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«The Effect of the Industrial Application of the Blockchain Technology on Firm Performance»

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Preface and Acknowledgements

As part of the Master of Science in Economics and Business - Strategy Economics degree program at the Erasmus School of Economics in Rotterdam, a master's thesis is required according to the curriculum. The master thesis provides evidence that students are able to apply the knowledge acquired during their studies to a given research topic.

I would like to express my deep gratitude to all the people who supported and motivated me in the elaboration of this master thesis. Foremost, I would like to thank my supervisor Gianluca Antonecchia and second assessor Dr. Zhiling Wang for their guidance and support during the process of this thesis. Throughout the entire journey of writing this thesis, I have learned many new insights and gained an understanding of the topic of Digital Economics in the context of Strategy Economics, that have greatly aroused my interest.

I hereby declare that the analysis and text presented in this thesis are original and that only sources cited in the bibliography have been used. No part of this thesis has been submitted elsewhere for any other qualification.

The Erasmus School of Economics is only responsible for the pedagogical supervision and tutoring and cannot be held responsible for the content other than that.

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Executive Summary

Blockchain technology is considered to be the technology that will have a big impact on the world in the coming years. It was originally developed to securely record cryptocurrency transactions, but the application of blockchain goes far beyond that. It has the ability to create more transparency and fairness in industries and is said to be very accurate and secure (Tapscott & Tapscott, 2016). This distributor-ledger method brings several new applications to strategically streamline processes and operations in industries and optimize efficiency. The industrial application of this technology within a firm can be described as building a scalable, enterprise-grade distributed system for the purposes of the firm, using a proven network design framework that drives operational agility while opening potential new revenue streams (IBM, 2022). This is a highly topical and relevant subject, as the field of blockchain in the IT sector has been growing very rapidly in recent years, resulting in a strong increase in industrial applications in particular.

In this thesis, a self-compiled dataset is conducted to examine whether the impact of a company's adoption of blockchain technology on its firm performance can be identified. A Differences-in-Differences (DID) method is performed, and a control and a treatment group are analysed to see if an effect on firm performance can be identified from the time a firm adopts blockchain technology.

The main finding of the whole study is that the coefficient of the main variable in the regression model, which is supposed to measure the impact of blockchain technology adoption on business performance, is negative and not significant at the 10% significance level, therefore the null hypothesis cannot be rejected.

In section 1 this thesis will first provide an outline of the current situation and relevance concerning blockchain technology. The section 2 develops the hypothesis, which will be tested in the following. Furthermore, it introduces the topic and defines what blockchain technology is and describes the most important terms in this context. After that, the focus lies on the application of this technology in the industry and different application areas and possibilities are highlighted.

Section 3 introduces the analysis part and thus the main part of this thesis. There it is explained how the data is collected and which variables are included. Section 4 is about the methodology, which and how the regressions were carried out in STATA. In section 5, tests are conducted, and the regression results are presented. The last part, section 6, summarizes the main findings of the study and finally the self-identified limitations of the analysis and some ideas for future research are proposed.

Key words: blockchain technology, firm performance, industrial application, Differences-in-Differences approach

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1 Introduction

The blockchain is a decentralized transaction and data manage technology that maintains a constantly growing list of records, each of which must be confirmed by the participating nodes. The information about all transactions that have ever been carried out are available in a recorded ledger for all the contractors who jointly use the system (Yli-Huumo, Ko, Choi, Park, & Smolander, 2016)**.** Blockchain technology has proliferated in the last few years, leading to the widespread development of blockchain-based applications, and revolutionizing not only the finance and financial services industry, but also many other industries (Rennock, Cohn, & Butcher, 2018).

The application of this technology can be seen as an innovative mechanism that can have an impact on business performance. Innovation is widely recognised in the literature as one of the most important sources of sustainable competitive advantage and thus positive business performance in a fast-changing world and a competitive environment of large international companies (Chen, 2017). The rationale for this is that innovation leads to product and process improvements that help companies grow faster, be more efficient and thus more profitable than before the introduction of an innovation (Atalaya, Anafarta, & Sarvan, 2013). In the case of blockchain technology, the mechanisms that lead to potentially higher business performance work through lower costs and lower risks (T-Systems, 2022).

Both the reduced costs and the reduced risks refer to the increased efficiency. In terms of costs, the main argument is the costs that are saved because the automated processes are executed faster and therefore time can be saved, and in terms of reduced risks, the main argument is that the automation processes are less prone to errors and that every step in the secure storage of data is documented (IBM, 2022).

This thesis is to be based on a broad pool of academic literature. In the following, three papers are highlighted, which introduce the subject of this thesis:

1. Yaga et al. (2018) address blockchain as a tamper-proof digital ledger that can be implemented in a decentralized manner (Yaga, Mell, Roby, & Scarfone, 2018). Additionally, they study how blockchain can potentially change our society in the

future, what it offers to users, the benefits but also the risks of using it and explains the background of what which term represents and aims mainly to help the reader understand how this technology works and what it entails (Yaga, Mell, Roby, & Scarfone, 2018).

2. The above-mentioned paper helps to understand the principle in theory, Al-Jaroodi and Mohamed (2019) focus on how the technology can be applied in practice in various industries and how blockchain technology can tie in and provide solutions to the industries' day-to-day challenges are outlined (Al-Jaroodi & Mohamed, 2019). Thus, problems that currently hinder further progress in different industries can be solved. Examples include the establishment of automated and efficient supply chains, increased transparency across the value chain, and the recording of transaction data (Al-Jaroodi & Mohamed, 2019).
3. Sheel and Nath (2019) elaborate further, proving, among other things, that blockchain technology adoption in a business impacts higher trust and thus better governance, and that blockchain improved supply chain alignment and improved agility of the company's supply chain leads to a competitive advantage, which in turn positively impacts business performance (Sheel & Nath, 2019).

There is little literature on the relationship between the adoption of blockchain technology and firm performance, and some of the papers that have been consulted on this topic, during the process of writing this thesis, are presented in section 2.2.2. These papers all study an indirect impact on firm performance, i.e., via an intermediate outcome, and conclude that if these components change positively due to the introduction of the technology, then this will also have a positive impact on firm performance. The research gap addressed by this thesis is, on the one hand, that the direct effect on firm performance is observed and, on the other hand, that Tobin's Q of equity is selected as the firm performance measure, whereas all of the papers publicly available at this time (July 2022) have selected other key performance indicators (KPIs).

The definition of the ordinary Tobin's Q is market value divided by book value of total assets. Since the book value of total assets equals the book value of debt, this study uses the Tobin's Q of equity, which is the ratio of market value of equity (market capitalization) divided by book value of equity (total shareholder’s equity) (Smirlock, Gilligan, & Marshall, 1984). The benefit, compared to other KPIs is that it is an easy-to-calculate measure that can be used to assess whether a particular company or market is under- or overvalued (Harney & Tower, 2003). A Q-ratio between 0 and 1, is a low ratio and means that the market undervalues the market capitalization of the company. As a result, the firm becomes more attractive and the share price will increase, which could be interesting for potential investors. The opposite is applicable for Q-ratios above 1, in which case the company's market capitalization is overvalued (Harney & Tower, 2003). Applied to an entire market, this ratio can be used to assess whether an entire market is relatively under- or overvalued. The measure provides an assessment of a firm's performance on the one hand and investment decisions on the other (Smirlock, Gilligan, & Marshall, 1984). The data that formed the basis for this measure and the work of James Tobin refer to the period from 1960 to 1974, when the Q-ratio was able to provide a good explanation and prediction of investment (Henwood, 1998). Nowadays, however, the fundamental values (e.g., the average profit rate) are considered to be much more predictive of investment outcomes, which is a limitation of the Q-ratio (Henwood, 1998).

1.1 Goal of the Thesis

This thesis aims to examine whether there is an effect on firm performance when a company adopts blockchain technology. The objective is to observe whether there is a significant and positive effect on firm performance in the sample conducted. As the implementation and organisation of the technology is complex and requires a lot of energy and costs, it is also interesting to see if it pays off. After receiving the results of the self-compiled dataset, the author would like to be able to make a statement on whether the implementation of blockchain can be considered a suitable strategy to increase firm performance.

1.1.1 Research Question

This leads to the following research question: ***What is the effect of the implementation of the blockchain technology on the firm performance?***

2 Theoretical Framework

In this section, the basic theory of blockchain and the technology behind it is explained briefly. Then it will be presented in which industries and areas this technology can be applied and which issues can be addressed, and solutions provided by blockchain. Afterwards, the context of the implementation of this technology and its impact on firm performance will be discussed. Subsequently, based on the academic papers, the hypothesis is developed, which is the focus of this thesis.

2.1 Blockchain Technology - Fundamentals

The technology holds blocks of uniquely identifiable transaction records in a chain (Treleaven, Brown, & Yang, 2017). The chain keeps growing when a new block is added. Transactions are grouped together in each block. As an example, these can be purchase orders, money transfers, securities and more. The core of a blockchain is that information is stored in a history (Treleaven, Brown, & Yang, 2017). Each piece of information forms a block, which is cryptographically encrypted with a kind of digital fingerprint, a so-called hash. Each block is connected to the previously used block by its hash value. The blocks are linked by the hashes and they form a chain, and the information can no longer be changed, as this would also change the hash of a block and the chain would break apart and the hashes of all subsequent blocks would have to be recalculated (Yaga, Mell, Roby, & Scarfone, 2018).

2.1.1 Two types of Networks

The data chains are stored on a large number of decentral networked computers, with no need for a central server (Yaga, Mell, Roby, & Scarfone, 2018). The same data chain with the same complex information is stored on each computer and a new block is not added until every computer in the network has verified it (Treleaven, Brown, & Yang, 2017). One of the first applications is cryptocurrencies, like bitcoin, but countless other applications are possible, such as in industry, like decentralized storage of patient data, seamless documentation of supply chains, and secure elections.

There are two types of networks:

1. Permitted blockchains: These are proprietary networks used by certain organizations or individuals. These networks are usually developed either by a single company for their own private commercial use or by the collaboration of several companies in an industry to jointly facilitate for transactions between them. As an example, consider a group of financial institutions that process banking transactions (Rennock, Cohn, & Butcher, 2018).
2. Permissionless/open blockchains: These are open-source networks that anyone can access and use (Rennock, Cohn, & Butcher, 2018). As an example, bitcoin users who use bitcoin as a means of payment among themselves can be referred to in this context (Narayanan & Clark, 2017).

An important distinction to be made is between two core components. On the one hand, distributed ledger technology and, on the other, smart contracts (Biais, Bisière, Bouvard, & Ccasamatta, 2018).

2.1.2 Distributed Ledger Technology

Blockchain technology is a distributed ledger technology that uses cryptography to secure data within the system (Beck, Avital, Rossi, & Thatcher, 2017). A distributed ledger is basically a type of distributed account book that records transactions between actors in a decentralized manner. The record is replicated and synchronized and secured by cryptographic sealing (Treleaven, Brown, & Yang, 2017). The participants of a network all have a common read and write access and the main communication mechanism is the consensus between all parties (Cong & He, 2018). It is important to understand the difference between a distributed ledger and a distributed database. The difference is that in a distributed ledger, nodes cannot trust other nodes and therefore, before they are used, each transaction must be independently verified (Catalini & Gans, 2019). Dynamic tracking of actors is possible under this use of a common protocol, facilitating or even eliminating internal and external review processes (Treleaven, Brown, & Yang, 2017).

2.1.3 Smart Contracts

Smart contracts are self-executing contracts designed to ensure that all transactions between different participants conform to the legal agreements between them (Nair & Sutter, 2018). The terms of the agreement between the participants are written directly into the lines of code of smart contracts, so the legal provisions they contain are integrated and coded by computer programming and then validated via a peer-to-peer network[1] (Zheng, Xie, Dai, Chen, & Wang, 2018). They are further verifying that the records managed by the distributed ledger technology are authoritative (Treleaven, Brown, & Yang, 2017).

2.2 Blockchain Technology in the Industry

In today's world, blockchain technology plays a major role in industrial development. In the following, several fields and industries are presented that can potentially benefit from the innovations that the technology entails, especially the decentralized storage, verification, data access and security of transactions within digital platforms (Idrees, Nowostawski, Jameel, & Mourya, 2021).

2.2.1 Fields of Application

In ***Table 1***, different sectors are highlighted and examples of the application of blockchain technology are provided. The column 1 shows the sector, the column 2 the potential area of usage and what the application of the blockchain may achieve and the column 3 the references. In the appendix, Annex 1, the application is further specified in more detail.

[1] By using a peer-to-peer network and the resulting decentralization and transparency, the function of a conventional intermediary can become obsolete, which can significantly reduce transaction costs (Tevasvold Aune, O'Hara, & Slama, 2016).

Table 1: *Possibilities of Application*

Sector	Effect and Mechanism	References
Banking, Financial Services and Law	• Fund transfer between different institutions almost in real time • Automated compliance process based on datasets that cannot be changed • Make reporting faster and more accurate • Smart contracts enable transactions without third-party oversight	(Cocco, Pinna, & Marchesi, 2017) (De Filippi & Hassan, 2018)
Insurance	• Improve efficiency and accuracy for insurers and policyholders • Automated platform that simplifies regulatory insurance reporting and helps meet compliance requirements	(Grima, Spiteri, & Romanova, 2020) (Brophy, 2019)
Retail and Consumer Goods	• Provide a common information chain that contractors can share to reduce the time and cost of invoice processing • Reduce administrative barriers through greater transparency and simplified cross-border movement of goods • Ensure efficient and secure tracking of consumer goods in the supply chain and access to compliance certification	(Chakrabarti & Chaudhuri, 2017) (Xu & He, 2021) (Al-Jaroodi & Mohamed, 2019) (IBM, 2022) (Walden, 2022)
Automotive	• Provide eWallet service for vehicles to pay fees and tariffs on roads cashless • Release funds only after a delivery is completed with satisfactory result • Make information across the supply chain accessible to suppliers, customers, maintainers, and authorities to combat counterfeiting and product recalls	(Fraga-Lamas & Férnandeu-Caramés, 2019) (IBM, 2022) (Sharma, Kumar, & Park, 2018)
Transport and Travel	• Use a single identifier that is stored and validated throughout the journey to avoid	(Di Vaio & Varriale, 2020) (Astarita, Giofrè, Mirabelli,

	multiple checks and eliminate waiting time • Track the condition and location of cargo using a common record • Recording of stock levels, tracking the life cycle of a part, detecting and sorting out counterfeit parts, and determine the data surrounding the components	& Solina, 2020) (Xu, et al., 2018) (Rejeb, Keogh, & Treiblmaier, 2019) (IBM, 2022) (Al-Jaroodi & Mohamed, 2019)
Healthcare and Pharmaceuticals	• Log the spread of diseases in real time and lock down patient data in a decentralized approach	(Khezr, Moniruzzaman, Yassine, & Benlamri, 2019) (Haq & Esuka, 2018)
Oil, Gas and Chemicals	• Increase the speed and completeness of transactions in this network through increased transparency • Jointly transparent transactions, to shorten the circulation of currency, to reduce the risk of fraud, cybercrime, and manipulation	(Kadry, 2020) (Maxeiner, Martini, & Sandner, 2018)
Manufacturing	• Enable an automated exchange of data that organizes workflows across national borders in a structured way and provides insight at any time for the contractors	(Aghamohammadzadeh & Valilai, 2019)
Telecommunication	• Protect customer data from spam callers and spam SMS senders	(IBM, 2022)
Media and Entertainment	• Complete transparency in digital transactions with immutable distributed ledgers to tackle fraud problems	(Andrewa, Canepa, Mangla, & Marchi, 2018)

These are some examples in which industry and in which areas, the blockchain technology can be implemented, numerous other application possibilities exist.

2.2.2 Impact on Firm Performance

The objective of this section is to address the question of whether the use cases of blockchain technology presented in the previous section, have an impact on firm performance.

Sheel and Nath (2019) examine, among other things, how the adoption of blockchain technology in a company has an impact on higher trust and thus better firm performance. Moreover, whether blockchain improved supply chain alignment and improved agility of the company's supply chain leads to a competitive advantage, which in turn has a positive impact on firm performance (Sheel & Nath, 2019). The authors show evidence of a positive and significant effect in all the above-mentioned scenarios (5% significance level). The trust generated by the adoption of blockchain, the increased transparency and reliability of transactions, on the one hand the recording and retrieval of data and on the other hand the traceability of inventories improved, which has a positive impact on firm performance (Sheel & Nath, 2019). Accelerate the development time for new products and the execution of business processes, which also has a positive impact on firm performance (Sheel & Nath, 2019).

Ceptureanu er al. (2021), aim to investigate how the adoption of blockchain technology changes supply chain variables and technology transfer of medium-sized enterprises (MSEs) in Romania (Ceptureanu, et al., 2021). They investigate whether the technology transfer triggered by the adoption of blockchain technology leads to higher firm performance. Further, whether the adoption of blockchain results in improved flexibility and responsiveness of the supply chain and improved supply chain integration and whether this has an impact on a company's competitive advantage. Finally, whether the assumed resulting competitive advantage really has a positive impact on the firm's performance (Ceptureanu, et al., 2021). The result of the data analysis shows that the above-mentioned supply chain variables, which were consulted in this context, all have a positive and significant effect (significance level 5%) on the competitive advantage, whereby a positive effect on the firm performance is assumed (Ceptureanu, et al., 2021). In addition, they show that technology transfer generated by the introduction has a positive and significant effect (significance level 5%) on firm performance (Ceptureanu, et al., 2021).

Huangfu, Pinsker and Xing (2022) study the adoption of blockchain technology as a business strategy and that it represents an opportunity to improve the relationship between business strategy and technology policy within a company, potentially resulting in higher firm performance. On the other hand, they address the risks and uncertainties that this technology brings (Huangfu, Pinsker, & Xing, 2022). The authors examine this using a sample of 208 companies, which they categorize based on their characteristics as either prospectors (risk takers) or defenders (interested in cost stability), examine the years 2015-2019, and find that first, prospectors are more likely to adopt blockchain technology than defenders, and for prospectors this also results in higher net benefits on average (Huangfu, Pinsker, & Xing, 2022). They find that aligning business strategy and technology policy in a company has a positive effect on firm performance (Huangfu, Pinsker, & Xing, 2022).

Li et al. (2022) aim to investigate the effect of blockchain-supported business model design (BMD) on supply chain resilience (SCR), and thus on firm performance (Li, Xue, Li, & Ivanov, 2022). Only companies that have their headquarters and main operations in China are examined (Li, Xue, Li, & Ivanov, 2022). They show that companies that place a high strategic emphasis on BM efficiency are more likely to adopt blockchain-supported BMD, resulting in higher SCR, which in turn results in higher firm performance, as innovative BMD supported by blockchain improves the agility portion of SCR, thereby improving firm performance (Li, Xue, Li, & Ivanov, 2022).

Ronghani (2022) examines the impact of blockchain technology adoption in newly founded companies on governance and firm performance (Ronaghi, 2022). The sample includes 397 companies from Iran (Ronaghi, 2022). The data analysis shows that the more companies have implemented blockchain technology, the stronger the effects on governance and thus on firm performance, which means that companies with a blockchain-based business model create a positive framework for effective corporate governance, resulting in a positive impact on firm performance (Ronaghi, 2022).

2.3 Hypothesis Formulation

The papers mentioned in the previous section examine the effect of the introduction of blockchain technology on firm performance, but always using an intermediate outcome. In the papers consulted listed earlier, a positive effect on firm performance was found in each of them, which is why this thesis seeks to investigate, with a self-compiled dataset, if such an effect can be detected. Here, the direct effect is to be examined and not indirectly via an intermediate result.

The research objective is to investigate whether the implementation of blockchain technology can be considered as a suitable strategy to increase business performance. Based on the evidence and the research question formulated in the introduction section, the following hypothesis is stated: ***The implementation of the blockchain technology affects the firm performance positively.***

In section 4, a regression model to this hypothesis is established and in section 5, the hypothesis is tested.

3 Data

The data set, with which the analysis is conducted, is self-compiled. Only firm-level data is used, and the analysis takes place with companies on a global level. But mainly with Western European, North American, and North-East Asian companies.

3.1.1 Data Collection

In the beginning, the data collection consisted of searching for listed companies that use blockchain technology. It is important that they are listed on the stock exchange, because on the one hand this increases the probability that accessible financial data is available, and on the other hand, due to the usually large size of the companies, they tend to have a global character, which means that the results have a certain informative value. Information about whether and when a company started using blockchain technology was not available from any university or publicly available database, so this information was obtained from freely available articles or the companies' websites or annual reports. Accordingly, a search was made for hundreds of companies that met these characteristics just mentioned, and a list was kept that included the company, the year of adoption, and the link to the website where this information about blockchain technology adoption was found. The difficulty was that many of the companies that are now using the technology initially launched a pilot project. Often in collaboration with companies in the same industry as well. At this point, care had to be taken because companies were selected that, regardless of whether or not they had first conducted a pilot project, had used the technology in their business process in the real economy. The list was then examined to see in which year the technology adoption was most clustered in order to obtain the largest possible sample. The year 2018 had the highest frequency, which is why it was selected. The remaining company-level data comes from the *Orbis*[2] database, which is accessible through the university and contains data on private companies, with the exception of the values for market capitalisation, which were obtained from the publicly accessible *Companies Market Cap*[3] database.

[2] The database is called *Orbis*, which be accessed through the library of the Erasmus University and the login with the student account. It can be consulted via the following link: https://orbis-bvdinfo-com.eur.idm.oclc.org.
[3] The website is called *Companies Market Cap*, is publicly accessible and can be obtained via the following link: https://companiesmarketcap.com.

3.1.2 Variable Definition and Descriptive Statistics

The dataset consists of panel data and contains 13 variables (including 2 panel identifiers, 1 dependent, 2 main independent and 6 control variables) and 3’120 observations. With the exception of the variable *companyname*, all are numeric variables. The numeric variables either have the unit of measurement US dollars or are ratios calculated from ratios with US dollars. The individual variables are categorised and described below. ***Table 2*** contains the descriptive statistics, followed by ***Table 3***, which displays the pattern of the observations and ***Table 4*** shows the individual correlations between the 13 variables.

<u>Panel Identifier</u>

companyname: This is the unit identifier. This variable displays all the names of the 60 companies included in this sample.

year: This is the time identifier. This variable contains four categories, the years 2016-2019, where each of the 60 units follows four waves. All the companies in the dataset and their corresponding values are therefore considered during four different periods, here the years 2016-2019.

<u>Dependent Variable</u>

tobinsq: This variable shows the Tobin's Q of equity[4] of the above units in a certain time. The mean is 0.755 with a minimum of 0.049 and a maximum of 13.347. The unit Tobin's Q is available as a ratio in *Orbis*, but here the Tobin's Q of equity is relevant, which is why it is calculated in STATA, using the market capitalisation and the total shareholder's equity. The dependent variable was generated by dividing the two following variables ratios.

mcap: This is the market capitalisation of the respective company. The mean is $5’614 m with a minimum of $5 m and a maximum of $92’022 m.

se: This is the total shareholder's equity of the respective company. The mean is $10’015 m with a minimum of $44 m and a maximum of $82’726 m.

[4] As a measure of firm performance, Tobin's Q of equity is chosen.

Main Independent Variables

The DID methodology is applied in the analysis, which requires a control group and a treatment group. Therefore, the two groups are mentioned in the following two explanatory variables, which is discussed in more detail in section 4, in the methodology.

blockchain: This is a dummy variable that takes the value 1 if a company belongs to the treatment group and takes the value 0 if a company belongs to the control group. A company belongs to the treatment group if it receives the treatment, i.e. adopts the blockchain technology.

post: This is a dummy variable that takes the value 1 if the intervention occurs in this period and takes the value 0 if the treatment does not occur. The companies included in the sample as a treatment group have all implemented blockchain technology since 2018, assuming that the effect of the implementation is reflected in the company financials from 2019 onwards. Therefore, the variable *post* takes the value 1 from the last period (2019) of the four periods. As only one post-treatment period is observed, on which the introduction of the technology has a potential impact, it is important to note that exclusively the short-term impact of its introduction is assessed.

Control Variables

turnover: This variable displays the operating revenue, i.e., the turnover of a company. The mean is $29'025 m, with a minimum of $232 m and a maximum of $232’880 m.

The following five control variables are all ratios:

profitmargin: This variable represents the profit margin of a company. The mean is 11.02% with a minimum of -0.61% and a maximum of 58.73%.

roe: This variable indicates the return on equity, using the profit/loss statement before tax. The mean is 28.427%, with a minimum of -1.65% and a maximum of 514.64%.

roa: This variable reports the return on assets, using the profit/loss statement before tax. The mean is 7.145%, with a minimum of -0.42% and a maximum of 33.08%.

priceearningsratio: This variable gives the annual average price-to-earnings ratio and is part of the annual stock valuation of a company. The mean is 25.805, with a minimum of 1.06 and a maximum of 434.64.

earningsyield: This variable displays the annual average earnings yield per share for a financial year. The mean is 8.582%, with a minimum of 0.23% and a maximum of 94.1%.

In the following ***Table 2***, the descriptive statistics of all variables are displayed in one table. The categorical/dummy variables, namely *year*, *blockchain* and *post*, are also shown in this table and not in tables of frequencies, as these would not have any informative value in this context.

Table 2: *Descriptive Statistics*

Variable	Obs	Mean	Std. Dev.	Min	Max
year	240	2017.5	1.12	2016	2019
companyname	240	30.5	17.354	1	60
tobinsq	240	.755	1.331	.049	13.347
mcap	240	5613.754	10393.059	5	92022
se	240	10014.767	15220.431	44	82726
blockchain	240	.333	.472	0	1
post	240	.25	.434	0	1
turnover	240	29024.8	35685.328	232	232887
profitmargin	240	11.023	10.509	-.61	58.73
roe	240	28.427	49.897	-1.65	514.64
roa	240	7.145	6.43	-.42	33.08
priceearningsratio	240	25.805	39.208	1.06	434.64
earningsyield	240	8.581	10.72	.23	94.1

Attrition is one of the biggest methodological problems in longitudinal studies, as it can strongly affect the generalizability of the results. Since the dataset is self-compiled, it has the advantage that there is no attrition, since only units with available data for all variables and years were included.

In ***Table 3***, the correlation between the 13 different variables can be identified. An important number to emphasise is that the correlation between the main independent variables *blockchain* and *post* is 0.00 and therefore very small. This means that multicollinearity between these variables is not an issue in this dataset.

Table 3: Matrix of Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) year	1.000												
(2) companyname	0.000	1.000											
(3) tobinsq	0.048	-0.087	1.000										
(4) mcap	0.057	-0.045	0.293	1.000									
(5) se	0.091	0.106	-0.097	0.616	1.000								
(6) blockchain	0.000	-0.010	0.093	0.371	0.386	1.000							
(7) post	0.775	0.000	0.026	0.048	0.080	0.000	1.000						
(8) turnover	0.052	-0.017	0.249	0.785	0.577	0.446	0.034	1.000					
(9) profitmargin	0.032	0.103	-0.001	-0.034	0.039	-0.031	0.020	-0.150	1.000				
(10) roe	0.014	0.040	0.727	0.149	-0.085	0.171	0.022	0.293	0.168	1.000			
(11) roa	-0.025	0.050	0.362	0.071	-0.057	0.058	-0.044	0.112	0.345	0.631	1.000		
(12) priceearningsratio	0.070	-0.131	0.070	0.125	0.018	0.098	0.023	0.098	-0.170	-0.042	-0.118	1.000	
(13) earningsyield	-0.116	0.121	-0.100	-0.084	-0.008	0.001	-0.072	-0.050	-0.021	-0.034	-0.046	-0.212	1.000

4 Methodology – Research Design

To test the hypothesis, the DID approach is used, to run an OLS regression with fixed effects and control variables. Additionally, robust standard errors are used to confront the problem of heteroskedasticity. The DID approach is chosen to create a counterfactual situation and assess the impact of the adoption of blockchain technology. To apply this approach, it is essential to use panel data or repeated cross section data. So, to implement this method, it is necessary to have repeated observations of treated and control units over time (Wooldridge, 2013).

In this method, two groups are considered, one receiving treatment and the other not. The main idea is that the trend of the outcome for the control group is a valid counterfactual of what should have happened to the treatment group in the absence of the intervention (Pischke & Angrist, 2008). Any deviation in the trend of the treatment group related to the trend of the control group, is the causal impact of the intervention. One can use the information of the trend, which one receives from the control group, to extrapolate what should have happened in the treatment group in the absence of the treatment. Any deviation in the observed outcome after the intervention for the treatment group with regards to the counterfactual outcome of the treatment group, in absence of the treatment, gives the DID estimate.

There are two assumptions that should be followed in this approach, the Parallel Trend Assumption, and the Stable Unit Treatment Value Assumption (Pischke & Angrist, 2008).
If these two assumptions of DID apply, then it is possible to exploit interventions to obtain the causal effect of the treatment on the outcome. In the context of applying an OLS regression, there is a risk that the OLS estimates are likely biased due to endogeneity (Imbens & Wooldridge, 2008).

4.1 Defining the Treatment and Control Group

The treatment group includes firms that explicitly introduced blockchain technology in 2018 and have been using it since then. As the firms all started using it at different time points in

2018, it is assumed here that the technology has an impact on firm performance for all of them from the financial year 2019 onwards. The interventions therefore occur between the two periods. From a theory perspective, this means that the treatment occurs between the 3rd and 4th period in this sample (2016-2019), i.e., between the years 2018 and 2019. To capture that, a repeated balanced panel is set up.

The control group consists of firms that have not yet adopted blockchain technology, which is the majority, or have only been using it for a year, which is after the study period, i.e., from the year 2020 onwards. The control group was selected with a matched or also called paired sample approach to the treatment group. First, the treated firms are determined and then selected peer firms from the same industry as the control group for each individual firm that does not use the technology. The control group includes more firms than the treatment group. These are that don't use blockchain technology and have similar characteristics to those in the treatment group.

4.2 Regression Model

To test the effect of the adoption of blockchain technology, expressed by the two main independent variables *blockchain* and *post*, on Tobin's Q of equity, expressed by the dependent variable *tobinsq*, an OLS regression with fixed effects and controls from panel data is chosen.

$$\begin{aligned} tobinsq_{it} = {} & \beta_0 + \beta_1\, treatment_i + \beta_2\, post_t + \beta_3\, blockchain_{it}\, X\, post_{it} + \beta_4\, turnover_{it} \\ & + \beta_5\, profitmargin_{it} + \beta_6\, roe_{it} + \beta_7\, roa_{it} + \beta_8\, priceearningsratio_{it} \\ & + \beta_9\, earningsyield_{it} + \varepsilon_{it} \end{aligned}$$

The interaction term ($blockchain_{it}\, X\, post_{it}$), expresses the DID estimator δ, which captures the difference in outcomes within the treatment group minus the difference in outcomes within the control group.

5 Results

In this section, the two assumptions of DID are first tested and then the regression results of STATA are presented and analysed.

5.1 Testing the Assumptions

To obtain unbiased DID estimates, two assumptions must hold. One is the Parallel Trends Assumption, also called Constant Bias Assumption, and the second one is the Stable Unit Treatment Value assumption (Lee, 2016).

5.1.1 Parallel Trends Assumption

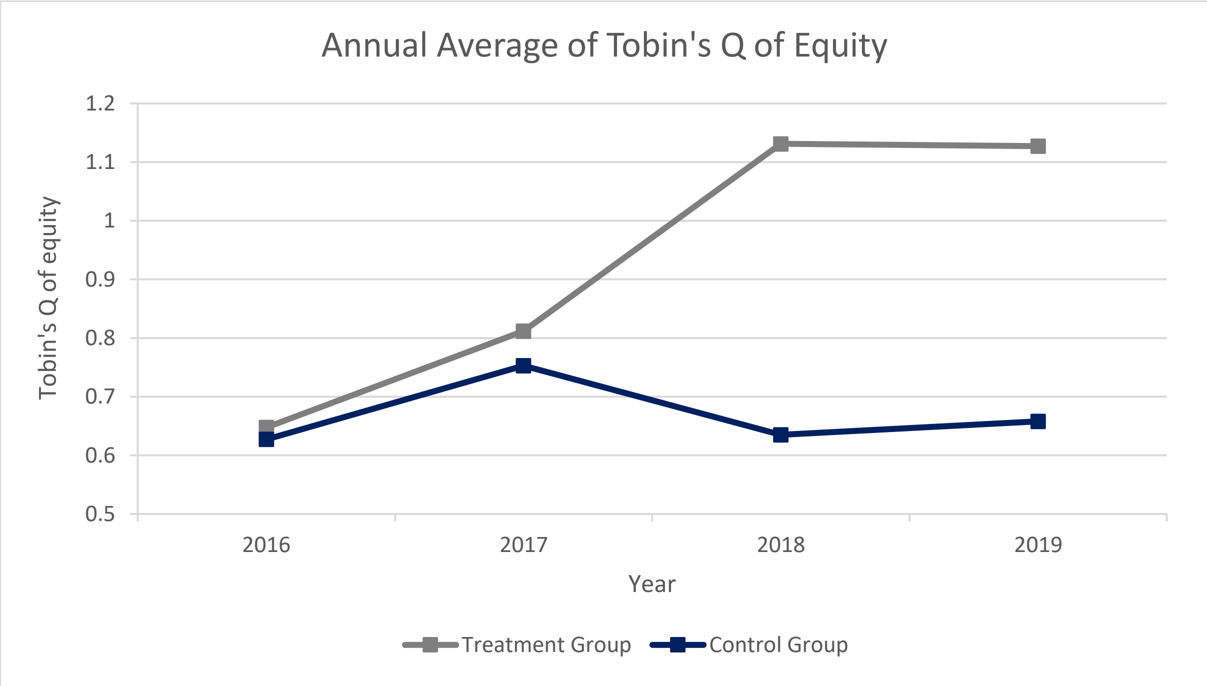
This assumption requires that the trends of the two groups in the pre-intervention period are parallel in order to identify whether the control group is a good counterfactual for the treatment group. This means that differences in levels are not relevant but must follow the same trend for this assumption to be fulfilled (Zeldow & Hatfield, 2019). It is essential that more than one period in the pre-intervention phase is reported. If this condition is not fulfilled, i.e., if trajectories in the pre-intervention period are different, then deviations in the post-intervention period cannot be attributed solely to the intervention (Wing, Simon, & Bello-Gomez, 2018).

There are two options to see if this condition is met. On the one hand, the trends can be displayed in a graph, and it can be assessed whether they run in parallel, and on the other hand, it can be tested statistically.

Figure 1 shows the trends of the treatment and control group in raw data over time. The evidence of the trends is shown in an intuitive and graphical way. The years 2016-2019 are shown on the X-axis and the Tobin's Q of equity of the companies in the sample is shown on the Y-axis, with the axis ranging from 0.5 to 1.2. The treatment group is represented by the grey and the control group by the blue line. The annual averages are indicated by the squares on the two lines.

In the periods 2016-2017, it can be said that the assumption is fulfilled, because the two lines are parallel. There is a difference in level, but it makes no difference. In 2018, last year before the intervention, the lines are no longer parallel. If we look at all three years before the intervention, we can only say that the assumption is partially met. Whether this is due to a few outliners cannot be assessed when looking at the graph, which is why the assumption is tested statistically in the following to provide clarity.

Figure 1: *Testing the Parallel Trends Assumption*



Subsequently, the assumption is further tested using statistical tests of the leads, the periods before the intervention, as shown in ***Table 4***. The test is whether there is a statistical difference between the two groups in the periods before the intervention.

If the null hypothesis that the coefficients are equal to zero cannot be rejected, then this means that the trends of the two groups in the periods before the intervention are similar and that the assumption is probably true (Zeldow & Hatfield, 2019). In contrast, if a significant difference from zero can be found in these parameters, then it means that the treated group is developing differently from the control group. The upper part of ***Table 4*** shows the time dummies, so how much the outcome is changing over time for each specific year and the lower part displays the leads and the lags. The important part for the evaluation is the lower part, i.e., the coefficients associated with the interaction whether a company is in the treatment group and the year. The first two rows in the second part of ***Table 4*** display the leads, i.e., the impact of the trend of the treated group in the pre-intervention phase and show

how different the trend of the treated group is, compared to the trend of the control group. The coefficients are all quite close to zero and are both not statistically different from zero, i.e., they are not significant at the 10% significance level. This means that for all years of the pre-intervention period for which we have data, the trend of the treated group is statistically similar to the trend of the control group and no statistical difference can be detected. For the lags, only one period is accessible in the dataset (2019) and there is an increase of the Tobin's Q of equity of about 0.449 units. This coefficient is not significant at the 10% significance level, indicating that the trends were not significantly different after the intervention, which can also be seen in ***Figure 1***.

Table 4: *Results of the Parallel Trends Assumptions and the Effect of the Intervention*

	Testing the Parallel Trends Assumption Tobin's Q of Equity
Blockchain	.0203808
	(.1777866)
Year	
2017	.1257266**
	(.041961)
2018	.0079541
	(.0523324)
2019	.0309954
	(.0886798)
Blockchain##post	
2017	.0387591
	(.1324272)
2018	.4758502
	(.6801144)
2019	.4487601
	(.5152153)
Constant	.6271649***
	(.109304)
Observations	240

Robust standard errors in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 5 shows the coefficients of the binary indicator for each specific year. This table reinforces that the coefficient for every year for the treated units in the pre-intervention period are not significantly different from zero, meaning they are statistically insignificant at the 10% significance level. From this it can be seen how different the trend of the treated group is compared to the control group. This means that the trend of the treated group is statistically similar to the one of the control group. So, in the pre-intervention period, no statistical difference can be observed between the trends of the treated and the control group, meaning the trend of the treated group is statistically similar to the trend of the control group.

Table 5: *Conditional Marginal Effects*

	Conditional Marginal Effects (dy/dx)
	Tobin's Q of Equity
0. Blockchain	(base outcome)
1. Blockchain	
Year	
2016	.0203808
	(.1777866)
2017	.0591399
	(.2830036)
2018	.4962309
	(.656582)
2019	.4691408
	(.621504)
Observations	240

Robust standard errors in parentheses

**** p<.01, ** p<.05, * p<.1*

Note: dy/dx for factor levels is the discrete change from the base level

5.1.2 Stable Unit Treatment Value Assumption

Unlike the previous assumption, it is not possible to test this assumption statistically. This assumption is unverifiable and needs to be discussed (Wing, Simon, & Bello-Gomez, 2018). To determine whether it is met, it must be satisfied that there are no interactions between the treatment and control units and no response from the treated or untreated units to the existence of the other group. If the Stable Unit Treatment Value Assumption does not apply, then this leads to a violation of the valid counterfactual, since the control trend includes the response to the treatment (Lee, 2016).

The information that a firm started using blockchain technology in 2018 is obtained from publicly available articles, firm websites, and annual reports when the treatment group was created. Therefore, it is very likely that the companies in the control group find out this information, especially if they search for it. However, the assumption will only be met, if the control group knows that this treatment of the introduction of blockchain technology is happening and then respond to that by either putting more or less effort into terms of the outcome. It is not likely that the control group will respond to the intervention in the treatment group. On the one hand, because in most cases this introduction is not widely publicised, and it is mainly through research that it is known whether a company applies this technology or not. On the other hand, it is unlikely that companies in the control group will behave differently once they learn that the companies mostly use this technology internally for themselves to simplify processes or make them more efficient. In my view, the assumption is not violated because the extent of the outcome of the control group is not a response to the intervention experienced by the treatment group.

5.2 Regression Results

Table 6 displays a regression table, which includes the regression that only includes the interaction term of the two main independent variables and the regression, which additionally contains six control variables. In order to make a comment on the significance of the coefficients, I choose the 10% significance level.

Model 1: OLS Regression with Fixed Effects

Before looking at the full model, the simple form of it is highlighted, as here the *constant* is the β_0 parameter and this means that the average outcome of the control group in the pre-intervention period is reflected. That is, the average Tobin's Q of equity of the control group before the intervention is 0.672 units, ceteris paribus. This coefficient is significant at the 10%

significance level. It is important to note that the Tobin's Q of equity is a ratio of two measures of a currency that dissolve when divided.

The coefficient in the first row is 0.192 when the variable *blockchain* equals 1 and there is no interaction. The parameter β_1 reflects the difference in levels between the treated and control unit in the period before the intervention. This means that treated entities have a 0.192 units higher Tobin's Q of equity in the pre-intervention period compared to the control group, ceteris paribus. However, this difference is not significant at the 10% significance level, suggesting that the two groups have statistically similar baseline values.

The coefficient in the second row is -0.014 when the *post* binary variable is equal to 1. The parameter β_2 reflects the change in outcomes over time for the control groups. Over time, the Tobin's Q of equity has decreased by 0.014 units, ceteris paribus. This is not significant at the 10% significance level. It is important to note that this only reflects the change in the trends of the control group and assumes that the same trend is reflected for the treated group.

The coefficient 0.277 in the third row, is the coefficient that responds to the interaction term *blockchain X post* and corresponds to the δ, the DID estimator. The interaction term includes the binary indicator for belonging to the treated group and the binary indicator for belonging to the pre- or post-intervention period. This result suggests that receiving this intervention increases outcome, i.e., Tobin's Q of equity, by 0.277 units, ceteris paribus. This effect is not significant at the 10% level of significance.

If it can be assumed that the control group is a valid counterfactual of the treatment group without the treatment, then the coefficient of 0.277 units reflects the true causal effect of the treatment on the outcome. Additionally, it is important to say that no control variables have been added here yet.

Model 2: OLS Regression with Controls and Fixed Effects

The regression of Model 2 differs from Model 1, because it contains six additional control variables, whereby the coefficients have changed, but the interpretation is analogous, except for the constant β_0.

The coefficient -0.286 reflects the parameter β_1 and shows the coefficient when the variable *blockchain* is equal to 1. This means that treated entities have a 0.286 units lower Tobin's Q of equity in the pre-intervention period, compared to the control group, ceteris paribus. This effect is not significant at the 10% significance level.

The coefficient .026 reflects the parameter β_2 and shows the coefficient when the variable *post* equals 1. This means that Tobin's Q of equity has increased by 0.026 units over time, ceteris paribus. This effect is not significant at the 10% significance level.

The coefficient -0.074 reflects the parameter β_3 in the regression equation, i.e. δ, the DID estimator, and shows the interaction term *blockchain##post*. This means that receiving the intervention decreases the Tobin's Q of equity by 0.074 units, ceteris paribus. This effect is not significant at the 10% significance level.

Table 6: *OLS Regression with Fixed Effects and Control Variables*

	Model 1	Model 2
	OLS Regression with Fixed Effects	OLS Regression with Controls and Fixed Effects
	Tobin's Q of Equity	Tobin's Q of Equity
1. Blockchain	.1919172	-.2859737
	(.2631446)	(.2882814)
1. Post	-.0135648	.0264513
	(.0802368)	(.0660538)
Blockchain##post	.2772236	-.0741702
	(.561765)	(.1410402)
Turnover		2.06e-06
		(2.34e-06)
Profitmargin		-.0240208**
		(.0103594)
Roe		.0269383***
		(.004563)
Roa		-.0092241
		(.016727)
Priceearningsratio		.0001427
		(.0008209)
Earningsyield		-.0056306
		(.0042297)
Constant	.6717251***	.4001017*
	(.1135499)	(.1920416)
Observations	240	240

Robust standard errors in parentheses

**** p<.01, ** p<.05, * p<.1*

6 Discussion

The coefficient of the variable of interest, the interaction term of *blockchain* and *post* differ in the regression with and without control variables, in terms of magnitude and direction.
This coefficient takes a value of 0.277 in the regression without control variables and -0.074 in the regression with control variables. Both coefficients are not significant at the 10% significance level.

The significance level 0.1, i.e., 10% is chosen. It describes the maximum probability that a null hypothesis is falsely rejected. The null hypothesis states that there is no statistically significant relationship between the independent and the dependent variable. Whereas the alternative hypothesis, which is formulated as part of this analysis and states that there is a statistically significant relationship between the independent and dependent variables. The alternative hypothesis is as follows: ***The implementation of the blockchain technology affects the firm performance.***

To conduct the hypothesis test, the p-value of the main independent variable *blockchain X post* is compared with the significance level of 10% to determine whether the effect is statistically significant (Lee, 2016). In the regression without control variables, it is 0.622 and in the regression with control variables it is 0.599. Both p-values are larger than the selected significance level and thus insignificant at the 10% significance level. Thus, this study fails to reject the null hypothesis.
The alternative hypothesis is rejected because there is no statistically significant correlation between Tobin's Q of equity and the adoption of blockchain technology, which is represented here by the DID estimator δ, in the sample of companies used.

It is important that the same method is used for both the treatment and the control group, which is the case here. Furthermore, the variables necessary to calculate this ratio are defined in the same way for all the companies included in the sample. In the context of this analysis, it is assumed in order to support the validity of this analysis that no other concurrent events happen besides the intervention, which might defer between the treatment and the control group.

As mentioned in section 3 on the collection of the data, attrition is not an issue in this study as the data was collected manually in a self-compiled dataset. There is, on the other hand, a sample selection bias, as the selection of the companies does not allow for a proper randomization, which does not ensure that this sample is representative of the population of all listed global companies to be analysed. This is due to the fact that only those companies were included for which the measures of all selected variables in this study were available in the data banks *Orbis* and *Market Cap* and were therefore not randomly selected, since companies for which not all measures required for the study were available, were excluded from the dataset.

6.1 Conclusion

After receiving the results, it cannot be concluded that the use of this technology is a suitable strategy to increase firm performance. However, this is not a general statement, but only related to the self-compiled dataset, which was generated within the context of this thesis, and the application of the DID method, here just a slightly positive but not significant effect can be observed. Potential reasons why the effect is not significant are discussed in the following section on limitations.

Even though the majority of the coefficients are insignificant, it is important to mention that they can still be interpreted and that also an insignificant result is an interesting and important result.

Besides all the advantages mentioned in section 2.2 about the possible applications in the industry, i.e. that it has a distributed structure and no central authority, which protects the system from corrupt nodes, the security that each block contains every piece of information of every transaction ever made in the system and once a part of the data is hacked, the system rejects the tampered information, the transparency that the whole value chain can be seen and that it is accessible and can be shared by different actors at the same time, there are of course also risks. Such as difficulties with updates, that once the information is entered it cannot be changed, the implementation is expensive, it consumes a lot of energy, which can have a negative impact on nature, and it still has a long development path to go in many cases before the system is mature.

The overall objective of this thesis is to address the research gap in the literature on the application of blockchain technology in industry as a strategic action to increase firm performance. In conclusion, this thesis does not allow the author to draw a definitive conclusion on whether or not companies should use blockchain technology to strategically streamline and increase their firm's performance.

6.1.1 Limitations

The panel data covers the periods 2016-2019, so four years are represented. In order to examine the effect of the intervention, this study only considers the 2019 financial year. It would be more meaningful if more years after the intervention were examined. However, this is intentional, as many international companies, especially their financial performance, were hit hard by the global COVID-19 pandemic from the business year 2020 onwards, which would have potentially distorted the effect. Therefore, just one period after the intervention and thus exclusively the short-term effects of the introduction of the technology is studied.

Another limitation is that the dataset is very small (3'120 observations), which can be explained by the fact that it was very difficult to find listed companies that introduced the technology in the same year and whose data is available in university or publicly accessible datasets. In addition, the majority of the insignificant effects can also be explained by the small dataset. Many companies that were originally selected for the treatment group dropped out of the sample, because certain measures were not publicly available. If a dataset is very small, the OLS results could be severely biased due to estimator consistency. Therefore, the size of the control group has been extended, compared to the treatment group, since it was possible to find more companies for this group and thus address this problem to a certain extent.

Another point concerns the choice of control variables. Controls that have an influence on Tobin's Q of equity were chosen. It is difficult to assess whether suitable controls were selected and whether this combination of controls achieved the best possible control for all other variables that have an influence on the dependent variable and thus, whether the effect can be optimally highlighted and delimited or not. For the controls, there appeared also the difficulty of publicly available information, which is why the choice was rather limited. The variable Research & Development (R&D) Expenses per company and year can be considered as an example to be an interesting control variable. As higher expenses in this field could strongly correlate with the adoption of blockchain technology. However, this metric was only publicly issued by a minority of the companies.

In regard to the DID method, there is a limitation that this method is not able to address time-varying unobserved factors, that are different between the treatment and control group. This implies that if there is something unobserved that varies over time and that is different for the two groups, we do not know if the deviation in the outcome of the treated group, is due to the variation, that we can observe or solely to the intervention.

6.1.2 Future Research

After examining the effect of the introduction of blockchain technology on firm performance, many other questions remain to be investigated. On the one hand, it would be an interesting option to investigate whether there is a stronger effect in certain industries compared to other industries. On the other hand, it would be an option to look within a company in which department the technology is used and compare whether the effect in a certain department is particularly strong in relation to others. In addition, companies that implement the blockchain in the same business area could be looked at, for example, to increase the validity. It could be narrowed down even more by only looking at companies from the same industry that have implemented the technology in the same area of operation. Furthermore, the companies could be divided into geographical impact regions with the aim of investigating whether the effect is stronger in one region compared to others. Accordingly, it can be said that this work still has a lot of room for sub hypotheses or further hypotheses to be considered based on the literature. In summary, whether the effect is stronger in certain sectors than in others and how the effect differs based on different firm characteristics, such as size and age of the firm.

With respect to the regression model, it would certainly be an alternative to include other or more control variables. At this point, for example, one could not only address firm-level data, but also region-level data.

Another point is the addressing of the dependent variable Tobin's Q of equity. In this context, it would be interesting to compare the effects of Tobin's Q of equity, which is studied in this framework, with those of conventional Tobin's Q.

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8 List of Illustrations

9 List of Tables

10 Appendix

10.1 Annex 1: Fields of Application in Industries

The application of blockchain technology in various sectors is described in more detail below, the short version of which is presented in ***Table 1*** in section 2.2.1 Fields of Application.

Banking, Financial Services and Law

Banks and other financial institutions are where the application of this technology began. It is used to guarantee faster processing. So, transferability of funds between different institutions is almost in real time state. Another point is an automated compliance process based on datasets that cannot be changed, making reporting faster and more accurate (Cocco, Pinna, & Marchesi, 2017). In addition, a point that could potentially have a big impact on business-to-business industries is smart contracts that enable transactions without third-party oversight (Cocco, Pinna, & Marchesi, 2017). For example, companies could conduct and execute things like mergers and fiduciary transactions via blockchain-backed platforms, which is particularly attractive to small businesses and start-ups, as the technology can be more cost-effective than an internal legal counsel, depending on the circumstances (De Filippi & Hassan, 2018).

Insurance

In the insurance industry, for example, blockchain can be used to improve efficiency and accuracy for insurers, policyholders, and even the state insurance department (Grima, Spiteri, & Romanova, 2020). This can take the form of an automated platform that simplifies regulatory insurance reporting and helps meet compliance requirements (Brophy, 2019).

Retail and Consumer Goods

In Commerce: There are many delays in verifying payments, due to lengthy invoicing processes across multiple systems (Chakrabarti & Chaudhuri, 2017). This can increase the cost of doing business and cause conflicts between different players. To address this friction in commerce, blockchain can provide a common information chain that contractors can share. In this particular way, time and costs for invoice processing can be reduced (Xu & He, 2021).

In the area of administration: A large part of the total costs in the transport of goods is accounted for by administrative management, such as trade documentation (Xu & He, 2021). With the application of blockchain technology, administrative barriers can be reduced through greater transparency and simplified cross-border movement of goods (Al-Jaroodi & Mohamed, 2019).

In the area of supply chain: There is a great level of mistrust in the food supply chain due to a lack of transparency between the various contracting parties (IBM, 2022). A blockchain-based solution can ensure efficient and secure tracking of consumer goods in the supply chain and access to compliance certification (Walden, 2022).

Automotive

In the area of mobility services: Many cars, especially of the new generation, contain complex software platforms that must fulfil many requirements regarding interactions with ridesharing services, worship infrastructure, such as charging of electric vehicles and so on (Fraga-Lamas & Férnandeu-Caramés, 2019). Blockchain technology in this field can, for example, use the trunk as a secure drop-off point with authorized access for parcels or a blockchain-based eWallet service for the car for cashless payment of fees and tariffs on roads (Fraga-Lamas & Férnandeu-Caramés, 2019).

In finance: Nearly every step in the supply chain in this industry is underpinned by payments. Blockchain technology can be used here to make transactions transparent and traceable. Smart contracts can go far beyond the transparency and traceability mentioned above and, for example, release funds only after a delivery is completed with satisfactory results (IBM, 2022).

In the supply chain area: Vehicle manufacturing is global, and a wide variety of parts are procured all over the world (Sharma, Kumar, & Park, 2018). Traceability of vehicle components is essential to combat counterfeiting and product recalls. This is where blockchain technology can be useful to make information across the supply chain accessible to suppliers, customers, maintainers, and authorities (Sharma, Kumar, & Park, 2018).

Transportation and Travel

In the area of passenger travel: For example, air travellers have to go through several checks where they have to show their ID and boarding pass. These multiple checks are cumbersome for both the customer and the people working at the transportation facility (Di Vaio & Varriale, 2020). Using blockchain technology, a single identifier that is stored and validated throughout the journey can be adopted. This can reduce the need for multiple travel documents and waiting times (Astarita, Giofrè, Mirabelli, & Solina, 2020).

In the area of cargo: Shipping goods commonly involves many different intermediaries, often all operating with a different system of record. Blockchain can help track the condition and location of cargo using a common record. This can eliminate redundant data and improve transparency of the cargo service (Xu, et al., 2018).

In the area of asset valuation: One of the biggest challenges in the transportation area, is the correct and timely execution of the transportation and maintenance of the components that are transported. As an example, there is the recording of stock levels, tracking the life cycle of a part and detecting and sorting out counterfeit parts (Rejeb, Keogh, & Treiblmaier, 2019). At this point, blockchain technology can be used to identify component data. By recording the data immutably, it creates a trustworthy and transparent business environment (Rejeb, Keogh, & Treiblmaier, 2019). This facilitates maintenance planning and through transparency, reduces the risk of fraud.

In the area of workforces: To continue the example using the airline industry, employees are employed by a variety of companies, the terminals are busy and at the same time planes need to be filled with fuel, shuttle carts need to be driven, people and their luggage need to be transported, catering needs to be provided and security checks have to be carried out, among other things (IBM, 2022). Blockchain can provide a centralized management mechanism here to offer insight into shared information. This prevents entries in the ledger from being falsified or altered, giving the transportation company the verification and insight, it needs counterparties (Al-Jaroodi & Mohamed, 2019).

Healthcare and Pharmaceuticals

In this field, for example, the technology can log the spread of diseases in real time and lock down patient data in a decentralized approach (Khezr, Moniruzzaman, Yassine, & Benlamri, 2019). A common problem in healthcare is medication counterfeiting; blockchain technology enables tracking of serial and lot numbers of prescription drugs, which can address this problem to a certain extent (Haq & Esuka, 2018).

Oil, Gas and Chemicals

The delivery chains in this industry are mostly spread across the globe, and their distance and complexity are high. Here, each actor involved in this supply chain keeps its own records and transactions that need to be reconciled with the other actors (Kadry, 2020). Blockchain can provide a solution to this problem by increasing the speed and completeness of transactions in this network through increased transparency, which also results in a reduction of effort. Through the jointly transparent transactions, the circulation of currency is shortened, furthermore, the risk of fraud, cybercrime and manipulation is reduced through the common unmodifiable ledger, and manual reconciliation processes, which are very time-consuming, are eliminated, thus saving costs, and increasing efficiency (Maxeiner, Martini, & Sandner, 2018).

Manufacturing

To make the best use of the various workforce, resources, and raw materials in the manufacturing process at the most competitive prices, the process expands across the globe. Due to a critical point in this international and very long supply chains, the system is stressed, and this can lead to complications (Aghamohammadzadeh & Valilai, 2019). Blockchain can be a solution to this, as it enables an automated exchange of data that organizes workflows across national borders in a structured way and provides insight at any time for the contractors (Ahmad A. A. KhKhanfar, Iranmanesh, Ghobakhloo, Senali, & Masood, 2021).

Telecommunication

In this context, blockchain can be applied in particular to data protection and data operations. An example of this is protecting customer data from spam callers and spam SMS senders or recording user preferences (IBM, 2022).

Media and Entertainment

There are many fraud problems in this area, especially related to online music theft, online advertising fraud, and ticket sales (IBM, 2022). At this point, blockchain technology can be applied so that there is complete transparency in digital transactions with immutable distributed ledgers (Andrewa, Canepa, Mangla, & Marchi, 2018).

10.2 Annex 2: Firms in the Dataset

Table 7: *Treatment and Control Group*

Treatment Group	Control Group
Pfizer	DKSH
Deutsche Post	NN Group
FedEx	Allstate
LG	Maruzen Chi
Aegon	Verizon
Comcast	SF Express
Lufthansa	Air Transport Services
Fidelity	Credit Acceptance
Maersk	Compal Electronics
Singapore Airlines	Lowe’s
Home Depot	Goertek
Accenture	Seazen
Prudential Financial	Air France-KLM
AIG	Expeditors
Red Eléctrica	Sinopharm
JLL	Manulife Financial
Unilever	Colbun
UPS	Eva Airways
Amazon	George Weston
Hewlett Packard	BPost
	Southern
	Petrochemical
	Royal Mail
	ANA
	Alaska Airlines
	Abbvie
	Brinks
	CTS
	Qube
	SG Holdings
	Easter Airlines
	Agilent Technologies
	Roper Technologies

Fortive

PerkinElmer

Sartorius

Teradyne

MKS Instruments

Bunge

Telefonica

Vertex

10.3 Annex 3: Bibliography of the used Sources

Table 8: *Treatment Group - Sources*

Treated Firms	Information that blockchain technology was introduced in 2018
Accenture	https://newsroom.accenture.com/subjects/blockchain/?page=2
Aegon	https://www.aegon.com/newsroom/news/2018/Significant-step-in-commercializing-blockchain-solutions-for-re-insurance/
AIG	https://bitcoinist.com/aig-blockchain-insurance-policy/#:~:text=AIG%20Uses%20Blockchain%20Ledger%20for%20Insurance%20Another%20first,insurance%20policy%20to%20the%20UK's%20Standard%20Chartered%20Bank.
Amazon	https://www.investopedia.com/news/amazon-getting-serious-about-blockchain/
Comcast	https://corporate.comcast.com/stories/blockchain-for-the-connected-home-combining-security-and-flexibility
Deutsche Post	https://lot.dhl.com/the-logistics-industry-needs-to-be-ready-for-blockchain-heres-why/#:~:text=DHL%2C%20too%2C%20has%20been%20actively%20assessing%20and%20exploring,way%20from%20the%20point%20of%20origin%20to%20consumers.
FedEx	https://www.ccn.com/fedex-turns-blockchain-transform-logistics-industry/
Fidelity	https://www.pymnts.com/news/investment-tracker/2018/fidelity-ai-blockchain-machine-learning/#:~:text=Fidelity%20Investments%2C%20the%20Boston-based%20fund%20company%2C%20is%20becoming,toward%20Fidelity%20blockchain%2C%20Fidelity%20AI%20and%20Fidelity%20VR.
Hewlett Packard	https://marketrealist.com/2017/11/look-hewlett-packard-enterprises-blockchain-product/#:~:text=Hewlett%20Packard%20Enterprise%20enters%20the%20blockchain%20space%20Earlier,part%20of%20the%20HPE%20Mission%20Critical%20Blockchain%20vertical.
Home Depot	https://www.eurofinance.com/news/home-depots-treasury-puts-suppliers-on-blockchain/#:~:text=US%20home%20improvement%20giant%20Home%20Depot%20has%20begun,face%20of%20competition%20from%20online%20retail%20giant%20Amazon.
LG	https://www.ledgerinsights.com/lg-blockchain-digital-currency-payments-ai-facial-recognition/
JLL	https://www.jll.com.sg/en/trends-and-insights/investor/how-blockchain-is-helping-investors-value-real-

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Lufthansa	https://en.cryptonomist.ch/2018/07/20/aviation-blockchain/
Maersk	https://merehead.com/blog/maersk-blockchain-use-case/
Pfizer	https://cryptobriefing.com/pfizer-multinational-explore-blockchain/
Prudential Financial	https://sbr.com.sg/financial-services/news/prudential-starhub-launch-blockchain-based-digital-trade-platform
Red Eléctrica	https://www.ree.es/en/press-office/news/press-releases/2018/11/red-electrica-signs-worlds-first-multi-currency-syndicated-loan
Sigapore Airlines	https://blockchainmagazine.net/singapore-airlines-board-blockchain-technology /
Unilever	https://www.blockchain-council.org/blockchain/unilever-taps-into-blockchain-to-manage-tea-supply-chain/
UPS	https://www.ccn.com/110-year-old-ups-eyes-blockchain-to-streamline-delivery-logistics/