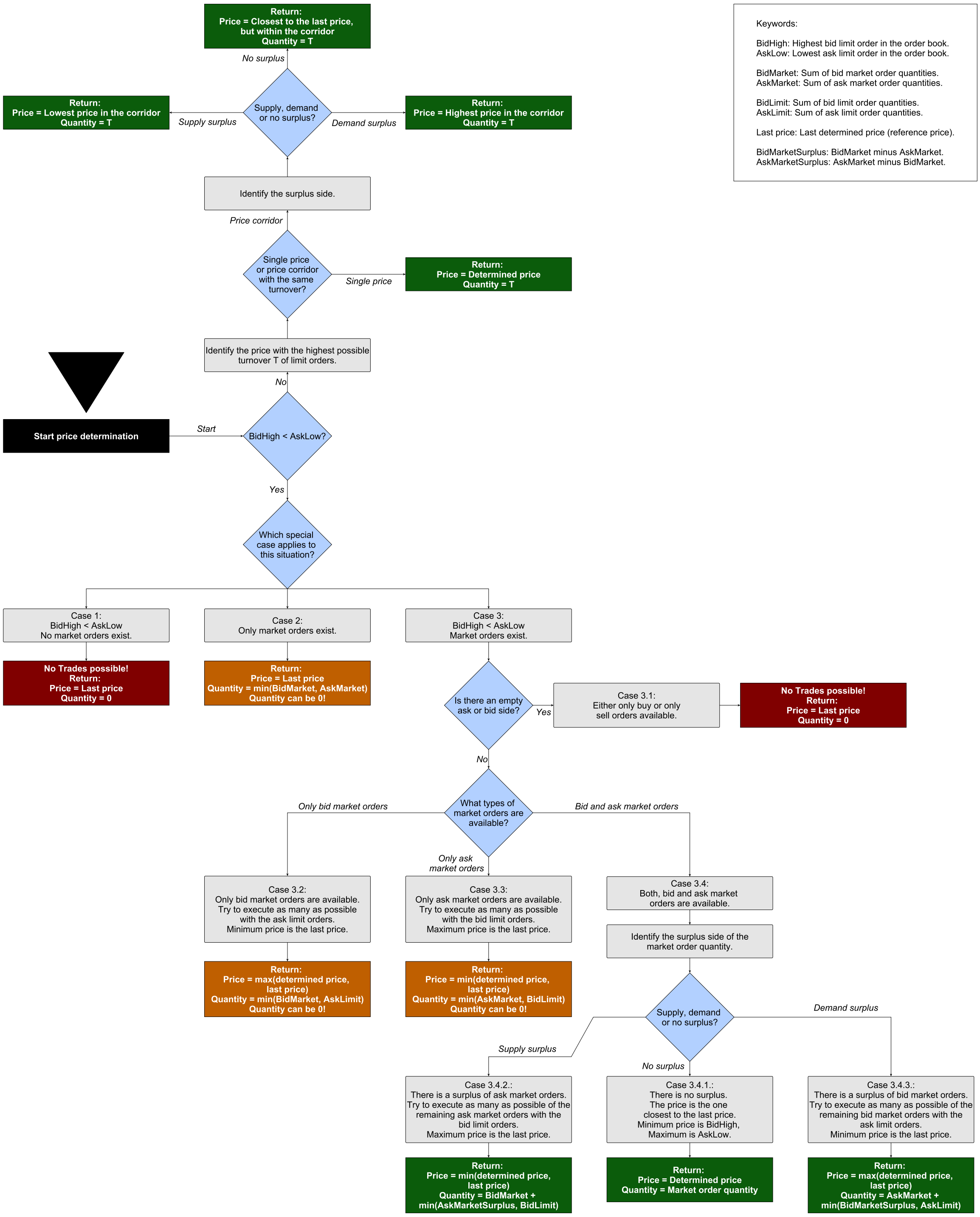


FIGURE B.2: *Price determination algorithm*

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.

Appendix C

Proofs & Calculus

C.1 Variable Definitions Chapter 5

Variable	Scope	Description
b	> 1	Number of competing banks
$\bar{R}$	$[1, R]$	Gross interest rate banks pay to raise funds
Π_t	-	Individual bank profits in period t
$R_{j,t}$	$[\bar{R}, R]$	Gross interest rate offered to entrepreneurs
t	{1,2}	Lending period
j	{H,L,P}	Equilibrium characteristics ($P =$ pooling, $H, P =$ separating)
$R_{P,1}$	$[\bar{R}, R]$	Period 1 pooling rate
$R_{H,2}$	$[\bar{R}, R]$	Period 2 interest rate offered to plums
$R_{L,2}$	$[\bar{R}, R]$	Period 2 interest rate offered to lemons
$R_{P,2}(0)$	$[\bar{R}, R]$	Period 2 pooling rate offered following default in period 1
$R_{P,2}(R)$	$[\bar{R}, R]$	Period 2 pooling rate offered following success in period 1
$\mu(H\|R)$	$[0, 1]$	Probability that a successful entrepreneur is a plum
$\mu(L\|R)$	$[0, 1]$	Probability that a successful entrepreneur is a lemon
$\mu(H\|0)$	$[0, 1]$	Probability that a defaulted entrepreneur is a plum
$\mu(L\|0)$	$[0, 1]$	Probability that a defaulted entrepreneur is a lemon

TABLE C.1: *Variable definitions banking perspective*

Variable	Scope	Description
R	> 1	Project return in the case of success
i	H, L	Entrepreneurial type
H	-	Good entrepreneur (plum)
L	-	Bad entrepreneur (lemon)
θ	$(0, 1)$	Share of plums in the market
$1 - \theta$	$(0, 1)$	Share of lemons in the market
a_i	> 0	Entrepreneurial quality of type i
$p^k_{i,t}$	$[0, 1]$	Effort level (success probability) of a type i entrepreneur in period t
k	$\{U, I\}$	Level of entrepreneurial information
U	-	Uninformed entrepreneur
I	-	Uninformed entrepreneur
$V_i(p^k_{i,t})$	$a_i {p^k_{i,t}}^2$	Disutility of effort of a type i entrepreneur
$U_i(p^k_{i,1}, p^k_{i,2})$	> 0	Total utility of type i entrepreneurs
$MC^k_{i,t}$	-	Marginal costs of type i entrepreneurs in period t
$MR^k_{i,t}$	-	Marginal returns of type i entrepreneurs in period t

TABLE C.2: *Variable definitions entrepreneurial perspective*

C.2 Proofs

Proposition 1: Banks' assessment of entrepreneurs

$$\underbrace{\underbrace{p_H}_{\text{Perfect info.}} \overset{?}{>} \underbrace{\mu(H|R)p_H + \mu(L|R)p_L}_{\text{Imperfect info.}}}_{\text{Period 2}} \overset{?}{>} \underbrace{\underbrace{\theta p_H + (1-\theta)p_L}_{\text{Full opacity}}}_{\text{Period 1}} \overset{?}{>} \underbrace{\underbrace{\mu(H|0)p_H + \mu(L|0)p_L}_{\text{Imperfect info.}} \overset{?}{>} \underbrace{p_L}_{\text{Perfect info.}}}_{\text{Period 2}}$$

While banks operate under full opacity in period 1, they acquire information about entrepreneurial characteristics before their second offer in period 2. However, their ability to distinguish between types depends on the features of the information system they acquire the information from. Under perfect information, their approximation of effort levels (i.e., success probabilities) is completely accurate. Under imperfect information on the other hand, banks underestimate (overestimate) the effort levels of plums (lemons). To show this, we compare the different information regimes and periods with each other.

To compare perfect with imperfect information, we have to consider the average effort levels of plums and non-defaulters and lemons and defaulters: For non-defaulters $p_H > \mu(H|R)p_H + \big(1-\mu(H|R)\big)p_L$ holds true, if $\mu(H|R) < 1$ and $p_H > p_L$. While $p_H > p_L$ is trivially true by assumption, $\mu(H|R) = \frac{p_H\theta}{\theta p_H + (1-\theta)p_L} < 1$ is only true, if $\theta < 1$. However, $\theta < 1$ is also fulfilled by assumption as there is at least one lemon in the market. As a result, the first part of proposition 1 is true and $p_H > \mu(H|R)p_H + \big(1-\mu(H|R)\big)p_L$ (I). The same logic applies to the comparison between defaulters and lemons. $\mu(H|0)p_H + \big(1-\mu(L|0)\big)p_L > p_L$ holds, if $\mu(H|0) > 0$ and $p_H > p_L$. Again, both conditions are trivially fulfilled by assumption as there is at least one lemon in the market and effort is more costly to lemons. In consequence, the last part of proposition 1 proofs to be correct as well (II).

For imperfect information and full opacity, $\mu(H|R)p_H + \big(1-\mu(H|R)\big)p_L > \theta p_H + (1-\theta)p_L$ is true, if $\mu(H|R) > \theta$ and $p_H > p_L$.

$$\mu(H|R) = \frac{p_H\theta}{\theta p_H + (1-\theta)p_L} > \theta \Leftrightarrow \frac{p_H}{\theta p_H + (1-\theta)p_L} > 1 \Leftrightarrow p_H > \theta p_H + (1-\theta)p_L$$

This is trivially true as $\theta \in (0,1)$ and $p_H > p_L$ and so is $\mu(H|R)p_H + \big(1-\mu(H|R)\big)p_L < \theta p_H + (1-\theta)p_L$ (III). Analogously, $\theta p_H + (1-\theta)p_L > \mu(H|0)p_L + \big(1-\mu(H|0)\big)$ follows from our assumption that $\theta \in (0,1)$ and $p_H > p_L$ (IV).

In total, this shows that when effort levels are positive and high enough to create lending, proposition 1 proofs to be true and

$$p_H \overset{(I)}{>} \mu(H|R)p_H + \mu(L|R)p_L \overset{(III)}{>} \theta p_H + (1-\theta)p_L \overset{(IV)}{>} \mu(H|0)p_H + \mu(L|0)p_L \overset{(II)}{>} p_L.$$

□

Proposition 2: Relationship between interest rates

$$\bar{R} \overset{?}{\leq} R_{H,2} \overset{?}{\leq} R_{P,2}(R) \overset{?}{\leq} R_{P,1} \overset{?}{\leq} R_{P,2}(0) \overset{?}{\leq} R_{L,2} \overset{?}{\leq} R$$

R represents the project return. $R_{H,2}$ and $R_{L,2}$ are the period 2 interest rates offered to plums (5.11) and lemons (5.12) under perfect information. To break even under imperfect information in period 2, banks offer either $R_{P,2}(0)$ or $R_{P,2}(R)$ conditional on period 1 default (5.8) or success (5.9). $R_{P,1}$ is the pooling rate banks offer without any information in period 1 (5.14). If a bank overcharges these break-even rates, its competitors can undercut profitably, while undercutting creates a loss on average.

To investigate the strictly increasing relationship between interest rates, we plug the interest rate formulas from sections 5.4.1 and 5.4.1 into the equation below and reduce the resulting fractions to lose $\bar{R}$. Finally, in combination with proposition 1 inverting the fractions shows that the proposed inequality relationship holds for all rates.

$$\begin{aligned}
& R_{H,2} \overset{?}{<} R_{P,2}(R) \overset{?}{<} R_{P,1} \overset{?}{<} R_{P,2}(0) \overset{?}{<} R_{L,2} \\
\Leftrightarrow & \frac{\bar{R}}{p_H} < \frac{\bar{R}}{\mu(H|R)p_H + \mu(L|R)p_L} < \frac{\bar{R}}{\theta p_H + (1-\theta)p_L} < \frac{\bar{R}}{\mu(H|0)p_H + \mu(L|0)p_L} < \frac{\bar{R}}{p_L} \\
\Leftrightarrow & \frac{1}{p_H} < \frac{1}{\mu(H|R)p_H + \mu(L|R)p_L} < \frac{1}{\theta p_H + (1-\theta)p_L} < \frac{1}{\mu(H|0)p_H + \mu(L|0)p_L} < \frac{1}{p_L} \\
\Leftrightarrow & p_H > \mu(H|R)p_H + \mu(L|R)p_L > \theta p_H + (1-\theta)p_L > \mu(H|0)p_H + \mu(L|0)p_L > p_L \\
\overset{\text{Prop. 1}}{\Rightarrow} & R_{H,2} < R_{P,2}(R) < R_{P,1} < R_{P,2}(0) < R_{L,2}
\end{aligned}$$

However, banks can never charge more than the project return R without risking a market collapse, and thus all rates are capped by R for sufficiently low effort levels. In consequence, "<" becomes "≤". In addition, if effort levels are below the banks' break-even thresholds, there is no lending. $\bar{R} \leq R_{H,2}$ follows directly from equation 5.11 and the assumption that entrepreneurs cannot exert more than 100% effort (i.e., $p_H \in [0,1]$). In total this shows that proposition 2 holds and

$$\bar{R} \leq R_{H,2} \leq R_{P,2}(R) \leq R_{P,1} \leq R_{P,2}(0) \leq R_{L,2} \leq R.$$

□

Proposition 3: Effort levels of uninformed entrepreneurs under imperfect information

$$p^U_{H,t} \overset{?}{>} p^U_{L,t} \ \forall t \in \{1,2\}$$

In period 1, $p^U_{H,1} > p^U_{L,1}$ holds, when the numerator of $p^U_{H,1}$ is greater than the numerator of $p^U_{L,1}$, while the denominator of $p^U_{H,1}$ is equal or lower than the denominator of $p^U_{L,1}$ or vice versa. To show that this is fulfilled for period 1 interest rates, we examine the relationship between numerators (I) and denominators (II) in the following. In combination, (I) and (II) confirm that plums exert higher period 1 effort than lemons on average.

$$p^U_{H,1} > p^U_{L,1} \Leftrightarrow \frac{R - R_{P,1} + \frac{\Delta R}{2a_H}\big(R - R_{P,2}(0)\big)}{2a_H - \frac{(\Delta R)^2}{2a_H}} \ \frac{>(\mathrm{I})}{<(\mathrm{II})}\ \frac{R - R_{P,1} + \frac{\Delta R}{2a_L}\big(R - R_{P,2}(0)\big)}{2a_L - \frac{(\Delta R)^2}{2a_L}} > 0$$

$$\begin{aligned}
(\mathrm{I}) \qquad & R - R_{P,1} + \frac{\Delta R}{2a_H}\big(R - R_{P,2}(0)\big) > R - R_{P,1} + \frac{\Delta R}{2a_L}\big(R - R_{P,2}(0)\big) \\
& \Leftrightarrow \frac{1}{2a_H} > \frac{1}{2a_L} \Leftrightarrow a_H \overset{\text{Ass.}}{<} a_L.
\end{aligned}$$

$$\begin{aligned}
(\mathrm{II}) \qquad & 2a_H - \frac{(\Delta R)^2}{2a_H} < 2a_L - \frac{(\Delta R)^2}{2a_L} \\
& \Leftrightarrow 2a_L - \frac{(\Delta R)^2}{2a_L} - 2a_H + \frac{(\Delta R)^2}{2a_H} \overset{a_L > a_H}{>} 2a_L - \frac{(\Delta R)^2}{2a_L} - 2a_H + \frac{(\Delta R)^2}{2a_L} > 0 \\
& \Leftrightarrow 2a_L - \frac{(\Delta R)^2}{2a_L} - 2a_H - \frac{(\Delta R)^2}{2a_H} > 2a_L - 2a_H = a_L - a_H \overset{\text{Ass.}}{>} 0.
\end{aligned}$$

To show that the proposed "$>$"-relationship also holds for period 2, we apply the same logic as in period 1. While (II) is trivially satisfied by the assumption about the quality differences, (I) directly follows from $p^U_{H,1} > p^U_{L,1}$ shown above.

$$p^U_{H,2} > p^U_{L,2} \Leftrightarrow \frac{R + p_{H,1}\Delta R - R_{P,2}(0)}{2a_H} \underset{<\text{(II)}}{\overset{>\text{(I)}}{-}} \frac{R + p_{L,1}\Delta R - R_{P,2}(0)}{2a_L} > 0$$

In consequence, $p^U_{H,t} > p^U_{L,t}$ holds for both periods $t \in \{1,2\}$.

$$p^U_{i,1} \overset{?}{\geq} p^U_{i,2} \; \forall i \in \{H, L\}$$

Similar to the relationship between type-specific effort levels, we compare numerators (I) and denominators (II) of the interest rate formulas to show that the ">"-relationship holds over time.

$$\text{(I)} \qquad R - R_{P,1} + \frac{\Delta R}{2a_i} \underbrace{\big(R - R_{P,2}(0)\big)}_{max R_{P,2}(0)=R \text{ (Prop. 2)}} - \big(R + p_{i,1}\Delta R - R_{P,2}(0)\big) \overset{?}{>} 0$$

$$\Leftrightarrow \cdots > R_{P,1} + R_{P,2}(0) - \underbrace{p_{i,1}}_{\geq 1} \Delta R > R_{P,1} + R_{P,2}(0) - \big(R_{P,2}(0) - R_{P,2}(R)\big) > 0$$

$$\Leftrightarrow \cdots > \cdots > R_{P,1} + R_{P,2}(0) > 0$$

$$\text{(II)} \qquad 2a_i - \underbrace{\left(2a_i - \frac{\overbrace{(\Delta R)^2}^{\Delta R \geq 0}}{2a_i}\right)}_{\leq 2a_i} \geq 0$$

As a result $p^U_{i,1} > p^U_{i,2}$ holds for all $i \in \{H, L\}$, and thus proposition 3 proofs to be true in total.

□

Proposition 4: Effort levels of uninformed entrepreneurs under perfect information

$$p^U_{H,t} \overset{?}{>} p^U_{L,t} \; \forall t \in \{1,2\}$$

To show that this proposition holds, we follow the same logic as in proposition 3. In period 1, the numerator $R - R_{P,1}$ - which results from the pooling of entrepreneurs in period 1 and the absence of stochastic price effects due to the distinct separation in period 2 - is constant over types, and thus we only need to show that the inequality holds true for the denominators. Again, this complies with our model's assumptions, and thus $p^U_{H,1} > p^U_{L,1}$ holds.

$$p^U_{H,1} > p^U_{L,1} \Leftrightarrow \frac{R - R_{P,1}}{2a_H} - \frac{R - R_{P,1}}{2a_L} > 0 \Leftrightarrow \frac{1}{2a_H} - \frac{1}{2a_L} > 0 \Leftrightarrow a_H \overset{\text{Ass.}}{<} a_L$$

In period 2, period 1 performance qualifies entrepreneurs for type-specific interest rates $R_{H,2} \leq R_{L,2}$ (proposition 2). This relationship between interest rates charged to plums and lemons trivially leads to (I), while (II) directly follows from the model assumption that $a_L > a_H > 0$. In consequence, $p^U_{H,2} > p^U_{L,2}$ also holds true for period 2.

$$p^U_{H,2} > p^U_{L,2} \Leftrightarrow \frac{R - R_{H,2}}{2a_H} \underset{<(\text{II})}{\overset{\geq(\text{I})}{-}} \frac{R - R_{L,2}}{2a_L} > 0$$

In total, this shows that $p^U_{H,t} > p^U_{L,t}$ is true for all $t \in \{1, 2\}$.

To proof the second part of proposition 4, we now examine the variation of effort levels over time.

$$p^U_{H,1} \overset{?}{<} p^U_{H,2} \Leftrightarrow \frac{R - R_{H,2}}{2a_H} - \frac{R - R_{P,1}}{2a_H} > 0 \Rightarrow R_{P,1} - R_{H,2} \overset{\text{Prop. 2}}{\geq} 0$$

$$p^U_{L,1} \overset{?}{>} p^U_{L,2} \Leftrightarrow \frac{R - R_{H,2}}{2a_H} - \frac{R - R_{P,1}}{2a_H} > 0 \Rightarrow R_{P,1} - R_{H,2} \overset{\text{Prop. 2}}{\geq} 0$$

In total, this shows that relationships formalized by proposition 4 hols over both types and time.

□

Proposition 5: Lock-in effect under imperfect information

$$p^I_{H,2} \overset{?}{<} p^U_{H,2}, \qquad p^I_{L,2} \overset{?}{>} p^U_{L,2}$$

For plums, plugging in the formulas from equations 5.16 and 5.20 highlights that the difference between period 2 efforts of uninformed and informed plums lies in the realization of the interest rate advantage ΔR. Substituting $p^I_{H,1}$ for $p^U_{L,1}$ and simplifying the relationship between both effort levels leads to $p^U_{H,1} - p^U_{L,1} > 0$, of which the correctness directly follows from proposition 3.

$$p^U_{H,2} - p^I_{H,2} > 0 \Leftrightarrow \frac{R + p^U_{H,1}\Delta R - R_{P,2}(0)}{2a_H} - \frac{R + \overbrace{p^I_{H,1}}^{:=p^U_{L,1}}\Delta R - R_{P,2}(0)}{2a_H} > 0 \Leftrightarrow p^U_{H,1} - p^U_{L,1} \overset{\text{Prop. 3}}{>} 0$$

For lemons, the same logic applies but with an inverse direction (i.e., lemons raise their effort to mimic plums). In consequence, $p^I_{L,2} > p^U_{L,2}$ follows from proposition 3.

$$p^I_{L,2} - p^U_{L,2} > 0 \Leftrightarrow \frac{R + \overbrace{p^I_{L,1}}^{:=p^U_{H,1}}\Delta R - R_{P,2}(0)}{2a_L} - \frac{R + p^U_{L,1}\Delta R - R_{P,2}(0)}{2a_L} > 0 \Leftrightarrow p^U_{H,1} - p^U_{L,1} \overset{\text{Prop. 3}}{>} 0$$

In total, this shows that $p^I_{H,2} < p^U_{H,2}$ and $p^I_{L,2} > p^U_{L,2}$.

□

Proposition 6: Utility of mimicking entrepreneurs under imperfect information

$$U_i\left(p^U_{-i,1}, p^I_{i,2}\right) \overset{?}{<} U_i\left(p^U_{i,1}, p^U_{i,2}\right) \; \forall i \in \{H, L\}$$

To show that this inequality holds for plums, we analyze the following utility effects: In period 1, $\Delta U_{H,1} < 0$ is trivially satisfied as the deviation from equilibrium effort to $p^I_{H,1} = p^U_{L,1} < p^U_{H,1}$ (Prop. 3) creates an imbalance between marginal costs and returns. To show that plums never experience utility gains from mimicking, we now investigate how deceptive behavior in period 1 impacts utility in period 2:

$$
\begin{aligned}
\Delta U_{H,2} =& \big(MC_{H,2}(p^I_{H,2}) - MC_{H,2}(p^U_{H,2})\big)p^U_{H,2} + \frac{1}{2}\Big[\big(MC_{H,2}(p^I_{H,2}) - MC_{H,2}(p^U_{H,2})\big)(p^I_{H,2} - p^U_{H,2})\Big] \\
=& 2a_H(p^I_{H,2} - p^U_{H,2})p^U_{H,2} + \frac{1}{2}\Big[2a_H(p^I_{H,2} - p^U_{H,2})^2\Big] \\
=& \underbrace{a_H}_{>0 \text{ Ass.}} \underbrace{(p^I_{H,2} - p^U_{H,2})}_{<0 \text{ (Prop. 5)}} \underbrace{(p^I_{H,2} + p^U_{H,2})}_{>0} < 0
\end{aligned}
$$

Formally, this underlines that the lock-in effect creates an utility loss in period 2 ($\Delta U_{H,2} < 0$). In aggregate, these utility losses in period 1 and 2 indicate that mimicking does not provide any benefits for plums and leads to $U_H\big(p^U_{L,1}, p^I_{H,2}\big) < U_H\big(p^U_{H,1}, p^U_{H,2}\big)$.

For lemons, the situation is a bit more complex: While deviation from equilibrium leads to utility losses in period 1, increasing efforts $p^I_{L,2} > p^U_{L,2}$ in period 2 ((Prop. 5)) provides access to a lower expected interest rates and creates an utility gain.

$$
\begin{aligned}
\Delta U_{L,2} =& \big(MC_{L,2}(p^I_{L,2}) - MC_{L,2}(p^U_{L,2})\big)p^U_{L,2} + \frac{1}{2}\Big[\big(MC_{L,2}(p^I_{L,2}) - MC_{L,2}(p^U_{L,2})\big)(p^I_{L,2} - p^U_{L,2})\Big] \\
=& 2a_L(p^I_{L,2} - p^U_{L,2})p^U_{L,2} + \frac{1}{2}\Big[2a_L(p^I_{L,2} - p^U_{L,2})^2\Big] \\
=& \underbrace{a_L}_{>0 \text{ Ass.}} \underbrace{(p^I_{L,2} - p^U_{L,2})}_{>0 \text{ (Prop. 5)}} \underbrace{(p^I_{L,2} + p^U_{L,2})}_{>0} > 0
\end{aligned}
$$

However, to show that these utility gains cannot outweigh the utility loss in period 1, we need to investigate whether the net utility change $\Delta U_L = \Delta U^U_{L,1} + \Delta U^U_{L,2}$ remains negative in all cases. Note that in the following, we compute the ΔU_L from a cost perspective $\Delta U_L = \Delta U^U_{L,1} - \Delta U^U_{L,2}$ and therefore costs dominate, when $\Delta U_L > 0$.

$$
\begin{aligned}
\Delta U_L =& \frac{1}{2}\Big[\big(MC^U_{L,1}(p^U_{H,1}) - MC^U_{L,1}(p^U_{L,1})\big)(p^U_{H,1} - p^U_{L,1})\Big] \\
& - \frac{1}{2}\Big[\big(MR^U_{L,1}(p^U_{H,1}) - MR^U_{L,1}(p^U_{L,1})\big)(p^U_{H,1} - p^U_{L,1})\Big] \\
=& \frac{1}{2}\Big[\big(2a_L((p^U_{H,1} - p^U_{L,1})) + \frac{\Delta R^2}{2a_L}(p^U_{H,1} - p^U_{L,1})\big)(p^U_{H,1} - p^U_{L,1})\Big] - \frac{1}{2}\frac{\Delta R^2}{a_L}(p^U_{H,1} - p^U_{L,1})^2 \\
=& \frac{1}{2}\underbrace{(p^U_{H,1} - p^U_{L,1})^2}_{>0 \text{ Prop. 3}} \underbrace{\Big[2a_L + \frac{\Delta R^2}{2a_L} - \frac{\Delta R^2}{a_L}\Big]}_{>0 \text{ (I)}} > 0
\end{aligned}
$$

The inequality of part (I) follows from the following logic: To estimate a lower bound, we first let $a_L \rightarrow 0$. As $a_L > a_H > 0$, this also pushes $a_H \rightarrow 0$ and infinitely cheap effort consequently raises effort levels for both types infinitely close to 1. As a result of these extremely high effort levels and the minimal difference in quality, interest rates rise and converge to R, and thus $\Delta(R) \rightarrow 0$. If we take a look a the equation below, we can easily see that this movement towards 0 is twice as fast for ΔR than for a_L. In addition, the fraction-based functional form of interest rates (i.e., $\frac{R}{\alpha p_H + (1-\alpha) p_L}$, where α represents some distribution of entrepreneurs) leads to an even stronger decrease compared to the quadratic and linear formalization of the disutility and return created by efforts. In consequence, $2a_L - \Delta R$ always remains > 0[41], and thus (I) holds true as long as lending occurs.

$$2a_L + \frac{\Delta R^2}{2a_L} - \frac{\Delta R^2}{a_L} = 4a_L^2 - \Delta R^2 > 0 \Leftrightarrow 2a_L > \Delta R$$

Eventually, this shows that $U_L\left(p^I_{L,1}, p^I_{L,2}\right) = U_L\left(p^U_{H,1}, p^I_{L,2}\right) < U_L\left(p^U_{L,1}, p^U_{L,2}\right)$ is true. In aggregate, the perspective of plums and lemons indicate that proposition 6 holds whenever lending occurs (i.e., $p_{i,t} > 0 \; \forall i \in \{H, L\},\; t \in \{1, 2\}$).

$\square$

Proposition 7: Lock-in effect under perfect information

$$p^I_{H,2} \overset{?}{<} p^U_{H,2}, \qquad p^I_{L,2} \overset{?}{>} p^U_{L,2}$$

Comparing the perfect information interest rates banks offer to uninformed (5.18) and informed (5.22) plums highlights the negative relationship between efforts and prices. In consequence, $p^I_{H,2} < p^U_{H,2}$ directly follows from proposition 2.

$$p^U_{H,2} - p^I_{H,2} > 0 \Leftrightarrow \frac{R - R_{H,2}}{2a_H} - \frac{R - R_{L,2}}{2a_H} > 0 \Leftrightarrow -R_{H,2} - (-R_{L,2}) > 0 \Leftrightarrow R_{L,2} - R_{H,2} \overset{\text{Prop. 2}}{>} 0$$

For lemons, the same logic applies with an inverse price effect and $p^I_{L,2} > p^U_{L,2}$ follows from proposition 2.

$$p^I_{L,2} - p^U_{H,2} > 0 \Leftrightarrow \frac{R - R_{H,2}}{2a_L} - \frac{R - R_{L,2}}{2a_L} > 0 \Leftrightarrow R_{L,2} - R_{H,2} \overset{\text{Prop. 2}}{>} 0$$

[41] ">" holds furthermore true as we never reach 0.

In total, this shows that plums and lemons are locked-in to their behavioral change from period 1 as $p^I_{H,2} < p^U_{H,2}$ and $p^I_{L,2} > p^U_{L,2}$. In addition, the strict inequality ">" holds as long as $R_{i,2} < R$, i.e. as long as effort levels are high enough (see section 5.4.1).

□

Proposition 8: Utility of mimicking plums under perfect information

$$U_H\big(p^I_{H,1}, p^I_{H,2}\big) \overset{?}{<} U_H\big(p^U_{H,1}, p^U_{H,2}\big)$$

Similar to imperfect information, plums experience an utility loss over both periods under perfect information. In period 1, $\Delta U_{H,1} < 0$ follows directly from $MR_{H,1} > MC_{H,1}$. In addition, lowering period 1 efforts to $p^I_{H,1} := p^U_{L,1}$ leads to a higher interest burden $R_{L,2} \geq R_{H,2}$. This burden lowers marginal returns $MR^U_{H,2} > MR^I_{H,2}$. In combination with the resulting decline of effort, utility drops and $\Delta U_{H,2} < 0$. To support that this reasoning holds whenever lending occurs and efforts are high enough, we refer to proposition 7 (figure 5.8 support this reasoning graphically).

$$\begin{aligned}
\Delta U_{H,1} &= \frac{1}{2}(p^U_{H,1} - \underbrace{p^I_{H,1}}_{:=p^U_{L,1}})\big(MC_{H,1}(p^U_{H,1}) - MC_{H,1}(\underbrace{p^I_{H,1}}_{:=p^U_{L,1}})\big) \\
&= \frac{1}{2}(p^U_{H,1} - p^I_{H,1})2a_H(p^U_{H,1} - p^I_{H,1}) = \underbrace{a_H}_{>0 \text{ (Ass.)}} \underbrace{(p^U_{H,1} - p^I_{H,1})^2}_{>0 \text{ (Prop. 4)}} > 0
\end{aligned}$$

$$\begin{aligned}
\Delta U_{H,2} &= p^I_{H,1}\big(MC_{H,2}(p^U_{H,2}) - MC_{H,2}(p^I_{H,2})\big) + \frac{1}{2}(p^U_{H,2} - p^I_{H,2})\big(MC_{H,2}(p^U_{H,2}) - MC_{H,2}(p^I_{H,2})\big) \\
&= \underbrace{a_H}_{>0 \text{ (Ass.)}} \underbrace{(p^U_{H,2} - p^I_{H,2})}_{>0 \text{ (Prop. 7)}} \underbrace{(p^I_{H,2} + p^U_{H,2})}_{>0 \text{ (when lending occurs)}} > 0
\end{aligned}$$

In total, this shows that $U_H\big(p^U_{L,1}, p^I_{H,2}\big) = U_H\big(p^I_{H,1}, p^I_{H,2}\big) < U_H\big(p^U_{H,1}, p^U_{H,2}\big)$, and thus plums do not experience any gains from mimicking.

□

Proposition 9: Utility of mimicking lemons under perfect information

$$U_L\left(p^I_{L,1}, p^I_{L,2}\right) \overset{?}{>} U_L\left(p^U_{L,1}, p^U_{L,2}\right)$$

In contrast to plums, under perfect information lemons experience an utility loss in period 1 (as $MR_{L,1} < MC_{L,1}$) and an utility gain in period 2. However, unlike lemons in the imperfect information regime, period 2 gains of mimicking can outweigh its cost in period 1, thereby making deception in period 1 profitable. To investigate in which situations mimicking provides a profitable alternative, we examine when the net utility gain over both periods $\Delta U_L = \Delta U_{L,2} - \Delta U_{L,1} > 0$.

$$\begin{aligned}
&\Delta U_L = \Delta U_{L,2} + \Delta U_{L,1} > 0 \\
\Leftrightarrow\, & a_L(p^U_{L,2} - p^I_{L,2})(p^I_{L,2} + p^U_{L,2}) - a_L(\underbrace{p^I_{L,1}}_{:=p^U_{H,1}} - p^U_{L,1})^2 > 0 \\
\Leftrightarrow\, & \left(\frac{R-R_{H,2}}{2a_L} - \frac{R-R_{L,2}}{2a_L}\right)\left(\frac{R-R_{H,2}}{2a_L} + \frac{R-R_{L,2}}{2a_L}\right) - \left(\frac{R-R_{P,1}}{2a_H} - \frac{R-R_{P,1}}{2a_L}\right)^2 > 0 \\
\Leftrightarrow\, & \frac{1}{4a_L^2}\Big[(R_{L,2}-R_{H,2})(2R-R_{H,2}-R_{L,2})\Big] - \frac{(R-R_{P,1})^2}{4a_H^2} - \frac{2R_{P,1})^2}{2a_H 2a_H} + \frac{R_{P,1})^2}{4a_L^2} > 0 \\
\Leftrightarrow\, & \frac{1}{4a_L^2}\Big[(R_{L,2}-R_{H,2})(2R-R_{H,2}-R_{L,2})\Big] - (R-R_{P,1})^2 \frac{a_L^2 - 2a_H a_L + a_H^2}{4a_H^2 4a_L^2} > 0 \\
\Leftrightarrow\, & \frac{1}{4a_L^2}\Big[(R_{L,2}-R_{H,2})(2R-R_{H,2}-R_{L,2})\Big] - (R-R_{P,1})^2 \frac{(a_L - a_H)^2}{4a_H^2 4a_L^2} > 0 \\
\Leftrightarrow\, & \underbrace{\underbrace{\frac{(R_{L,2}-R_{H,2})(2R-R_{H,2}-R_{L,2})}{(R-R_{P,1})^2}}_{\text{Relative price effect}} - \underbrace{\frac{(\overbrace{a_L - a_H}^{\Delta a})^2}{a_H^2}}_{\text{Relative cost effect}}}_{\text{Net utility gain}} > 0
\end{aligned}$$

Eventually, the quality difference $\Delta a > 0$ and its connection to interest rates via[42] supports the inequality $\Delta U_L > 0$, and thus shows that $U_L\left(p^U_{H,1}, p^I_{L,2} = U_L\left(p^I_{L,1}, p^I_{L,2}\right)\right) > U_L\left(p^U_{L,1}, p^U_{L,2}\right)$.

□

[42]For details on the underlying logic, we refer to proposition 6, where we apply the same but inverse rationale.

Proposition 10: Welfare effect

$$\Delta W \overset{?}{>} 0$$

To evaluate the welfare effect ΔW of blockchain adoption, we compare the welfare generated by informed entrepreneurs (i.e., mimicking lemons) with the welfare generated by uninformed entrepreneurs. As the plums do not change their behavior, the $\Delta W_H = 0$. In addition, the costs of capital $\bar{R}$ are constant, and thus do not play a role in the comparison between informed and uninformed lemons. As a result, ΔW is reduced to the utility change of mimicking lemons, and thus $\Delta W > 0$ directly follows from proposition 9 and our assumption that there is at least on lemon/plum in the market.

$$\begin{aligned}
\Delta W =& W(p^U_{H,1}, p^U_{H,2}, p^I_{L,1}, p^I_{L,2}) - W(p^U_{H,1}, p^U_{H,2}, p^U_{L,1}, p^U_{L,2}) \\
=& (1-\theta)\big[p^I_{L,1} R - \bar{R} - V_L(p^I_{L,1}) + p^I_{L,2} R - \bar{R} - V_L(p^I_{L,2}) \\
& - p^U_{L,1} R + \bar{R} + V_L(p^U_{L,1}) - p^U_{L,2} R + \bar{R} + V_L(p^U_{L,2})\big] \\
=& (1-\theta)\Big[\underbrace{p^I_{L,1} R - V_L(p^I_{L,1}) - \big(p^U_{L,1} R - V_L(p^U_{L,1})\big)}_{\Delta U_{L,1}} + \underbrace{p^I_{L,2} R - V_L(p^I_{L,2}) - \big(p^U_{L,2} R - V_L(p^U_{L,2})\big)}_{\Delta U_{L,2}}\Big] \\
=& \underbrace{(1-\theta)}_{>0 \text{Ass.}} \underbrace{\Delta U_L}_{>0 \text{ Prop. 9}} > 0
\end{aligned}$$

□

Proposition 11: Market collapse

To break even in the face of perfect competition, banks use the success probabilities of past (uninformed generations) to compute adequate interest rates for plums and lemons. The break-even condition for period 2 is equal to:

$$\Pi^U_2 = \theta\big[p^U_{H,2} R_{H,2} - \bar{R}\big] + (1-\theta)\big[p^U_{L,2} R_{L,2} - \bar{R}\big] = 0$$

However, when lemons change their the resulting success probabilities the break-even condition for period 2 does not hold anymore:

$$\Pi_2^I = \theta \underbrace{\left[p^U_{H,2} R_{H,2} - \bar{R}\right]}_{=0} + (1-\theta)\left[p^I_{L,2} R_{H,2} - \bar{R}\right] \overset{?}{=} 0$$

$$\Leftrightarrow p^I_{L,2} R_{H,2} - \bar{R} \overset{?}{=} 0 \Leftrightarrow p^I_{L,2} \frac{\bar{R}}{p^U_{H,2}} - \bar{R} \overset{?}{=} 0 \Leftrightarrow \frac{p^I_{L,2}\bar{R}}{p^U_{H,2}} - \frac{p^U_{H,2}\bar{R}}{p^U_{H,2}} \overset{?}{=} 0 \Leftrightarrow (p^I_{L,2} - p^U_{H,2})\bar{R} \overset{?}{=} 0$$

$$\Leftrightarrow \left(\frac{R - R_{H,2}}{2a_L} \underbrace{\frac{=}{>}}_{\text{Ass.}} \frac{R - R_{H,2}}{2a_H} \right) < 0$$

As a result, banks are not able to roll over their funding at the end of period 2 and go bankrupt.

□

C.3 Calculus

Banking Perspective

Period 2 break-even success probabilities (imperfect information):

$$\mu(H|0)p_H R + \mu(L|0)p_L R - \bar{R} \overset{!}{=} 0$$

$$\Leftrightarrow \frac{(1-p_H)\theta}{\theta(1-p_H) + (1-\theta)(1-p_L)} p_H R + \frac{(1-p_L)(1-\theta)}{\theta(1-p_H) + (1-\theta)(1-p_L)} p_L R - \bar{R} \overset{!}{=} 0$$

$$\Leftrightarrow (1-p_H)\theta p_H R + (1-p_L)(1-\theta)p_L R - \bar{R}\left[\theta(1-p_H) + (1-\theta)(1-p_L)\right] \overset{!}{=} 0$$

$$\Leftrightarrow (p_H - p_H^2)\theta R + (p_L - p_L^2)(1-\theta)R - \bar{R}\left[\theta(1-p_H) + (1-\theta)(1-p_L)\right] \overset{!}{=} 0$$

Solving for p_H or p_L respectively yields the corresponding upper and lower limits for for lending at the given rates p'_H, p''_H, p'_L, and p''_L for the period 1 defaulters. Applying the same approach to the break-even condition for successful entrepreneurs $\mu(H|R)p_H R + \mu(L|R)p_L R - \bar{R} \overset{!}{=} 0$ yields p'_H, p''_H, p'_L, and p''_L.

Period 1 Break-even success probabilities: In period 1, banks cannot distinguish between entrepreneurial types and offer a pooling rate to both of them. However, to provide lending at this rate, entrepreneurial effort levels need to allow banks to break even on the total pool's expected profits. For the lowest possible p_i's this means that $R_{P,1} = R$, while banks require all project returns to break even. Based on the profits under perfect competition $\theta p_H R + (1-\theta)p_L R - \bar{R} \stackrel{!}{=} 0$, this break-even threshold is given by $p_H + p_L \frac{(1-\theta)}{\theta} \geq \frac{\bar{R}}{\theta R}$ (I). In consequence, when $p_L = 0$, the average success probability of plums $p_H(p_L = 0)$ has to be greater than or equal to $\frac{\bar{R}}{\theta R}$ (II). Similarly, $p_L(p_H = 0) \geq \frac{\bar{R}}{(1-\theta)R}$, when plums have zero success probability (III). Figure C.1 illustrates the resulting lending areas for in greater detail (lending areas A and B). Note that when we assume $p_H > p_L$ - such as we do in section 5.4.1 for instance - the lending area is limited to probability combinations that comply with this restriction (lending area A only).

$$
\begin{aligned}
\text{(I)} \qquad p_H &= \frac{\bar{R} - (1-\theta)p_L R}{\theta R} \\
\Leftrightarrow p_H &= \frac{\bar{R}}{\theta R} - \frac{(1-\theta)p_L R}{\theta R} = \frac{\bar{R}}{\theta R} - \frac{(1-\theta)p_L}{\theta} \\
\Rightarrow p_H + p_L \frac{(1-\theta)}{\theta} &= \frac{\bar{R}}{\theta R}
\end{aligned}
$$

Entrepreneurial Perspective

To find the optimal effort choices of entrepreneurs, we consider first and second order conditions and apply the following four-step approach: Step 1 identifies potential optimal effort levels in periods 1 and 2. Step 2 evaluates whether these choices are indeed maxima by showing that the determinant of the hessian matrix $|H_{U_i}| > 0$ and $\frac{\partial \partial U_i}{\partial p_{i,t} \partial p_{i,t}} < 0$. Step 3 checks whether the optimal effort levels lie within the defined range of $p_i \in (0,1)$ Finally, step 4 compares entrepreneurial utility of the effort choices identified in step 1 with the utility at the boundary points $p_{i,t} = 0$ and $p_{i,t} = 1$. However, we keep this step short, as the convexity of utility trivially ensures that the argument holds for all combinations of boundary effort choices.

The difference between plums and lemons lies in the marginal cost of effort ($0 < a_i < a_L$) and the resulting effort levels ($p_{H,t} > p_{L,t}$). In the uninformed scenarios, the limited access scope of the information system prevents entrepreneurs from learning about other entrepreneurs' behavior. As a result, they choose effort levels in periods 1 and 2 to maximize

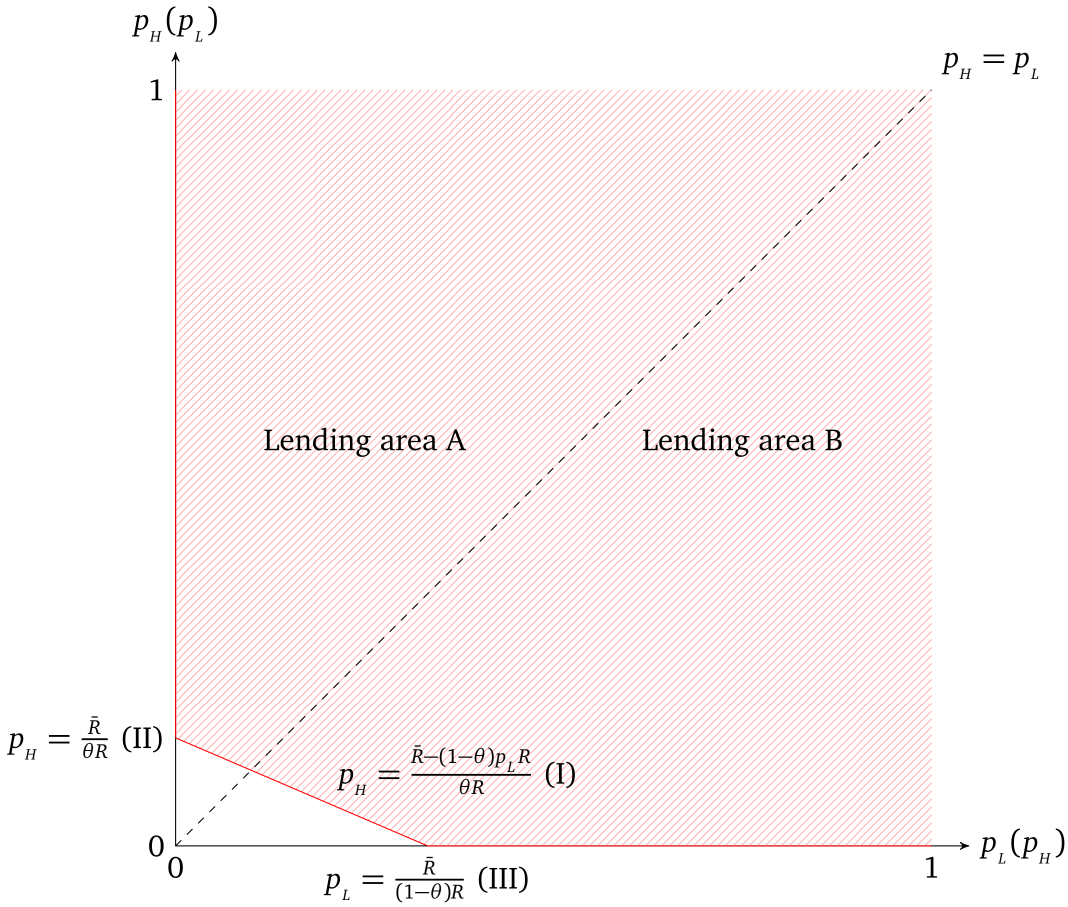


FIGURE C.1: *Lending areas under full opacity and pooling.*

their individual utility independently of each other. In informed scenarios, entrepreneurs have knowledge about the average success probability of plums and lemons (from past generations), and thus can change their effort levels in period 1 in order to mimic the respective other type. Based on this change, they maximize their utility by choosing effort levels in period 2. In addition, the information available (imperfect/perfect) to the banks varies, and thus interest rates change accordingly. Eventually, this results in four analytic scenarios: Uninformed entrepreneurs who face imperfectly informed banks, uninformed entrepreneurs who face perfectly informed banks, informed entrepreneurs who face imperfectly informed banks, and informed entrepreneurs who face perfectly informed banks. To facilitate the understanding of the underlying rationale, we provide detailed calculations for the behavior of uninformed entrepreneurs under imperfect information. For the sake of brevity however, we limit the calculations for the remaining 3 scenarios to central results of each step.

Effort choices of uninformed entrepreneurs in the imperfect information regime: In the imperfect information regime, banks have to rely on project outcomes from period 1 (i.e., default (0) or success (R)) to approximate entrepreneurial types. As a result, both plums and lemons are offered a pooling rate dependent on default or success in period 1.

Note that entrepreneurs only differ in their marginal cost of effort $(0 < a_H < a_L)$. In consequence, we formalize rationales from a general perspective and denote type-specific variables with the subscript $i \in \{H, L\}$.

$$\begin{aligned}
U_i(p_{i,1}, p_{i,2}) &= \underbrace{p_{i,1}(R - R_{P,1}) - a_i p_{i,1}^2}_{\text{Period 1 utility}} + \underbrace{p_{i,2}(R - E[R_{P,2}]) - a_i p_{i,2}^2}_{\text{Period 2 utility}} \\
&= p_{i,1}(R - R_{P,1}) - a_i p_{i,1}^2 + p_{i,2}\left(R - \left[p_{i,1} R_{P,2}(R) + (1 - p_{i,1}) R_{P,2}(0)\right]\right) - a_i p_{i,2}^2 \\
&= p_{i,1}(R - R_{P,1}) - a_i p_{i,1}^2 + p_{i,2}\left(R + p_{i,1} \underbrace{\left[R_{P,2}(0) - R_{P,2}(R)\right]}_{=\Delta R} - R_{P,2}(0)\right) - a_i p_{i,2}^2 \\
&= p_{i,1}(R - R_{P,1}) - a_i p_{i,1}^2 + p_{i,2}\left(R + p_{i,1} \Delta R - R_{P,2}(0)\right) - a_i p_{i,2}^2
\end{aligned}$$

Step 1: Identification of optimal effort choices

$$\begin{aligned}
\frac{\partial U_i}{\partial p_{i,2}} &= \underbrace{R + p_{i,1} \Delta R - R_{P,2}(0)}_{MR_{i,2}} - \underbrace{2 a_i p_{i,2}}_{MC_{i,2}} \overset{!}{=} 0 \\
\Rightarrow p_{i,2}^U(p_{i,1}) &= \frac{R + p_{i,1} \Delta R - R_{P,2}(0)}{2 a_i}
\end{aligned}$$

$$U_i(p_{i,1}, p_{i,2}^U(p_{i,1})) = p_{i,1}(R - R_{P,1}) - a_i p_{i,1}^2 + \underbrace{p_{i,2}^U(p_{i,1})\left(R + p_{i,1} \Delta R - R_{P,2}(0)\right)}_{\text{(I)}} - \underbrace{a_i \left(p_{i,2}^U(p_{i,1})\right)^2}_{\text{(II)}}$$

$$
\begin{aligned}
\frac{\partial U_i}{\partial p_{i,1}} &= R - R_{P,1} - 2a_i p_{i,1} + \underbrace{\frac{\Delta R}{a_i}\big(R + p_{i,1}\Delta R - R_{P,2}(0)\big)}_{\text{(I)'}} - \underbrace{\frac{\Delta R}{2a_i}\big(R + p_{i,1}\Delta R - R_{P,2}(0)\big)}_{\text{(II)'}} \\
&= \underbrace{R - R_{P,1} + \frac{\Delta R}{a_i}\big(R + p_{i,1}\Delta R - R_{P,2}(0)\big)}_{MR_{i,1}} - \underbrace{2a_i p_{i,1} - \frac{\Delta R}{2a_i}\big(R + p_{i,1}\Delta R - R_{P,2}(0)\big)}_{MC_{i,1}} \\
&= R - R_{P,1} - 2a_i p_{i,1} + \frac{\Delta R}{2a_i}\big(R + p_{i,1}\Delta R - R_{P,2}(0)\big) \\
&= R - R_{P,1} + \frac{\Delta R}{2a_i}\big(R - R_{P,2}(0)\big) + p_{i,1}\left(\frac{(\Delta R)^2}{2a_i} - 2a_i\right) \overset{!}{=} 0 \\
\Rightarrow p^U_{i,1} &= \frac{R - R_{P,1} + \frac{\Delta R}{2a_i}\big(R - R_{P,2}(0)\big)}{2a_i - \frac{(\Delta R)^2}{2a_i}}
\end{aligned}
$$

(I)
$$
\begin{aligned}
\frac{\partial (I)}{\partial p_{i,1}} &= p^{U\prime}_{i,2}(p_{i,1}) \cdot \big(\ldots\big) + p^U_{i,2}(p_{i,1}) \cdot \big(\ldots\big)' \\
&= \frac{\Delta R}{2a_i} \cdot \big(R + p_{i,1}\Delta R - R_{P,2}(0)\big) + \frac{R + p_{i,1}\Delta R - R_{P,2}(0)}{2a_i} \cdot \Delta R \\
&= \frac{\Delta R}{a_i}\big(R + p_{i,1}\Delta R - R_{P,2}(0)\big)
\end{aligned}
$$

(II)
$$
\begin{aligned}
\frac{\partial (II)}{\partial p_{i,1}} &= 2a_i p^U_{i,2}(p_{i,1}) \cdot p^{U\prime}_{i,2}(p_{i,1}) \\
&= 2a_i \frac{R + p_{i,1}\Delta R - R_{P,2}(0)}{2a_i} \cdot \frac{\Delta R}{2a_i} \\
&= \frac{\Delta R}{2a_i}\big(R + p_{i,1}\Delta R - R_{P,2}(0)\big)
\end{aligned}
$$

Step 2: Evaluation of optimal effort choices

$$\frac{\partial\partial U_i}{\partial p_{i,2}\partial p_{i,2}} = -2a_i, \quad \frac{\partial\partial U_i}{\partial p_{i,2}\partial p_{i,1}} = \Delta R, \quad \frac{\partial\partial U_i}{\partial p_{i,1}\partial p_{i,1}} = -2a_i, \quad \frac{\partial\partial U_i}{\partial p_{i,1}\partial p_{i,2}} = \Delta R$$

$$\Rightarrow H_{U_i} = \begin{pmatrix} -2a_i & \Delta R \\ \Delta R & -2a_i \end{pmatrix} \Rightarrow Det\left(H_{U_i}\right) = \begin{vmatrix} -2a_i & \Delta R \\ \Delta R & -2a_i \end{vmatrix} = \underbrace{(-2a_i)(-2a_i)}_{a_L > a_H > 0} - \underbrace{(\Delta R)^2}_{<1} > 0$$

$$\frac{\partial\partial U_i}{\partial p_{i,1}\partial p_{i,1}} = -2a_i < 0 \Rightarrow p^U_{i,1} \text{ is a maximum,} \quad \frac{\partial\partial U_i}{\partial p_{i,2}\partial p_{i,2}} = -2a_i < 0 \Rightarrow p^U_{i,2} \text{is a maximum}$$

Step 3: Admissibility of optimal effort choices

Proposition: $p^U_{i,2} \geq 0$

$$p^U_{i,2}(p_{i,1}) = \frac{R + p_{i,1}\Delta R - R_{P,2}(0)}{\underbrace{2a_i}_{>0}} \geq 0$$

$$\Leftrightarrow R + p_{i,1}\Delta R - R_{P,2}(0) \overset{min\, p_{i,1}=0}{\geq} \underbrace{R - R_{P,2}(0) \geq 0}_{\text{No lending for } R < R_{P,2}(0)} .$$

Even if plums do not exert effort in period 1, negative effort levels remain infeasible in period 2 as banks would not lend at these levels.

Proposition: $p^U_{i,2} \leq 1$

$$\begin{aligned}
&p^U_{i,2}(p_{i,1}) = \frac{R + p_{i,1}\Delta R - R_{P,2}(0)}{2a_i} \leq 1 \\
\Leftrightarrow &R + p_{i,1}\Delta R - R_{P,2}(0) \leq 2a_i \\
\Leftrightarrow &R + p_{i,1}\Delta R - R_{P,2}(0) \overset{max\ p_{i,1}=1}{\leq} R + \underbrace{\Delta R}_{R_{P,2}(0)-R_{P,2}(R)} - R_{P,2}(0) \leq 2a_i \\
\Leftrightarrow &R + p_{i,1}\Delta R - R_{P,2}(0) \leq \underbrace{R - R_{P,2}(R)}_{\text{Best case period 2 net return}} \leq 2a_i
\end{aligned}$$

Increasing the period 2 net return (in a best case scenario - i.e., when $p_{i,1} = 1$) can push plums' equilibrium effort levels in period 2 beyond the domain of $[0, 1]$. However, entrepreneurs cannot invest more than 100% effort. In consequence, we set $p^U_{i,2}$ to 1, if $R - R_{P,2}(R) > 2a_i$.

Proposition: $p^U_{i,1} \geq 0$

$$p^U_{i,1} = \frac{\overbrace{R - R_{P,1}}^{R_{P,1}=R \Rightarrow 0} + \overbrace{\frac{\Delta R}{2a_i}}^{\geq 0}\Big(\overbrace{R - R_{P,2}(0)}^{max\ R_{P,2}(0)=R \Rightarrow \geq 0}\Big)}{\underbrace{2a_i - \frac{(\Delta R)^2}{2a_i}}_{\overset{?}{\geq} 0 \Rightarrow \text{(I)}}} \geq 0.$$

$$\begin{aligned}
\text{(I)} \qquad &2a_i - \frac{(\Delta R)^2}{2a_i} \geq 0 \mid \cdot 2a_i \\
\Leftrightarrow &(2a_i)^2 - (\Delta R)^2 \geq 0 \\
\Leftrightarrow &(2a_i)^2 \geq (\Delta R)^2 \mid \sqrt{} \\
\Leftrightarrow &2a_i \geq \Delta R.
\end{aligned}$$

The proposition $p^U_{i,1} \geq 0$ holds true, if the interest rate differential $R_{P,2}(0) - R_{P,2}(R) = \Delta R$ does not outweigh the marginal costs of effort: $2a_i \geq \Delta R$. We assume this to be true, as interest rates usually differ on the decimal level in practical contexts (a difference of 2 would be equal to 200 percentage points). Economically, this result indicates that in equilibrium plums exert positive effort as along as the marginal punishment for default is lower than the marginal cost of effort. The severity of punishment furthermore increases with the fraction of lemons in the market and their average success probability (see proposition 2).

Proposition: $p^U_{i,1} \leq 1$

$$
\begin{aligned}
& p^U_{i,1} = \frac{R - R_{P,1} + \frac{\Delta R}{2a_i}\big(R - R_{P,2}(0)\big)}{2a_i - \frac{(\Delta R)^2}{2a_i}} \leq 1 \\
\Leftrightarrow & R - R_{P,1} + \frac{\Delta R}{2a_i}\big(R - R_{P,2}(0)\big) \leq 2a_i - \frac{(\Delta R)^2}{2a_i} \\
\Leftrightarrow & R - R_{P,1} + \frac{\Delta R}{2a_i}R - \frac{\Delta R}{2a_i}R_{P,2}(0) \leq 2a_i - \frac{\Delta R}{2a_i}\big(R_{P,2}(0) - R_{P,2}(R)\big) \\
\Leftrightarrow & \underbrace{R - R_{P,1}}_{\text{Period 1 net return}} + \underbrace{\frac{\Delta R}{2a_i}\big(R - R_{P,2}(R)\big)}_{\text{Period 2 net benefit}} \leq 2a_i
\end{aligned}
$$

Similar to period 2, increasing period 1 net returns and period 2 net benefits can lead to equilibrium effort levels greater then 1 as U_i becomes strictly increasing. However, entrepreneurs still cannot invest more than 100% effort in each period. In consequence, we set $p^U_{i,1}$ to 1, if $R - R_{P,1} + \frac{\Delta R}{2a_i}\big(R - R_{P,2}(R)\big) > 2a_i$.

Step 4: Maximum utility and comparison to boundary points

In combination with $p_{i,t} \in [0,1]$, the convexity of the total and partial utility (period 1, period 2) ensures that $U_i(p^U_{i,1}, p^U_{i,2})$ is indeed a maximum and no boundary points offer higher utility. In some special cases however (i.e., when $R - R_{P,2}(R) > 2a_i$ or $R - R_{P,1} + \frac{\Delta R}{2}\big(R - R_{P,2}(R)\big) > 2a_i$) the optimal effort levels $p^U_{i,2}$ and $p^U_{i,1}$ can be equal to 1. In these special situations maximum utility is realized at the boundary of the specified domain of $p_{i,t}$.

Effort choices of uninformed entrepreneurs in the perfect information regime: In contrast to imperfect information, the information broker in the perfect information regime allows banks to acquire information about entrepreneurial types after period 1. As a result, they are able to offer risk-adjusted interest rates conditional on an entrepreneur's type at the beginning of period 2. In consequence, we apply the following logic to find the equilibrium effort choices of plums and lemons:

$$U_i(p_{i,1}, p_{i,2}) = \underbrace{p_{i,1}(R - R_{P,1}) - a_i p_{i,1}^2}_{\text{Period 1 utility}} + \underbrace{p_{i,2}(R - R_{i,2}) - a_i p_{i,2}^2}_{\text{Period 2 utility}}$$

Step 1: Identification of optimal effort choices

$$\frac{\partial U_L}{\partial p_{i,1}} = \underbrace{R - R_{P,1}}_{MR_{i,1}} - \underbrace{2a_i p_{i,1}}_{MC_{i,1}} \stackrel{!}{=} 0 \qquad \frac{\partial U_L}{\partial p_{i,2}} = \underbrace{R - R_{i,2}}_{MR_{i,2}} - \underbrace{2a_i p_{i,2}}_{MC_{i,2}} \stackrel{!}{=} 0$$

$$\Rightarrow p_{i,1}^U = \frac{R - R_{P,1}}{2a_i} \qquad \Rightarrow p_{2,1}^U = \frac{R - R_{i,2}}{2a_i}$$

Step 2: Evaluation of optimal effort choices

$$H_{U_L} = \begin{pmatrix} -2a_i & 0 \\ 0 & -2a_i \end{pmatrix} \Rightarrow Det(H_{U_L}) = \begin{vmatrix} -2a_i & 0 \\ 0 & -2a_i \end{vmatrix} = \underbrace{(-2a_i)(-2a_i)}_{a_i > 0} - 0^2 > 0.$$

$$\frac{\partial \partial U_L}{\partial p_{i,1} \partial p_{i,1}} = -2a_i < 0 \Rightarrow p_{i,1}^U \text{ is a maximum,} \quad \frac{\partial \partial U_H}{\partial p_{i,2} \partial p_{i,2}} = -2a_i < 0 \Rightarrow p_{i,2}^U \text{is a maximum}$$

Step 3: Admissibility of optimal effort choices

$$p_{i,1}^U = \frac{\overbrace{R - R_{P,1}}^{max\, R_{P,1} = R}}{\underbrace{2a_i}_{a_i > 0}} \geq 0, \qquad p_{i,2}^U = \frac{\overbrace{R - R_{i,2}}^{max\, R_{i,2} = R}}{\underbrace{2a_i}_{a_i > 0}} \geq 0.$$

$$p_{i,1}^U = \frac{R - R_{P,1}}{2a_i} \leq 1. \qquad p_{i,2}^U = \frac{R - R_{i,2}}{2a_i} \leq 1.$$

Similar to the previous scenarios, high net returns can push $p_{i,t}^U$ beyond 1, and thus we set $p_{i,t}^U := 1$ in these cases.

Step 4: Comparison to boundary points

The inferiority of boundary points follows directly from the (strict) convexity of U_L.

Effort choices of informed entrepreneurs in the perfect information regime: We implement the deceptive behavior of entrepreneurs by setting period 1 effort levels to a fixed value $p^U_{-i,1}$ drawn from the blockchain-based information system. To find period 2 choices, we then use the resulting utility function and the conditional interest rates charged under pooling to find $p^I_{i,2}$.

$$\begin{aligned}U_i\left(p^U_{-i,1}, p_{i,2}\right) =& \underbrace{p^U_{-i,1}\left(R - R_{P,1}\right) - a_i (p^U_{-i,1})^2}_{\text{Period 1 utility}} + \underbrace{p_{i,2}\left(R - E[R_{P,2}]\right) - a_i p^2_{i,2}}_{\text{Period 2 utility}} \\ =& p^U_{-i,1}\left(R - R_{P,1}\right) - a_i (p^U_{-i,1})^2 + p_{i,2}\left(R + p^U_{-i,1}\Delta R - R_{P,2}(0)\right) - a_i p^2_{i,2}\end{aligned}$$

Step 1: Identification of optimal effort choices

$$\begin{aligned}\frac{\partial U_i}{\partial p_{i,2}} =& \underbrace{R + p^*_{-i,1}\Delta R - R_{P,2}(0)}_{MR_{i,2}} - \underbrace{2a_i p_{i,2}}_{MC_{i,2}} \overset{!}{=} 0 \\ \Rightarrow p^I_{i,2}(p^U_{-i,1}) =& \frac{R + p^*_{-i,1}\Delta R - R_{P,2}(0)}{2a_i}\end{aligned}$$

Step 2: Evaluation of optimal effort choices

The second order condition is satisfied, because of the convexity of U_i directly follows from the convexity of V_i. More specifically, $\frac{\partial\partial U_i}{\partial p_{i,2}\partial p_{i,2}} = -2a_H < 0\ \forall i \in \{H, L\}$. In addition, this holds true for both types, as marginal effort is strictly more expensive for lemons but always positive $(0 > a_H > a_H)$. As a result, $p^I_{i,2}$ proofs to be a maximum.

Step 3: Admissibility of optimal effort choices

The admissibility of $p^I_{i,2}$ follows the same principle as in the other cases before: $p^I_{i,2}$ is greater than 0 as both numerator and denominator are both ≥ 0. In consequence, all $p^I_{i,2}$ trivially qualify as admissible. With respect to the upper bound of $p_{i,2} \leq 1$ we set $p^I_{i,2}$ to 1, whenever high net returns or low marginal costs would push effort beyond 100%. More specifically, we set $p^I_{i,2}$ to 1, if $R - R_{P,2}(R) > 2a_i$ and $p^I_{H,1}$ to 1.

Step 4: Comparison to boundary points

Again, the convexity of total and partial utility - which follows directly from the strict convexity of V_i - ensures the validity of $p^I_{i,2}$.

Effort choices of informed entrepreneurs in the perfect information regime: Similar to imperfect information, entrepreneurs set period 1 efforts to effort levels from their counterparts to mimic them. The lending bank then acquires this from the information system at the beginning and offers a type-specific interest in the period 2 separating equilibrium. In consequence, utility for type i is equal to:

$$U_i\left(p^U_{-i,1}, p_{i,2}\right) = \underbrace{p^U_{-i,1}\left(R - R_{P,1}\right) - a_i (p^U_{-i,1})^2}_{\text{Period 1 utility}} + \underbrace{p_{i,2}\left(R - R_{-i,2}\right) - a_i p^2_{i,2}}_{\text{Period 2 utility}}$$

Step 1: Identification of optimal effort choices

$$\frac{\partial U_L}{\partial p_{i,2}} = \underbrace{R - R_{-i,2}}_{MR_{i,2}} - \underbrace{2a_i p_{i,2}}_{MC_{i,2}} \overset{!}{=} 0$$
$$\Rightarrow p^I_{i,2} = \frac{R - R_{-i,2}}{2a_i}$$

Step 2: Evaluation of optimal effort choices

Analogous to the imperfect information regime, the second order condition is trivially satisfied, because of the convexity of U_i. More specifically, $\frac{\partial \partial U_i}{\partial p_{i,2} \partial p_{i,2}} = -2a_i < 0 \; \forall i \in \{H, L\}$, as marginal effort is strictly more expensive for lemons but always positive ($0 > a_H > a_H$). As a result, $p^I_{i,2}$ proofs to be a maxmimum for both types respectively.

Step 3: Admissibility of optimal effort choices

$$p^I_{i,2} = \frac{\overbrace{R - R_{i,2}}^{max\, R_{i,2}=R}}{\underbrace{2a_i}_{a_i>0}} \geq 0, \qquad p^I_{i,2} = \frac{R - R_{-i,2}}{2a_i} \leq 1.$$

Similar to the other cases, high net returns and/or low marginal costs can push $p^I_{i,2}$ beyond 1, and thus we set $p^I_{i,t} := 1$ in these cases.

Step 4: Comparison to boundary points

The inferiority of boundary points follows directly from the (strict) convexity of U_i.

Appendix D

Data & Analyses

D.1 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 Börse 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**

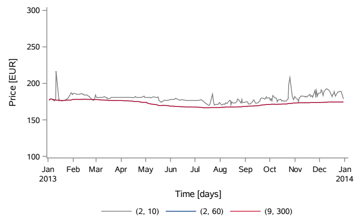
TABLE D.1: *Volume groups*
Volume groups based on the EUR trading volume, the number of submissions, and the number of executions at the Stuttgart stock exchange during the observation period (2013 to 2017).

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

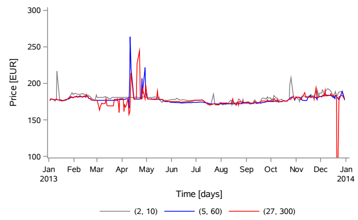
Year	2013	2014	2015	2016	2017	Total
Trading Days	253	252	253	237	236	1,231
	Total Executions					
Total	307,771	257,521	286,388	264,048	208,129	1,323,857
High	196,011	163,782	183,782	177,954	120,303	841,832
Medium	82,137	69,788	75,117	61,261	56,995	345,298
Low	29,623	23,951	27,489	24,833	30,831	136,727
	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 D.2: *Detailed summary statistics of the input sample by year and volume group.*

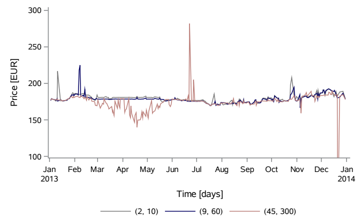
D.2 Replicated Market Outcomes



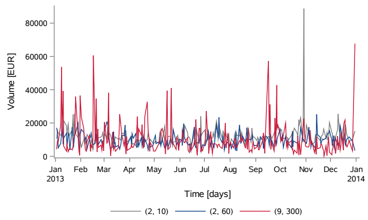
(A) *Prices BS = min*



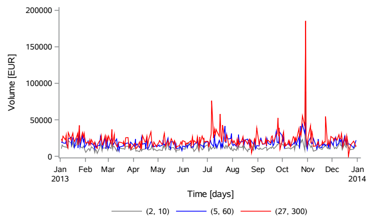
(B) *Prices BS = med*



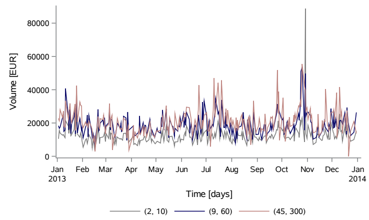
(C) *Prices BS = max*



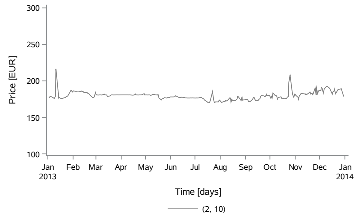
(D) *Volumes BS = min*



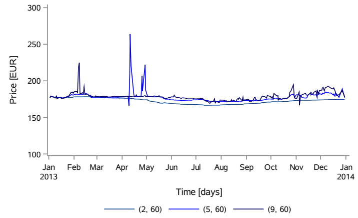
(E) *Volumes BS = med*



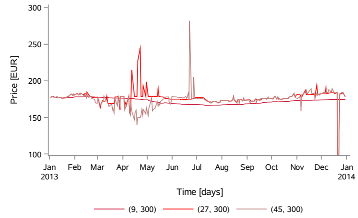
(F) *Volumes BS = max*



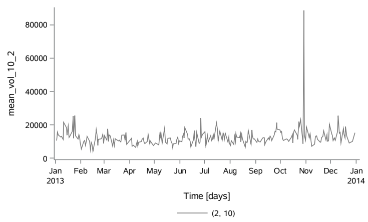
(G) *Prices BCT = 10*



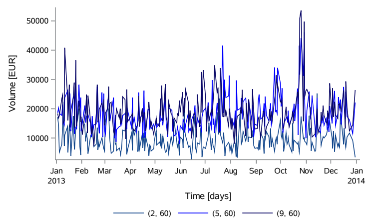
(H) *Prices BCT = 60*



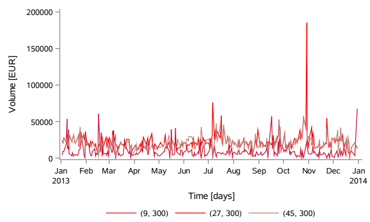
(I) *Prices BCT = 300*



(J) *Volumes BCT = 10*

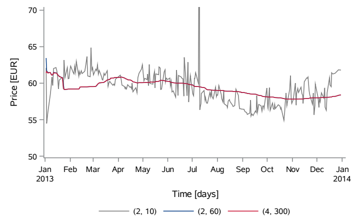


(K) *Volumes BCT = 60*

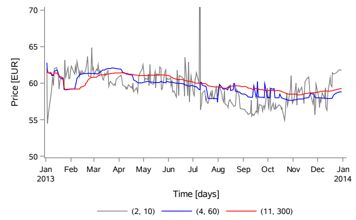


(L) *Volumes BCT = 300*

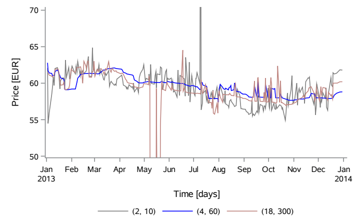
FIGURE D.1: *Comparative statics market outcomes VW AG*
Each panel illustrates the replicated trade prices or trading volumes for VW AG in 2013 (253 trading days), while holding either the BS or the BCT fixed. Prices are computed as daily averages and volumes as daily totals. The line color indicates the respective blockchain configuration (BS, BCT).



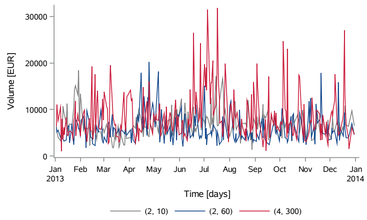
(A) *Prices BS = min*



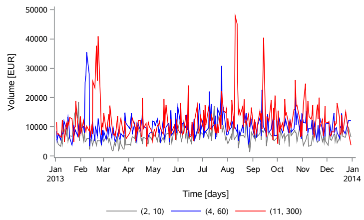
(B) *Prices BS = med*



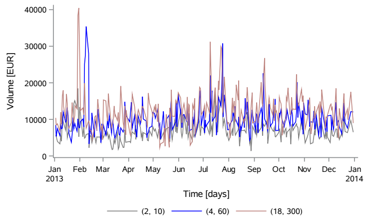
(C) *Prices BS = max*



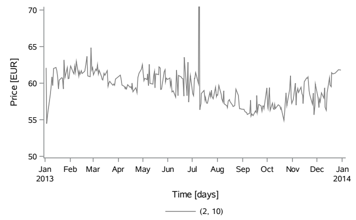
(D) *Volumes BS = min*



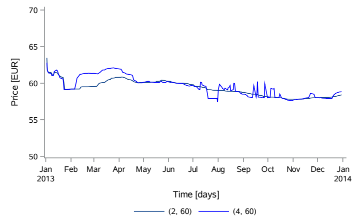
(E) *Volumes BS = med*



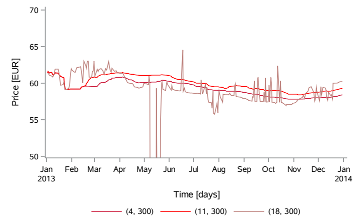
(F) *Volumes BS = max*



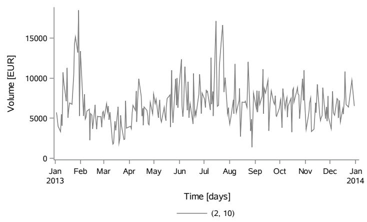
(G) *Prices BCT = 10*



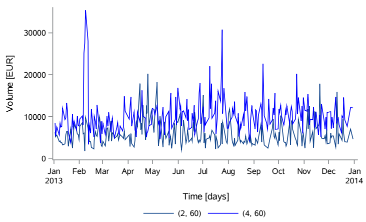
(H) *Prices BCT = 60*



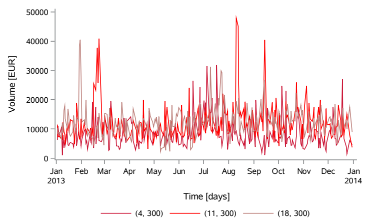
(I) *Prices BCT = 300*



(J) *Volumes BCT = 10*

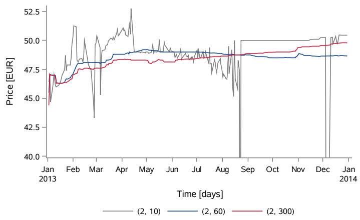


(K) *Volumes BCT = 60*

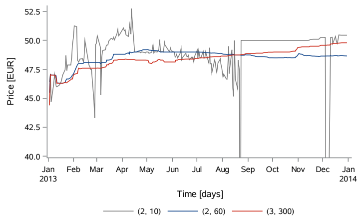


(L) *Volumes BCT = 300*

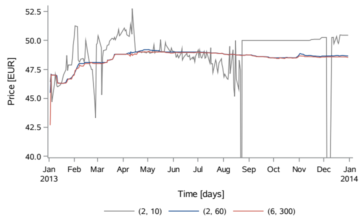
FIGURE D.2: *Comparative statics market outcomes SAP SE*
Each panel illustrates the replicated trade prices or trading volumes for SAP SE in 2013 (253 trading days), while holding either the BS or the BCT fixed. Prices are computed as daily averages and volumes as daily totals. The line color indicates the respective blockchain configuration (BS, BCT).



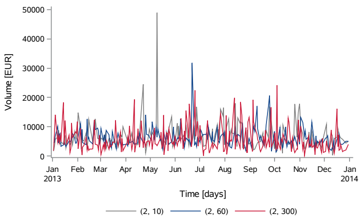
(A) *Prices BS = min*



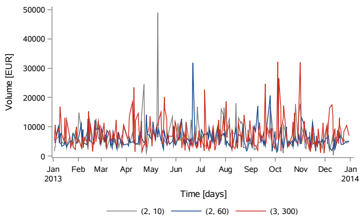
(B) *Prices BS = med*



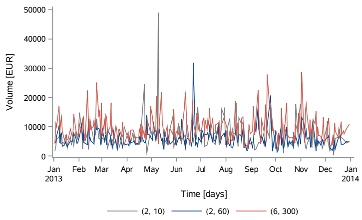
(C) *Prices BS = max*



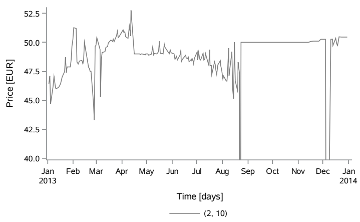
(D) *Volumes BS = min*



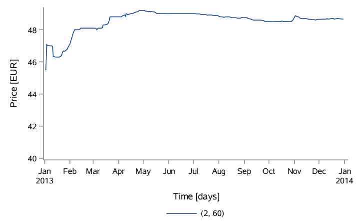
(E) *Volumes BS = med*



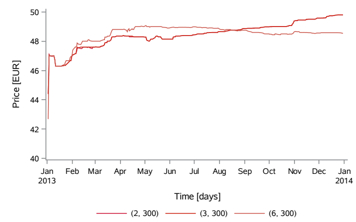
(F) *Volumes BS = max*



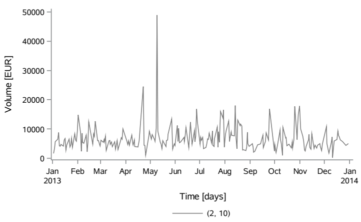
(G) *Prices BCT = 10*



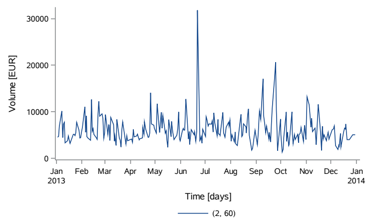
(H) *Prices BCT = 60*



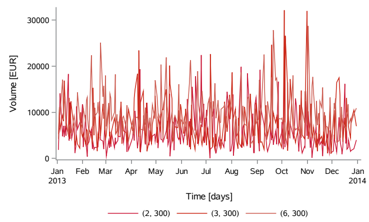
(I) *Prices BCT = 300*



(J) *Volumes BCT = 10*



(K) *Volumes BCT = 60*



(L) *Volumes BCT = 300*

FIGURE D.3: *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 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).

D.3 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 D.3: *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.*

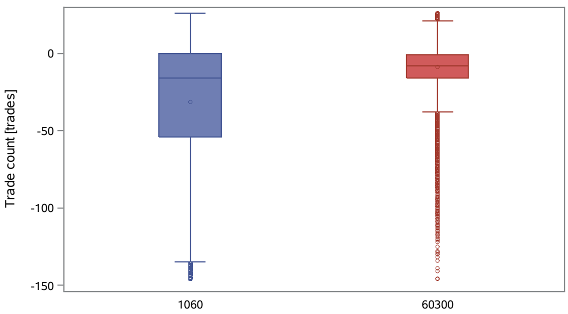
Quality Dimension	Activity			Liquidity		Information
Dependent Variable:	**TC**	**TO**	**ATS**	**DILLIQ**	**RQP**	**ABI**
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-108.44	-2,144,752.55	156.71	161.0954	0.7995	269.4001
	(-0.00)	(-0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	345,790.91	4,997,767,543.00	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 D.4: *Robustness – Alternative trading hours*

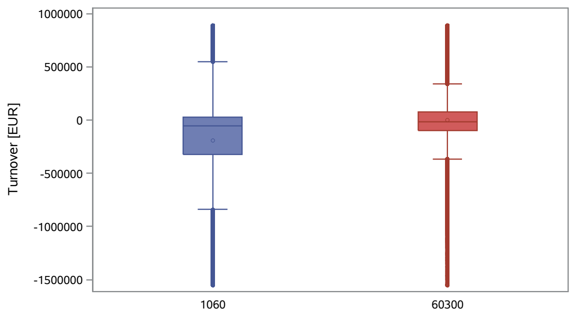
*This table presents full specification regressions (model 6) with a modified data panel for each MQM. Consistent with Xetra's trading hours, we only consider orders submitted between 9 a.m. and 5.30 p.m. to replicate market outcomes for 2017. We report β coefficients, t-statistics (in parentheses), 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

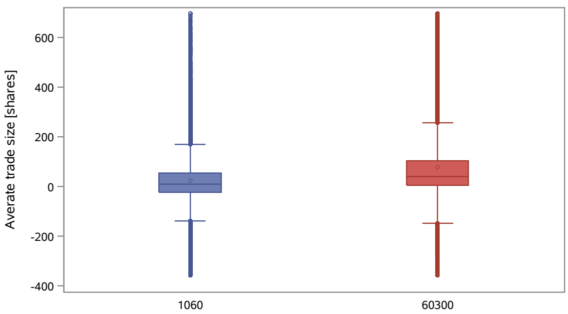
TABLE D.5: *Robustness – Additional controls and block direction*
*This table shows the regression results with RQP as additional control (columns 1 to 3) and for subsets with a positive (column 4) and a negative block direction (column 5). Blocks with a block direction of 0 are excluded. We report β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



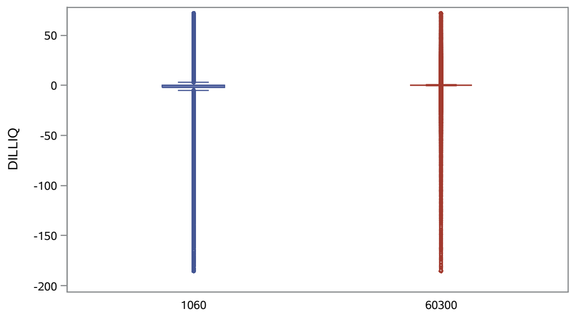
(A) Δ *TC*



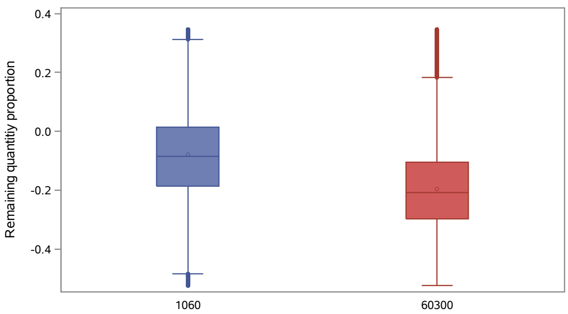
(B) Δ *TO*



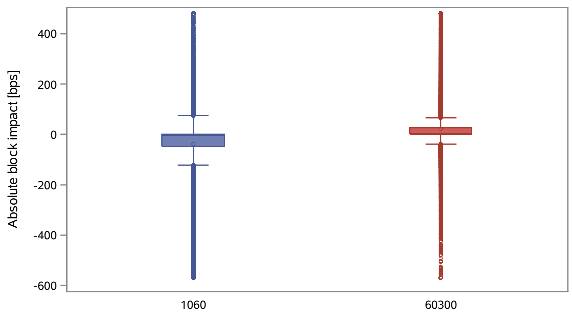
(C) Δ *ATS*



(D) Δ *DILLIQ* $\cdot 10^6$



(E) Δ *RQP*



(F) Δ *ABI* $\cdot 10^4$

FIGURE D.4: *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

Ahangama, S. and D. C. C. Poo (2016). Credibility of Algorithm Based Decentralized Computer Networks Governing Personal Finances: The Case of Cryptocurrency. In *Proceedings of the 3rd International Conference on HCI in Business, Government, and Organizations (HCIBGO)*, Volume 9751 of *Lecture Notes in Computer Science*, pp. 165–176. Springer International Publishing.

Akerlof, G. A. (1970). The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics 84*(3), 488–500.

Al Khalil, F., T. Butler, L. O'Brien, and M. Ceci (2017). Trust in Smart Contracts is a Process, As Well. In *Proceedings of the International Conference on Financial Cryptography and Data Security*, Volume 10323 of *Lecture Notes in Computer Science*, pp. 510–519. Springer International Publishing.

Albin, P. and D. K. Foley (1992). Decentralized, dispersed exchange without an auctioneer: A simulation study. *Journal of Economic Behavior & Organization 18*(1), 27 – 51.

Allen, F. and A. M. Santomero (1997). The theory of financial intermediation. *Journal of Banking & Finance 21*(11), 1461 – 1485.

Alt, R. and T. Puschmann (2016). *Digitalisierung der Finanzindustrie: Grundlagen der Fintech-Evolution*. Berlin and Heidelberg: Springer Gabler.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Amsden, R. and D. Schweizer (2018). Are Blockchain Crowdsales the New 'Gold Rush'? Success Determinants of Initial Coin Offerings. *SSRN Electronic Journal*.

Anagnostopoulos, I. (2018). Fintech and regtech: Impact on regulators and banks. *Journal of Economics and Business 100*, 7 – 25. FinTech – Impact on Consumers, Banking and Regulatory Policy.

Androulaki, E., Y. Manevich, S. Muralidharan, C. Murthy, B. Nguyen, M. Sethi, G. Singh, K. Smith, A. Sorniotti, C. Stathakopoulou, M. Vukolić, A. Barger, S. W. Cocco, J. Yellick, V. Bortnikov, C. Cachin, K. Christidis, A. D. Caro, D. Enyeart, C. Ferris, and G. Laventman (2018). Hyperledger fabric. In *Proceedings of the 13th EuroSys Conference (EuroSys '18)*. ACM Press.

Angelis, S. D., L. Aniello, R. Baldoni, F. Lombardi, A. Margheri, and V. Sassone (2018). Pbft vs proof-of-authority: applying the cap theorem to permissioned blockchain.

Ante, L., P. Sandner, and I. Fiedler (2018). Blockchain-Based ICOs: Pure Hype or the Dawn of a New Era of Startup Financing? *Journal of Risk and Financial Management 11*(4), 80.

Antonopoulos, A. M. (2017). *Mastering Bitcoin: Programming the open blockchain* (Second ed.). O'Reilly Media, Inc.

Aune, R. T., A. Krellenstein, M. O'Hara, and O. Slama (2017). Footprints on a blockchain: Trading and information leakage in distributed ledgers. *The Journal of Trading 12*(3), 5–13.

Avital, M., R. Beck, J. King, M. Rossi, and R. Teigland (2016). Jumping on the Blockchain Bandwagon: Lessons of the Past and Outlook to the Future. In *Proceedings on the 37th International Conference on System Sciences*.

Babus, A. and T.-W. Hu (2017). Endogenous intermediation in over-the-counter markets. *Journal of Financial Economics 125*(1), 200 – 215.

Babus, A. and P. Kondor (2018). Trading and information diffusion in over-the-counter markets. *Econometrica 86*(5), 1727–1769.

Back, A. (2002). Hashcash – a denial of service counter-measure.

Baiyere, A. and H. Salmela (2015). Wicked yet Empowering - When IT Innovations are also Disruptive Innovations. In *Proceedings of the 36th International Conference on Information Systems (ICIS)*.

Barclay, M. J., T. Hendershott, and D. T. McCormick (2003). Competition among trading venues: Information and trading on electronic communications networks. *The Journal of Finance 58*(6), 2637–2665.

Bariviera, A. F., M. J. Basgall, W. Hasperué, and M. Naiouf (2017). Some stylized facts of the bitcoin market. *Physica A: Statistical Mechanics and its Applications 484*, 82 – 90.

Barratt, M. J. (2015). Drugs on the Dark Net: How Cryptomarkets Are Transforming the Global Trade in Illicit Drugs. *Drug and Alcohol Review 34*(4), 458–459.

Barth, J. R., C. Lin, P. Lin, and F. M. Song (2009). Corruption in bank lending to firms: Cross-country micro evidence on the beneficial role of competition and information sharing. *Journal of Financial Economics 91*(3), 361 – 388.

Bartoletti, M. and L. Pompianu (2017). An Empirical Analysis of Smart Contracts: Platforms, Applications, and Design Patterns. In *Proceedings of the International Conference on Financial Cryptography and Data Security*, Volume 10323 of *Lecture Notes in Computer Science*, pp. 494–509. Springer International Publishing.

Bauer, I., L. Zavolokina, F. Leisibach, and G. Schwabe (2019). Exploring Blockchain Value Creation: The Case of the Car Ecosystem. In *Proceedings of the 52nd Hawaii International Conference on System Sciences (HICSS)*.

Beck, R., M. Avital, M. Rossi, and J. B. Thatcher (2017). Blockchain technology in business and information systems research. *Business & Information Systems Engineering 59*(6), 381–384.

Beck, R., C. Müller-Bloch, and J. L. King (2018). Governance in the Blockchain Economy: A Framework and Research Agenda. *Journal of the Association for Information Systems 19*(10), 1020–1034.

Beck, R., J. Stenum Czepluch, N. Lollike, and S. Malone (2016). Blockchain - The Gateway to trustfree cryptographic transactions. In *Proceeding of the 24th European Conference on Information Systems (ECIS)*.

Beck, T., A. Demirgüç-Kunt, and V. Maksimovic (2004). Bank Competition and Access to Finance: International Evidence. *Journal of Money, Credit and Banking 36*(3), 627–648.

Behr, P. and S. Sonnekalb (2012). The effect of information sharing between lenders on access to credit, cost of credit, and loan performance – evidence from a credit registry introduction. *Journal of Banking & Finance 36*(11), 3017 – 3032.

Benbasat, I. and R. W. Zmud (2003). The Identity Crisis within the Is Discipline: Defining and Communicating the Discipline's Core Properties. *MIS Quarterly 27*(2), 183–194.

Bennardo, A., M. Pagano, and S. Piccolo (2015). Multiple Bank Lending, Creditor Rights, and Information Sharing. *Review of Finance 19*(2), 519–570.

Bentov, I., C. Lee, A. Mizrahi, and M. Rosenfeld (2014). Proof of Activity: Extending Bitcoin's Proof of Work via Proof of Stake. *SIGMETRICS Perform. Eval. Rev. 42*(3), 34–37.

Berthoud, J. (1999). Ntu talks with milton friedman. Interview, National Taxpayers Union Foundation (NTUF). https://www.youtube.com/watch?v=mlwxdyLnMXM.

Bertrand, M. and A. Morse (2011). Information Disclosure, Cognitive Biases, and Payday Borrowing. *The Journal of Finance 66*(6), 1865–1893.

Bester, H. (1987). The role of collateral in credit markets with imperfect information. *European Economic Review 31*(4), 887 – 899.

Biais, B., C. Bisiere, M. Bouvard, and C. Casamatta (2018). The Blockchain Folk Theorem. *SSRN Electronic Journal*.

Block, C. A. (2010). *Agile Market Engineering: Bridging the gap between business concepts and running markets*. Ph. D. thesis, Karlsruhe Institute of Technology.

Bloomfield, R. and M. O'Hara (1999). Market Transparency: Who Wins and Who Loses? *The Review of Financial Studies 12*(1), 5–35.

Bogner, A., M. Chanson, and A. Meeuw (2016). A Decentralised Sharing App running a Smart Contract on the Ethereum Blockchain. In *Proceedings of the 6th International Conference on the Internet of Things (IoT'16)*, pp. 177–178. ACM.

Böhme, R., N. Christin, B. Edelman, and T. Moore (2015). Bitcoin: Economics, Technology, and Governance. *Journal of Economic Perspectives 29*(2), 213–238.

Bond, E. W. (1982). A Direct Test of the "Lemons" Model: The Market for Used Pickup Trucks. *The American Economic Review 72*(4), 836–840.

Boot, A. W. (2000). Relationship Banking: What Do We Know? *Journal of Financial Intermediation 9*(1), 7 – 25.

Boot, A. W. A. and A. V. Thakor (2000). Can Relationship Banking Survive Competition? *The Journal of Finance 55*(2), 679–713.

Borisov, N. (2006). Computational puzzles as sybil defenses. In *Proceedings of the 6th IEEE International Conference on Peer-to-Peer Computing (P2P'06)*, pp. 171–176.

Bos, M., E. Breza, and A. Liberman (2018). The Labor Market Effects of Credit Market Information. *The Review of Financial Studies 31*(6), 2005–2037.

Bouckaert, J. and H. Degryse (2006). Entry and Strategic Information Display in Credit Markets. *The Economic Journal 116*(513), 702–720.

Bouri, E., P. Molnár, G. Azzi, D. Roubaud, and L. I. Hagfors (2016). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters 20*, 192 – 198.

Brenig, C., R. Accorsi, and G. Müller (2015). Economic Analysis of Cryptocurrency Backed Money Laundering. In *Proceedings of the 23rd European Conference on Information Systems (ECIS)*.

Brenig, C., J. Schwarz, and N. Rückeshäuser (2016). Value of Decentralized Consensus Systems – Evaluation Framework. In *Proceedings of the 24th European Conference on Information Systems (ECIS)*.

Brière, M., K. Oosterlinck, and A. Szafarz (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management 16*(6), 365–373.

Brogaard, J., T. Hendershott, and R. Riordan (2014). High-Frequency Trading and Price Discovery. *The Review of Financial Studies 27*(8), 2267–2306.

Brown, M., T. Jappelli, and M. Pagano (2009). Information sharing and credit: Firm-level evidence from transition countries. *Journal of Financial Intermediation 18*(2), 151 – 172.

Brown, M. and C. Zehnder (2010). The emergence of information sharing in credit markets. *Journal of Financial Intermediation 19*(2), 255 – 278.

Brown, R. G., J. Carlyle, I. Grigg, and M. Hearn (2016). Corda: An introduction. Whitepaper, R3 CEV.

Budish, E., P. Cramton, and J. Shim (2014). Implementation Details for Frequent Batch Auctions: Slowing Down Markets to the Blink of an Eye. *The American Economic Review 104*(5), 418–424.

Budish, E., P. Cramton, and J. Shim (2015). The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response. *The Quarterly Journal of Economics 130*(4), 1547–1621.

Burghardt, M. and C. Weinhardt (2008). Nonlinear pricing of e-market transaction services. *International Journal of Electronic Business 6*(1), 4.

Burleson, J. (2013). Bitcoin: The Legal Implications of a Novel Currency. *Review of Banking & Financial Law 33*(1), 99–105.

Buterin, V. (2013). A Next-Generation Smart Contract and Decentralized Application Platform. Whitepaper.

Buyukkarabacak, B. and N. Valev (2012). Credit information sharing and banking crises: An empirical investigation. *Journal of Macroeconomics 34*(3), 788 – 800.

Cachin, C. (2016). Architecture of the hyperledger blockchain fabric. In *Proceedings of the Workshop on Distributed Cryptocurrencies and Consensus Ledgers*, Volume 310.

Cachin, C. and M. Vukolic (2017). Blockchain Consensus Protocols in the Wild. arXiv preprint 1707.01873.

Calem, P. S., M. B. Gordy, and L. J. Mester (2006). Switching costs and adverse selection in the market for credit cards: New evidence. *Journal of Banking & Finance 30*(6), 1653 – 1685.

Cao, C., O. Hansch, and X. Wang (2009). The information content of an open limit-order book. *Journal of Futures Markets 29*(1), 16–41.

Catalini, C. and J. Gans (2016). Some Simple Economics of the Blockchain. NBER Working Paper 22952, National Bureau of Economic Research.

Catalini, C. and J. Gans (2018). Initial Coin Offerings and the Value of Crypto Tokens. NBER Working Paper 24418, National Bureau of Economic Research.

Chaum, D. (1985). Security without identification: Transaction systems to make big brother obsolete. *Communications of the ACM 28*(10), 1030–1044.

Cheah, E.-T. and J. Fry (2015). Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. *Economics Letters 130*, 32 – 36.

Chiu, J. and T. V. Koeppl (2017). The Economics of Cryptocurrencies — Bitcoin and Beyond. *SSRN Electronic Journal*.

Chiu, J. and T. V. Koeppl (2018). Blockchain-Based Settlement for Asset Trading. *SSRN Electronic Journal*.

Chohan, U. W. (2017). The Double Spending Problem and Cryptocurrencies. *SSRN Electronic Journal*.

Christidis, K. and M. Devetsikiotis (2016). Blockchains and Smart Contracts for the Internet of Things. *IEEE Access 4*, 2292–2303.

Clapham, B. and K. Zimmermann (2016). Price discovery and convergence in fragmented securities markets. *International Journal of Managerial Finance 12*(4), 381–407.

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

Coase, R. H. (1937). The Nature of the Firm. *Economica 4*(16), 386–405.

Coase, R. H. (2013). The Problem of Social Cost. *The Journal of Law & Economics 56*(4), 837–877.

Cong, L. W. and Z. He (2018). Blockchain Disruption and Smart Contracts. NBER Working Paper 24399, National Bureau of Economic Research.

Connolly, T. M. and C. E. Begg (2015). *Database systems: A practical approach to design, implementation, and management* (6. ed. ed.). Boston: Pearson.

Consultancy.uk (2016). Two thirds of European FinTech startups eye strong revenue growth. Industry survey, Consultancy.uk.

Cooper, H. M. (1988). Organizing knowledge syntheses: A taxonomy of literature reviews. *Knowledge in Society 1*(1), 104–126.

Copeland, T. E. and D. Galai (1983). Information Effects on the Bid-Ask Spread. *The Journal of Finance 38*(5), 1457–1469.

Croman, K., C. Decker, I. Eyal, A. E. Gencer, A. Juels, A. Kosba, A. Miller, P. Saxena, E. Shi, E. G. Sirer, D. Song, and R. Wattenhofer (2016). On Scaling Decentralized Blockchains. In *Proceedings of the International Conference on Financial Cryptography and Data Security*, Volume 9604 of *Lecture Notes in Computer Science*, pp. 106–125. Springer International Publishing.

Dahlberg, T., H. Bouwman, N. Cerpa, and J. Guo (2015). M-Payment - How Disruptive Technologies Could Change The Payment Ecosystem. In *Proceedings of the 23rd European Conference on Information Systems (ECIS)*.

Daian, P., S. Goldfeder, T. Kell, Y. Li, X. Zhao, I. Bentov, L. Breidenbach, and A. Juels (2019). Flash Boys 2.0: Frontrunning, Transaction Reordering, and Consensus Instability in Decentralized Exchanges. arXiv preprint 1904.05234.

Darrat, A. F., S. Rahman, and M. Zhong (2003). Intraday trading volume and return volatility of the DJIA stocks: A note. *Journal of Banking & Finance 27*(10), 2035 – 2043.

Dauer, D., F. Vom Scheidt, and C. Weinhardt (2016). Towards smart distribution grids: a structured market engineering review. In *Proceedings of the 6th Karlsruhe Service Summit (KSS)*.

Davidson, S., P. D. Filippi, and J. Potts (2016). Economics of Blockchain. *SSRN Electronic Journal*.

de Reuver, M., C. Sørensen, and R. C. Basole (2017). The digital platform: a research agenda. *Journal of Information Technology*, 1–12.

de Velde, J. V., A. Scott, K. Sartorius, I. Dalton, B. Shepherd, C. Allchin, M. Dougherty, P. Ryan, and E. Rennick (2016). Blockchain in Capital Markets - The Prize and the Journey. Whitepaper, euroclear.

de Vries, A. (2018). Bitcoin's Growing Energy Problem. *Joule 2*(5), 801–805.

Debus, J. (2017). Consensus methods in blockchain systems. Fsbc working paper, Frankfurt School of Finance & Management.

Dell'Ariccia, G. and R. Marquez (2004). Information and bank credit allocation. *Journal of Financial Economics 72*(1), 185 – 214.

Demsetz, H. (1967). *Toward a Theory of Property Rights*, Volume 57, pp. 347–359.

Deutsche Bundesbank and Deutsche Börse (2016). Joint Deutsche Bundesbank and Deutsche Börse blockchain prototype. Media release.

Dev, J. A. (2014). Bitcoin mining acceleration and performance quantification. In *Proceedings of the IEEE 27th Canadian Conference on Electrical and Computer Engineering (CCECE)*, pp. 1–6.

Dhillon, G. (2016). Money Laundering and Technology Enabled Crime: a cultural analysis. In *Proceedings of the 22nd Americas Conferences on Information Systems (AMCIS)*.

Diamond, D. W. (1989). Reputation Acquisition in Debt Markets. *Journal of Political Economy 97*(4), 828–862.

Dierkes, M., C. Erner, T. Langer, and L. Norden (2013). Business credit information sharing and default risk of private firms. *Journal of Banking & Finance 37*(8), 2867 – 2878.

Dinger, J. and H. Hartenstein (2006). Defending the Sybil attack in P2P networks: taxonomy, challenges, and a proposal for self-registration. In *Proceedings of the First International Conference on Availability, Reliability and Security (ARES'06)*.

Djankov, S., C. McLiesh, and A. Shleifer (2007). Private credit in 129 countries. *Journal of Financial Economics 84*(2), 299 – 329.

Doblas-Madrid, A. and R. Minetti (2013). Sharing information in the credit market: Contract-level evidence from U.S. firms. *Journal of Financial Economics 109*(1), 198 – 223.

Duffie, D., N. Garleanu, and L. H. Pedersen (2005). Over-the-Counter Markets. *Econometrica 73*(6), 1815–1847.

Dyhrberg, A. H. (2016a). Bitcoin, gold and the dollar – A GARCH volatility analysis. *Finance Research Letters 16*, 85–92.

Dyhrberg, A. H. (2016b). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters 16*, 139–144.

Dziembowski, S., S. Faust, V. Kolmogorov, and K. Pietrzak (2015). Proofs of space. In *Proceedings of the Annual Cryptology Conference (CRYPTO 2015 – Advances in Cryptology)*, Volume 9216 of *Lecture Notes in Computer Science*, pp. 585–605. Springer International Publishing.

Economides, N. and R. A. Schwartz (1995). Electronic Call Market Trading. *The Journal of Portfolio Management 21*(3), 10–18.

Economist (2015). The trust machine: The promise of the blockchain. Article, The Economist.

Elmasri, R. and S. Navathe (2010). *Fundamentals of Database Systems* (6. ed. ed.). Addison-Wesley Publishing Company.

Ethereum (2016). Proof of Stake FAQ. Ethereum wiki.

European Commission (2018). 2018 reform of eu data protection rules.

Eyal, I. (2015). The Miner's Dilemma. In *Proceedings of the IEEE Symposium on Security and Privacy (SP)*, pp. 89–103.

Eyal, I. and E. G. Sirer (2018). Majority is not enough. *Communications of the ACM 61*(7), 95–102.

Fairfield, J. (2015). BitProperty. *Southern California Law Review 88*, 261–277.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*(1), 3 – 56.

Fama, E. F. and M. C. Jensen (1983). Separation of Ownership and Control. *The Journal of Law and Economics 26*(2), 301–325.

Fanning, K. and D. P. Centers (2016). Blockchain and Its Coming Impact on Financial Services. *Journal of Corporate Accounting & Finance 27*(5), 53–57.

Farmer, J. D. and S. Skouras (2012). Review of the benefits of a continuous market vs. randomised stop auctions and of alternative Priority Rules (policy options 7 and 12). Economic impact assessment eia11, Foresight, UK Government Office for Science.

Farmer, P. (2014). Speculative Tech: The Bitcoin Legal Quagmire & the Need for Legal Innovation. *Journal of Business & Technology Law 9*(1), 85.

Foss, N. J. (1996). Spontaneous Social Order: Economics and Schützian Sociology. *The American Journal of Economics and Sociology 55*(1), 73–86.

Frey, R., D. Wörner, and A. Ilic (2016). Collaborative Filtering on the Blockchain: A Secure Recommender System for e-Commerce. In *22nd Americas Conference on Information Systems (AMCIS)*.

Fricke, D. and A. Gerig (2018). Too fast or too slow? Determining the optimal speed of financial markets. *Quantitative Finance 18*(4), 519–532.

Friedlmaier, M., A. Tumasjan, and I. Welpe (2018). Disrupting Industries with Blockchain: The Industry, Venture Capital Funding, and Regional Distribution of Blockchain Ventures. In *Proceedings of the 51st Hawaii International Conference on System Sciences (HICSS)*.

Fröwis, M. and R. Böhme (2017). In code we trust? In *Proceedings of the International Workshop on Data Privacy Management, Cryptocurrencies and Blockchain Technology (DPM 2017, CBT 2017)*, Number 10436 in Lecture Notes in Computer Science, pp. 357–372. Springer International Publishing.

Fry, J. and E.-T. Cheah (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis 47*, 343–352.

Fujimura, S., H. Watanabe, A. Nakadaira, T. Yamada, A. Akutsu, and J. J. Kishigami (2015). BRIGHT: A concept for a decentralized rights management system based on blockchain. In *Proceedings of the 5th IEEE International Conference on Consumer Electronics - Berlin (ICCE-Berlin)*, pp. 345–346.

Fürstenau, D. and N. Kliewer (2014). Standards Diffusion in Growing Networks: Modelling Interaction Patterns. In *Proceedings of the 22nd European Conference on Information Systems (ECIS)*.

Gartner (2016). 3 Trends Appear in the Gartner Hype Cycle for Emerging Technologies.

Gartner (2018). 5 Trends Emerge in the Gartner Hype Cycle for Emerging Technologies.

Gavazza, A., A. Lizzeri, and N. Roketskiy (2014). A Quantitative Analysis of the Used-Car Market. *American Economic Review 104*(11), 3668–3700.

Gehrig, T. and R. Stenbacka (2007). Information sharing and lending market competition with switching costs and poaching. *European Economic Review 51*(1), 77 – 99.

Gencer, A. E., R. van Renesse, and E. G. Sirer (2017). Short paper: Service-oriented sharding for blockchains. In *Proceedings of the International Conference on Financial Cryptography and Data Security*, Volume 10323 of *Lecture Notes in Compuer Science*, pp. 393–401. Springer International Publishing.

Genesove, D. (1993). Adverse Selection in the Wholesale Used Car Market. *Journal of Political Economy 101*(4), 644–665.

Geng, D. (2016). Data Analytics on Consumer Behavior in Omni-Channel, Retail Banking, Card and Payment Services. In *Proceedings of the 20th Pacific Asia Conference on Information Systems (PACIS)*.

Gervais, A., G. O. Karame, K. Wüst, V. Glykantzis, H. Ritzdorf, and S. Capkun (2016). On the Security and Performance of Proof of Work Blockchains. In *Proceedings of the ACM SIGSAC Conference on Computer and Communications Security*, pp. 3–16.

Ghosh, M., M. Richardson, B. Ford, and R. Jansen (2014). A TorPath to TorCoin: proof-of-bandwidth altcoins for compensating relays. In *Proceedings of the 7th Workshop on Hot Topics in Privacy Enhancing Technologies (HotPETs)*.

Giaglis, G. M. and K. N. Kypriotaki (2014). Towards an Agenda for Information Systems Research on Digital Currencies and Bitcoin. In *Proceedings of the Business Information Systems Workshops (BIS)*, Volume 183 of *Lecture Notes in Business Information Processing*, pp. 3–13.

Giannetti, M., J. M. Liberti, and J. Sturgess (2017). Information Sharing and Rating Manipulation. *The Review of Financial Studies 30*(9), 3269–3304.

Gimpel, H., N. R. Jennings, G. E. Kersten, A. Ockenfels, and C. Weinhardt (2008). Market Engineering: A Research Agenda. In *Negotiation, Auctions, and Market Engineering*, Volume 2 of *Lecture Notes in Business Information Processing*, pp. 1–15. Berlin, Heidelberg: Springer.

Glaser, F. (2017). Pervasive Decentralisation of Digital Infrastructures: A Framework for Blockchain enabled System and Use Case Analysis. In *Proceedings of the 50th Hawaii International Conference on System Sciences (HICSS)*.

Glaser, F. and L. Bezzenberger (2015). Beyond Cryptocurrencies - A Taxonomy of Decentralized Consensus Systems. In *Proceedings of the 23rd European Conference on Information Systems (ECIS)*.

Glaser, F., F. Hawlitschek, and B. Notheisen (2019). Blockchain as a Platform. In *Business Transformation through Blockchain* (1st Ed. ed.), Volume I, Chapter 4. Palgrave Macmillan.

Glaser, F., K. Zimmermann, M. Haferkorn, M. C. Weber, and M. Siering (2014). Bitcoin-Asset or Currency? Revealing Users' Hidden Intentions. In *Proceedings of the 22nd European Conference on Information Systems (ECIS)*.

Gomber, P., R. J. Kauffman, C. Parker, and B. W. Weber (2018). On the fintech revolution: interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems 35*, 220–265.

Gomber, P., R. J. Kauffman, and B. W. Weber (2016). FINANCIAL IS, UNDERLYING TECHNOLOGIES, AND THE FINTECH REVOLUTION: A Call for Papers: Special Issue of the Journal of Management Information Systems.

Gozman, D., J. Hedman, K. Sylvest, and D. Bank (2018). Open Banking: Emergent Roles, Risks & Opportunities. In *Proceedings of the 26th European Conference on Information Systems (ECIS)*.

Grajzl, P. and N. Laptieva (2016). Information sharing and the volume of private credit in transition: Evidence from ukrainian bank-level panel data. *Journal of Comparative Economics 44*(2), 434 – 449.

Gregor, S. and A. R. Hevner (2013). Positioning and Presenting Design Science Research for Maximum Impact. *MIS Quarterly 2*(37), 337–355.

Greiner, M. and W. Hui (2015). Trust-free Systems - a New Research and Design Direction to Handle Trust-Issues in P2P Systems: The Case of Bitcoin. In *Proceedings of the 21st Americas Conference on Information Systems (AMCIS)*.

Gubbi, J., R. Buyya, S. Marusic, and M. Palaniswami (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems 29*(7), 1645–1660.

Gump, A. and C. Leonard (2016). Blockchain: regulating the future of finance. *International Financial Law Review 35*(13).

Guo, Y. and C. Liang (2016). Blockchain application and outlook in the banking industry. *Financial Innovation 2*(1), 12–24.

Haber, S. and W. S. Stornetta (1991). How to time-stamp a digital document. *Journal of Cryptology 3*(2), 99–111.

Hari, A. and T. V. Lakshman (2016). The Internet Blockchain. In *Proceedings of the 15th ACM Workshop on Hot Topics in Networks - HotNets '16*, pp. 204–210.

Harris, L. (2003). *Trading and exchanges: Market microstructure for practitioners*. Financial Management Association Survey and Synthesis. New York: Oxford University Press.

Hasbrouck, J. (1991a). Measuring the Information Content of Stock Trades. *The Journal of Finance 46*(1), 179–207.

Hasbrouck, J. (1991b). Security Markets, Information and Liquidity. *Financial Practice and Education 1*(2), 7–16.

Hasbrouck, J. (1991c). The summary informativeness of stock trades: An econometric analysis. *The Review of Financial Studies 4*(3), 571–595.

Hasbrouck, J. (1995). One Security, Many Markets: Determining the Contributions to Price Discovery. *The Journal of Finance 50*(4), 1175–1199.

Hawlitschek, F. (2019). *Trust in the Sharing Economy: A Behavioral Perspective on Peer-to-Peer Markets*. Ph. D. thesis, Karlsruhe Institute of Technology.

Hawlitschek, F., B. Notheisen, and T. Teubner (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.

Hawlitschek, F., T. Teubner, M. T. P. Adam, N. S. Borchers, M. Möhlmann, and C. Weinhardt (2016). Trust in the Sharing Economy: An Experimental Framework. In *Proceedings of the 37th International Conference on Information Systems (ICIS)*.

Hawlitschek, F., T. Teubner, and H. Gimpel (2016). Understanding the Sharing Economy – Drivers and Impediments for Participation in Peer-to-Peer Rental. In *Proceedings of the 49th Hawaii International Conference on System Sciences (HICSS)*.

Hellmann, T. and J. Stiglitz (2000). Credit and Equity Rationing in Markets with Adverse Selection. *European Economic Review 44*(2), 281 – 304.

Hendel, I. and A. Lizzeri (2002). The Role of Leasing under Adverse Selection. *Journal of Political Economy 110*(1), 113–143.

Hendel, I., A. Lizzeri, and M. Siniscalchi (2005). Efficient sorting in a dynamic adverse-selection model. *The Review of Economic Studies 72*(2), 467–497.

Hendershott, T., C. M. Jones, and A. J. Menkveld (2011). Does Algorithmic Trading Improve Liquidity? *The Journal of Finance 66*(1), 1–33.

Hendershott, T. and P. C. Moulton (2011). Automation, speed, and stock market quality: The NYSE's Hybrid. *Journal of Financial Markets 14*(4), 568–604.

Hertzberg, A., J. M. Liberti, and D. Paravisini (2011). Public Information and Coordination: Evidence from a Credit Registry Expansion. *The Journal of Finance 66*(2), 379–412.

Hevner, A. R., S. T. March, J. Park, and R. Sudha (2004). Design Science in Information Systems Research. *MIS Quarterly 1*(28), 75–105.

Hjelholt, M. and J. Damsgaard (2012). The Genesis and Evolution of Digital Payment Platforms. In *Proceedings of the 20th European Conference on Information Systems (ECIS)*.

Hodgson, G. M. (2006). What are Institutions? *Journal of Economic Issues 40*(1), 1–25.

Houston, J. F., C. Lin, P. Lin, and Y. Ma (2010). Creditor rights, information sharing, and bank risk taking. *Journal of Financial Economics 96*(3), 485 – 512.

Huang, R. D. and H. R. Stoll (1996). Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE. *Journal of Financial Economics 41*(3), 313–357.

Huckle, S., R. Bhattacharya, M. White, and N. Beloff (2016). Internet of Things, Blockchain and Shared Economy Applications. *Procedia Computer Science 98*, 461–466.

Hugonnier, J., B. Lester, and P.-O. Weill (2014). Heterogeneity in decentralized asset markets. NBER Working Paper 20746, National Bureau of Economic Research.

Hur, Y., S. Jeon, and B. Yoo (2015). Is Bitcoin a Viable E-Business?: Empirical Analysis of the Digital Currency's Speculative Nature. In *Proceedings of the 36th International Conference on Information Systems (ICIS)*.

Hyytinen, A. and L. Väänänen (2006). Where Do Financial Constraints Originate from? An Empirical Analysis of Adverse Selection and Moral Hazard in Capital Markets. *Small Business Economics 27*(4), 323–348.

Iansiti, M. and K. R. Lakhani (2017). The truth about blockchain. *Harvard Business Review 95*(1), 118–127.

Imeri, A., D. Khadraoui, and N. Agoulmine (2019). Blockchain Technology for the Improvement of SCM and Logistics Services: A Survey. In *Lecture Notes in Management and Industrial Engineering*, pp. 349–361. Springer International Publishing.

Ingram, C. and M. Morisse (2016). Almost an MNC: Bitcoin Entrepreneurs' Use of Collective Resources and Decoupling to Build Legitimacy. In *Proceedings of the 49th Hawaii International Conference on System Sciences (HICSS)*, pp. 4083–4092.

Ingram, C., M. Morisse, and R. Teigland (2015). 'A Bad Apple Went Away': Exploring Resilience Among Bitcoin Entrepreneurs. In *23rd European Conference on Information Systems (ECIS)*.

Irwin, A. S. M. and G. Milad (2016). The use of crypto-currencies in funding violent jihad. *Journal of Money Laundering Control 19*(4), 407–425.

Jappelli, T. and M. Pagano (2002). Information sharing, lending and defaults: Cross-country evidence. *Journal of Banking & Finance 26*(10), 2017–2045.

Jensen, M. C. and W. H. Meckling (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics 3*(4), 305 – 360.

Jentzsch, C. (2016). Decentralized autonomous organization to automate governance. Whitepaper, Slock.it.

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

John, N. A. (2013). Sharing and Web 2.0: The emergence of a keyword. *New Media & Society 15*(2), 167–182.

Jones, C. M., G. Kaul, and M. L. Lipson (1994). Transactions, Volume, and Volatility. *The Review of Financial Studies 7*(4), 631–651.

Kallberg, J. G. and G. F. Udell (2003). The value of private sector business credit information sharing: The US case. *Journal of Banking & Finance 27*(3), 449 – 469.

Karame, G. (2016). On the Security and Scalability of Bitcoin's Blockchain. In *Proceedings of the ACM SIGSAC Conference on Computer and Communications Security (CCS'16)*, pp. 1861–1862.

Karapetyan, A. and B. Stacescu (2014). Information Sharing and Information Acquisition in Credit Markets. *Review of Finance 18*(4), 1583–1615.

Karlan, D. and J. Zinman (2009). Observing Unobservables: Identifying Information Asymmetries With a Consumer Credit Field Experiment. *Econometrica 77*(6), 1993–2008.

Kassin, I. (2016). How Fintech Companies Can Capture The Millennial Market.

Katz, J., A. J. Menezes, P. C. Van Oorschot, and S. A. Vanstone (1997). *Handbook of applied cryptography* (First ed.). CRC press.

Kazan, E. and J. Damsgaard (2014). An Investigation of Digital Payment Platform Designs: a Comparative Study of Four European solutions. In *Proceedings of the 22nd European Conference on Information Systems (ECIS)*.

Kazan, E., C.-W. Tan, and E. T. Lim (2015). Value Creation in Cryptocurrency Networks: Towards A Taxonomy of Digital Business Models for Bitcoin Companies. In *Proceedings of the 21st Americas Conference on Information Systems (AMCIS)*.

Kazan, E., C.-W. Tan, and E. T. K. Lim (2014). Towards a Framework of Digital Platform Disruption. In *Proceedings of the 25th Australasian Conference on Information Systems (ACIS)*.

Keymolen, E. (2013). Trust and technology in collaborative consumption. why it is not just about you and me. *Bridging distances in technology and regulation 135*, 135–150.

King, S. and S. Nadal (2012). Ppcoin: Peer-to-peer crypto-currency with proof-of-stake. *self-published paper*.

Kirschenmann, K. (2016). Credit rationing in small firm-bank relationships. *Journal of Financial Intermediation 26*, 68 – 99.

Kloker, S., F. Klatt, J. Höffer, and C. Weinhardt (2018). Analyzing prediction market trading behaviour to select Delphi-experts. *Foresight 20*(4), 364–374.

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

Kosba, A., A. Miller, E. Shi, Z. Wen, and C. Papamanthou (2016). Hawk: The Blockchain Model of Cryptography and Privacy-Preserving Smart Contracts. In *Proceedings of the IEEE Symposium on Security and Privacy (SP)*, pp. 839–858.

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

Kranz, T. T., F. Teschner, and C. Weinhardt (2015). Beware of performance indicators. *Business & Information Systems Engineering 57*(6), 349–361.

Kroll, J. A., I. C. Davey, and E. W. Felten (2013). The economics of Bitcoin mining, or Bitcoin in the presence of adversaries. In *Proceedings of the 12th Workshop on the Economics of Information Security (WEIS)*.

Lamport, L., R. Shostak, and M. Pease (1982). The Byzantine Generals Problem. *ACM Transactions on Programming Languages and Systems 4*(3), 382–401.

Lange, O. (1942). The Foundations of Welfare Economics. *Econometrica 10*(3/4), 215–228.

Lannquist, A. (2018). Blockchain in Enterprise: How Companies are Using Blockchain Today. Blockchain at berkely, University of California.

Lee, J.-N. and Y.-G. Kim (1999). Effect of Partnership Quality on IS Outsourcing Success: Conceptual Framework and Empirical Validation. *Journal of Management Information Systems 15*(4), 29–61.

Lee, L. (2016). New Kids on the Blockchain: How Bitcoin's Technology Could Reinvent the Stock Market. *Hastings Business Law Journal 12*(2), 81–132.

Levenshtein, V. (1965). Binary codes capable of correcting spurious insertions and deletions of ones. *Problems of information Transmission 1*(1), 8–17.

Lewis, G. (2011). Asymmetric Information, Adverse Selection and Online Disclosure: The Case of eBay Motors. *The American Economic Review 101*(4), 1535–1546.

Li, D. and N. Schürhoff (2019). Dealer networks. *The Journal of Finance 74*(1), 91–144.

Liberti, J. M. and M. A. Petersen (2018). Information: Hard and Soft. *Review of Corporate Finance Studies 8*(1), 1–41.

Liebenau, J. M., S. M. Elaluf-Calderwood, and C. M. Bonina (2014). Modularity and Network Integration: Emergent Business Models in Banking. In *Proceedings of the 8th IEEE International Symposium on Service-Oriented System Engineering (SOSE)*, pp. 1183–1192.

Lin, M., H. C. Lucas Jr., and G. Shmueli (2013). Research Commentary - Too Big to Fail: Large Samples and the p-Value Problem. *Information Systems Research 24*(4), 906–917.

Luckner, S., F. Kratzer, and C. Weinhardt (2005). STOCCER-A Forecasting Market for the FIFA World Cup 2006. In *Proceedings of the 4th Workshop on e-Business (WeB)*.

Lustig, C. and B. Nardi (2015). Algorithmic Authority: The Case of Bitcoin. In *Proceedings of the 48th Hawaii International Conference on System Sciences (HICSS)*, pp. 743–752.

Madhavan, A. (1992). Trading Mechanisms in Securities Markets. *The Journal of Finance 47*(2), 607–641.

Mai, F., Q. Bai, Z. Shan, X. Wang, and R. H. Chiang (2015). From Bitcoin to Big Coin: The Impacts of Social Media on Bitcoin Performance. In *Proceedings of the 36th International Conference on Information Systems (ICIS)*.

Malamud, S. and M. Rostek (2017). Decentralized exchange. *American Economic Review 107*(11), 3320–62.

Malinova, K. and A. Park (2017). Market Design with Blockchain Technology. *SSRN Electronic Journal*.

March, S. T. and G. F. Smith (1995). Design and natural science research on information technology. *Decision Support Systems 15*(4), 251–266.

Marian, O. Y. (2013). Are Cryptocurrencies 'Super' Tax Havens? *Michigan Law Review* (38).

Mazieres, D. (2015). The stellar consensus protocol: A federated model for internet-level consensus. Whitepaper, Stellar Development Foundation.

Mengelkamp, E., J. Gärttner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt (2018). Designing microgrid energy markets. *Applied Energy 210*, 870–880.

Mengelkamp, E., B. Notheisen, C. Beer, D. Dauer, and C. Weinhardt (2017). A blockchain-based smart grid: towards sustainable local energy markets. *Computer Science - Research and Development 33*(1-2), 207–214.

Miller, A., A. Juels, E. Shi, B. Parno, and J. Katz (2014). Permacoin: Repurposing bitcoin work for data preservation. In *Proceedings of the IEEE Symposium on Security and Privacy (SP)*, pp. 475–490.

Millon, M. H. and A. V. Thakor (1985). Moral Hazard and Information Sharing: A Model of Financial Information Gathering Agencies. *The Journal of Finance 40*(5), 1403–1422.

Mills, D. C. et al. (2016). Distributed Ledger Technology in Payments, Clearing, and Settlement. *FEDS Working Paper No. 2016-095*.

Mingxiao, D., M. Xiaofeng, Z. Zhe, W. Xiangwei, and C. Qijun (2017). A review on consensus algorithm of blockchain. In *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 2567–2572.

Mittendorf, C. (2016). What Trust means in the Sharing Economy: A provider perspective on Airbnb.com. In *Proceedings of the 22nd Americas Conference on Information Systems (AMCIS)*.

Möhlmann, M. (2016). Digital Trust and Peer-to-Peer Collaborative Consumption Platforms: A Mediation Analysis. *SSRN Electronic Journal*.

Morabito, V. (2017). *Blockchain Governance* (1st Ed. ed.)., pp. 41–59. Cham: Springer.

Morisse, M. (2015). Cryptocurrencies and Bitcoin: Charting the Research Landscape. In *Proceedings of the 21st Americas Conference on Information Systems (AMCIS)*.

Moser, M., R. Böhme, and D. Breuker (2013). An inquiry into money laundering tools in the Bitcoin ecosystem. In *Proceedings of the 21st European Conference on Information Systems (ECIS)*.

Nadarajah, S. and J. Chu (2017). On the inefficiency of Bitcoin. *Economics Letters 150*, 6–9.

Næs, R., J. A. Skjeltorp, and B. A. Ødegaard (2011). Stock market liquidity and the business cycle. *The Journal of Finance 66*(1), 139–176.

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. Whitepaper.

Navarro, G. (2001). A guided tour to approximate string matching. *ACM Computing Surveys 33*(1), 31–88.

Nayak, K., S. Kumar, A. Miller, and E. Shi (2016). Stubborn Mining: Generalizing Selfish Mining and Combining with an Eclipse Attack. In *Proceedings of the IEEE European Symposium on Security and Privacy (EuroS&P)*.

Nofer, M., P. Gomber, O. Hinz, and D. Schiereck (2017). Blockchain. *Business & Information Systems Engineering 59*(3), 183–187.

North, D. C. (1991). Institutions. *Journal of Economic Perspectives 5*(1), 97–112.

Notheisen, B., J. B. Cholewa, and A. P. Shanmugam (2017). Trading Real-World Assets on Blockchain - An Application of Trust-Free Transaction Systems in the Market for Lemons. *Business & Information Systems Engineering 59*(6), 425–440.

Notheisen, B., M. Gödde, and C. Weinhardt (2017). Trading Stocks on Blocks - Engineering Decentralized Markets. In *DESRIST 2017: Designing the Digital Transformation*, Volume 10243 of *Lecture Notes in Computer Science*, pp. 474–478. Springer International Publishing.

Notheisen, B., F. Hawlitschek, and C. Weinhardt (2017). Breaking Down the Blockchain Hype – Towards a Blockchain Market Engineering Approach. In *Proceedings of the 25th European Conference on Information Systems (ECIS)*.

Notheisen, B., V. Marino, D. Englert, and C. Weinhardt (2018). Trading Stocks on Blocks – The Quality of Decentralized Markets. *SSRN Electronic Journal*.

Notheisen, B. and C. Weinhardt (2018). The Blockchain, Plums, and Lemons - Information Asymmetries in Decentralized Markets. *SSRN Electronic Journal*.

Notheisen, B., S. Willrich, M. Diez, and C. Weinhardt (2019). Requirement-driven Taxonomy Development – A Classification of Blockchain Technologies for Securities Post-Trading. In *Proceedings of the 52th Hawaii International Conference on System Sciences (HICSS)*.

O'Dwyer, K. J. and D. Malone (2014). Bitcoin Mining and its Energy Footprint. In *25th IET Irish Signals & Systems Conference and China-Ireland International Conference on Information and Communities Technologies (ISSC/CIICT)*. Institution of Engineering and Technology.

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

Oliveira, L., L. Zavolokina, I. Bauer, and G. Schwabe (2018). To Token or not to Token: Tools for Understanding Blockchain Tokens. In *Proceedings of the 39th International Conference on Information Systems (ICIS)*.

Ostrom, E. (1986). An Agenda for the Study of Institutions. *Public Choice 48*(1), 3–25.

Padilla, A. and M. Pagano (2000). Sharing default information as a borrower discipline device. *European Economic Review 44*(10), 1951 – 1980.

Padilla, A. J. and M. Pagano (1997). Endogenous Communication Among Lenders and Entrepreneurial Incentives. *The Review of Financial Studies 10*(1), 205–236.

Paech, P. (2017). The Governance of Blockchain Financial Networks. *The Modern Law Review 80*(6), 1073–1110.

Pagano, M. and T. Jappelli (1993). Information Sharing in Credit Markets. *The Journal of Finance 48*(5), 1693–1718.

Pagano, M. and A. Röell (1996). Transparency and liquidity: A comparison of auction and dealer markets with informed trading. *The Journal of Finance 51*(2), 579–611.

Panarello, A., N. Tapas, G. Merlino, F. Longo, and A. Puliafito (2018). Blockchain and IoT Integration: A Systematic Survey. *Sensors 18*(8), 2575.

Pancs, R. (2012). Comparing Market Structures: Allocative and Informational Efficiencies of Continuous Trading, Periodic Auctions, and Dark Pools. Working paper.

Parker, G. and M. Van Alstyne (2018). Innovation, Openness, and Platform Control. *Management Science 64*(7), 3015–3032.

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

Patel, J., R. Zeckhauser, and D. Hendricks (1991). The Rationality Struggle: Illustrations from Financial Markets. *The American Economic Review 81*(2), 232–236.

Pawczuk, L., R. Massey, and D. Schatsky (2018). Breaking blockchain open - Deloitte's 2018 global blockchain survey. Industry survey, Deloitte.

Pazaitis, A., P. de Filippi, and V. Kostakis (2017). Blockchain and value systems in the sharing economy: The illustrative case of Backfeed. *Technological Forecasting and Social Change 125*, 105–115.

Peffers, K., T. Tuunanen, M. Rothenberger, and S. Chatterjee (2007). A design science research methodology for information systems research. *Journal of Management Information Systems 24*(3), 45–77.

Peters, G., E. Panayi, and A. Chapelle (2015). Trends in cryptocurrencies and blockchain technologies: a monetary theory and regulation perspective. *Journal of Financial Perspectives 3*(3).

Peterson, J. R. and H. S. Schneider (2014). Adverse selection in the used-car market: evidence from purchase and repair patterns in the Consumer Expenditure Survey. *The RAND Journal of Economics 45*(1), 140–154.

Peterson, M. (2018). Blockchain and the Future of Financial Services. *The Journal of Wealth Management 21*(1), 124–131.

Pinna, A. and W. Ruttenberg (2016). Distributed Ledger Technologies in Securities Post-Trading. Occasional Paper Series 172, European Central Bank.

Poteshman, A. M. and V. Serbin (2003). Clearly Irrational Financial Market Behavior: Evidence from the Early Exercise of Exchange Traded Stock Options. *The Journal of Finance 58*(1), 37–70.

Puschmann, T., R. Nueesch, and R. Alt (2012). Transformation Towards Customer-Oriented Service Architectures in the Financial Industry. In *Proceedings of the 20th European Conference on Information Systems (ECIS)*.

Quinn, J. B. and F. G. Hilmer (1994). Strategic outsourcing. *Sloan management review 35*(4), 43.

Raskin, M. and D. Yermack (2016). Digital Currencies, Decentralized Ledgers, and the Future of Central Banking. NBER Working Paper 22238, National Bureau of Economic Research.

Riordan, R. and A. Storkenmaier (2012). Latency, liquidity and price discovery. *Journal of Financial Markets 15*(4), 416–437.

Riordan, R., A. Storkenmaier, M. Wagener, and S. S. Zhang (2013). Public information arrival: Price discovery and liquidity in electronic limit order markets. *Journal of Banking & Finance 37*(4), 1148–1159.

Risius, M. and K. Spohrer (2017). A Blockchain Research Framework. *Business & Information Systems Engineering 59*(6), 385–409.

Ritzer, G., P. Dean, and N. Jurgenson (2012). The Coming of Age of the Prosumer. *American Behavioral Scientist 56*(4), 379–398.

Rivest, R. L., A. Shamir, and L. Adleman (1978). A method for obtaining digital signatures and public-key cryptosystems. *Communications of the ACM 21*(2), 120–126.

Roth, A. E. (2002). The Economist as Engineer: Game Theory, Experimentation, and Computation as Tools for Design Economics. *Econometrica 70*(4), 1341–1378.

Rousseau, D. M., S. B. Sitkin, R. S. Burt, and C. Camerer (1998). Not so different after all: A cross discipline view of trust. *Academy of Management Review 23*(3), 393–404.

Ruault, P. (2016). Collateral management — Winners or losers in five years' time? *Journal of Securities Operations & Custody 8*(1), 41–45.

Saleh, F. (2018). Blockchain Without Waste: Proof-of-Stake. *SSRN Electronic Journal*.

Salviotti, G., L. M. De Rossi, and N. Abbatemarco (2018). A structured framework to assess the business application landscape of blockchain technologies. In *Proceedings of the 51st Hawaii International Conference on System Sciences (HICSS)*.

Sas, C. and I. E. Khairuddin (2015). Exploring Trust in Bitcoin Technology. In *Proceedings of the ACM Annual Meeting of the Australian Special Interest Group for Computer Human Interaction (OzCHI '15)*, pp. 338–342.

Sasson, E. B., A. Chiesa, C. Garman, M. Green, I. Miers, E. Tromer, and M. Virza (2014). Zerocash: Decentralized Anonymous Payments from Bitcoin. In *Proceedings of the IEEE Symposium on Security and Privacy*.

Schwartz, D., N. Youngs, A. Britto, et al. (2014). The ripple protocol consensus algorithm. Whitepaper.

Shapira, Z. and I. Venezia (2001). Patterns of behavior of professionally managed and independent investors. *Journal of Banking & Finance 25*(8), 1573 – 1587.

Sharma, P. (2017). Is more information always better? a case in credit markets. *Journal of Economic Behavior & Organization 134*, 269 – 283.

Sharpe, S. A. (1990). Asymmetric Information, Bank Lending, and Implicit Contracts: A Stylized Model of Customer Relationships. *The Journal of Finance 45*(4), 1069–1087.

Shermin, V. (2017). Disrupting governance with blockchains and smart contracts. *Strategic Change 26*(5), 499–509.

Sixt, E. (2017). *Kryptoökonomie*, pp. 1–4. Springer.

Smith, V. L. (2003). Constructivist and Ecological Rationality in Economics. *The American Economic Review 93*(3), 465–508.

Söllner, M., A. Hoffmann, and J. M. Leimeister (2016). Why different trust relationships matter for information systems users. *European Journal of Information Systems 25*(3), 274–287.

Stiglitz, J. E. and A. Weiss (1981). Credit Rationing in Markets with Imperfect Information. *The American Economic Review 71*(3), 393–410.

Stummer, C., D. Kundisch, and R. Decker (2018). Platform Launch Strategies. *Business & Information Systems Engineering 60*, 167–173.

Subrahmanyam, A. (1994). Circuit Breakers and Market Volatility: A Theoretical Perspective. *The Journal of Finance 49*(1), 237–254.

Subrahmanyam, A. (2007). Behavioural Finance: A Review and Synthesis. *European Financial Management 14*(1), 12–29.

Sun, J., J. Yan, and K. Z. K. Zhang (2016). Blockchain-based sharing services: What blockchain technology can contribute to smart cities. *Financial Innovation 2*(1), 93.

Sundararajan, A. (2016). *The Sharing Economy: The End of Employment and the Rise of Crowd-Based Capitalism*. MIT Press.

Szabo, N. (1997). Formalizing and securing relationships on public networks. *First Monday 2*(9).

Tapscott, D. and A. Tapscott (2017). How blockchain will change organizations. *MIT Sloan Management Review 58*(2), 10.

ter Huurne, M., A. Ronteltap, C. Rense, and V. Buskens (2017). Antecedents of trust in the sharing economy: A systematic review. *Journal of Consumer Behaviour 16*, 485–498.

Teschner, F., T. T. Kranz, and C. Weinhardt (2014). The Impact of customizable Market Interfaces on Trading Performance. *Electronic Markets 25*(4), 325–334.

Teubner, T., F. Hawlitschek, and D. Dann (2017). Price Determinants on AirBnB: How Reputation Pays Off in the Sharing Economy. *Journal of Self-Governance and Management Economics 5*(4), 53.

Tirole, J. (2012). Overcoming Adverse Selection: How Public Intervention Can Restore Market Functioning. *American Economic Review 102*(1), 29–59.

Todd, P. (2014). Setting the record straight on proof-of-publication. Bitcoin development mailing list, Linux Foundation. https://lists.linuxfoundation.org/pipermail/bitcoin-dev/2014-December/006982.html.

Tran, A. B., X. Xu, I. Weber, M. Staples, and P. Rimba (2017). Regerator: a Registry Generator for Blockchain. *CAiSE Forum and Doctoral Consoritum Papers*, 81–88.

Tschorsch, F. and B. Scheuermann (2016). Bitcoin and Beyond: A Technical Survey on Decentralized Digital Currencies. *IEEE Communications Surveys Tutorials 18*(3), 2084–2123.

Tuomela, R. (1995). *The Importance of Us: A Philosophical Study of Basic Social Notions*. Stanford University Press.

Tussyadiah, I. P. (2016). Factors of satisfaction and intention to use peer-to-peer accommodation. *International Journal of Hospitality Management 55*, 70–80.

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

Varriale, G. (2013). Market poll: the best way to regulate Bitcoin. *International Financial Law Review*, 39.

Vercammen, J. A. (1995). Credit Bureau Policy and Sustainable Reputation Effects in Credit Markets. *Economica 62*(248), 461–478.

Viana, D. (2018). Two Technical Images: Blockchain and High-Frequency Trading. *Philosophy & Technology 31*(1), 77–102.

Vom Brocke, J., A. Simons, B. Niehaves, B. Niehaves, K. Reimer, R. Plattfaut, and A. Cleven (2009). Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process. In *Proceedings of the 17th European Conference on Information Systems (ECIS)*.

Vukolić, M. (2016). The Quest for Scalable Blockchain Fabric: Proof-of-Work vs. BFT Replication. In *iNetSec 2015: Open Problems in Network Security*, Volume 9591 of *Lecture Notes in Computer Science*, pp. 112–125.

Wah, E., D. R. Hurd, and M. P. Wellman (2016). Strategic Market Choice: Frequent Call Markets vs. Continuous Double Auctions for Fast and Slow Traders. *EAI Endorsed Transactions on Serious Games 3*(10).

Walsh, C., P. O'Reilly, R. Gleasure, J. Feller, S. Li, and J. Christoforo (2016). New kid on the block: a strategic archetypes approach to understanding the Blockchain. In *Proceedings of the 37th International Conference on Information Systems (ICIS)*.

Wang, S., J.-P. J. Vergne, and Y.-Y. Hsieh (2017). The internal and external governance of blockchain-based organizations: Evidence from cryptocurrencies. In *Bitcoin and Beyond*, pp. 48–68. Routledge.

Weaver, N. (2018). Risks of cryptocurrencies. *Communications of the ACM 61*(6), 20–24.

Webster, J. and R. T. Watson (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly 26*(2), xiii–xxiii.

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

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

Weinhardt, C., C. Holtmann, and D. Neumann (2003). Market-Engineering. *WIRTSCHAFTSINFORMATIK 45*(6), 635–640.

Williamson, O. E. (1979). Transaction-Cost Economics: The Governance of Contractual Relations. *The Journal of Law and Economics 22*(2), 233–261.

Wilson, C. (1980). The Nature of Equilibrium in Markets with Adverse Selection. *The Bell Journal of Economics 11*(1), 108–130.

Wilson, M., K. Robson, and E. Botha (2017). Crowdsourcing in a time of empowered stakeholders: Lessons from crowdsourcing campaigns. *Business Horizons 60*(2), 247–253.

Wolinsky, A. (1983). Prices as Signals of Product Quality. *The Review of Economic Studies 50*(4), 647.

Wood, G. (2014). Ethereum: A Secure Decentralised Generalised Transaction Ledger. Yellowpaper.

Workie, H. and K. Jain (2017). Distributed ledger technology: Implications of blockchain for the securities industry. *Journal of Securities Operations & Custody 9*(4), 347–355.

World Bank (2011). General Principles For Credit Reporting. Financial Infrastructure Series - Credit Reporting Policy and Research, World Bank.

World Bank (2013). The Role of the State in Financial Infrastructure. Global Financial Development Report, World Bank.

Wörner, D., T. von Bomhard, Y.-P. Schreier, and D. Bilgeri (2016). The Bitcoin Ecosystem: Disruption Beyond Financial Services? In *Proceedings of the 24th European Conference on Information Systems (ECIS)*.

Wüst, K. and A. Gervais (2017). Do you need a Blockchain? *IACR Cryptology ePrint Archive*.

Xu, X., C. Pautasso, L. Zhu, V. Gramoli, A. Ponomarev, A. B. Tran, and S. Chen (2016). The Blockchain as a Software Connector. In *Proceedings of the 13th Working IEEE/IFIP Conference on Software Architecture (WICSA)*, pp. 182–191.

Xu, X., I. Weber, M. Staples, L. Zhu, J. Bosch, L. Bass, C. Pautasso, and P. Rimba (2017). A Taxonomy of Blockchain-Based Systems for Architecture Design. In *Proceedings of the IEEE International Conference on Software Architecture (ICSA)*, pp. 243–252.

Yeow, K., A. Gani, R. W. Ahmad, J. J. P. C. Rodrigues, and K. Ko (2018). Decentralized Consensus for Edge-Centric Internet of Things: A Review, Taxonomy, and Research Issues. *IEEE Access 6*, 1513–1524.

Yermack, D. (2017). Corporate Governance and Blockchains. *Review of Finance 21*(1), 7–31.

Zhang, S. S., M. Wagener, A. Storkenmaier, and C. Weinhardt (2011). The Quality of Electronic Markets. In *Proceedings of the 44th Hawaii International Conference on System Sciences (HICSS)*, Volume 00, pp. 1–10.

Zhang, Y. and J. Wen (2017). The IoT electric business model: Using blockchain technology for the internet of things. *Peer-to-Peer Networking and Applications 10*(4), 983–994.

Özsu, M. T. and P. Valduriez (2011). *Principles of Distributed Database Systems* (3rd Ed. ed.). New York: Springer.

Zyskind, G., O. Nathan, and A. S. Pentland (2015). Decentralizing Privacy: Using Blockchain to Protect Personal Data. In *Proceedings of the IEEE Security and Privacy Workshops (SPW)*, pp. 180–184.

List of Abbreviations

List of Figures

List of Tables

Affidavit

I hereby affirm truthfully that this thesis has been written only by the undersigned and without any assistance from third parties. Furthermore, I confirm that no resources have been used in the preparation of this thesis other than those indicated in the thesis itself, including quoted and adapted contents of publications from other authors and myself.

Eidesstattliche Versicherung

gemäß §6 Abs. 1 Ziff. 4 der Promotionsordnung des Karlsruher Instituts für Technologie
für die Fakultät für Wirtschaftswissenschaften

1. Bei der eingereichten Dissertation zu dem Thema "Engineering Decentralized Markets – A Blockchain Approach" handelt es sich um meine eigenständig erbrachte Leistung.

2. Ich habe nur die angegebenen Quellen und Hilfsmittel benutzt und mich keiner unzulässigen Hilfe Dritter bedient. Insbesondere habe ich wörtlich oder sinngemäß aus anderen Werken übernommene Inhalte als solche kenntlich gemacht.

3. Die Arbeit oder Teile davon habe ich bislang nicht an einer Hochschule des In- oder Auslands als Bestandteil einer Prüfungs- oder Qualifikationsleistung vorgelegt.

4. Die Richtigkeit der vorstehenden Erklärungen bestätige ich.

5. Die Bedeutung der eidesstattlichen Versicherung und die strafrechtlichen Folgen einer unrichtigen oder unvollständigen eidesstattlichen Versicherung sind mir bekannt. Ich versichere an Eides statt, dass ich nach bestem Wissen die reine Wahrheit erklärt und nichts verschwiegen habe.

Karlsruhe, June 11, 2019

Benedikt Notheisen

Eidesstattliche Versicherung - Belehrung

Die Universitäten in Baden-Württemberg verlangen eine Eidesstattliche Versicherung über die Eigenständigkeit der erbrachten wissenschaftlichen Leistungen, um sich glaubhaft zu versichern, dass der Promovend die wissenschaftlichen Leistungen eigenständig erbracht hat.

Weil der Gesetzgeber der Eidesstattlichen Versicherung eine besondere Bedeutung beimisst und sie erhebliche Folgen haben kann, hat der Gesetzgeber die Abgabe einer falschen eidesstattlichen Versicherung unter Strafe gestellt. Bei vorsätzlicher (also wissentlicher) Abgabe einer falschen Erklärung droht eine Freiheitsstrafe bis zu drei Jahren oder eine Geldstrafe.

Eine fahrlässige Abgabe (also Abgabe, obwohl Sie hätten erkennen müssen, dass die Erklärung nicht den Tatsachen entspricht) kann eine Freiheitsstrafe bis zu einem Jahr oder eine Geldstrafe nach sich ziehen.

Die entsprechenden Strafvorschriften sind in §156 StGB (falsche Versicherung an Eides Statt) und in §161 StGB (fahrlässiger Falscheid, fahrlässige falsche Versicherung an Eides Statt) wiedergegeben.

§156 StGB: Falsche Versicherung an Eides Statt
Wer vor einer zur Abnahme einer Versicherung an Eides Statt zuständigen Behörde eine solche Versicherung falsch abgibt oder unter Berufung auf eine solche Versicherung falsch aussagt, wird mit Freiheitsstrafe bis zu drei Jahren oder mit Geldstrafe bestraft.

§161 StGB: Fahrlässiger Falscheid, fahrlässige falsche Versicherung an Eides Statt
Abs. 1: Wenn eine der in den §154 bis 156 bezeichneten Handlungen aus Fahrlässigkeit begangen worden ist, so tritt Freiheitsstrafe bis zu einem Jahr oder Geldstrafe ein.
Abs. 2: Straflosigkeit tritt ein, wenn der Täter die falsche Angabe rechtzeitig berichtigt. Die Vorschriften des §158 Abs. 2 und 3 gelten entsprechend.

Karlsruhe, June 11, 2019

Benedikt Notheisen