Master Thesis

Digital technology on financial performance.

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Abstract

This Master Thesis investigates the effect of digital technologies on the financial performance of companies listed in Norway. By adopting a Resource-Based View, this paper investigates 18 different digital technologies by using a quantitative text analysis approach on 212 989 announcements and 1169 annual reports from 2014 until today. An extensive literature review addresses the potential benefits of applying the named technologies. The paper finds a small significant increase in performance for the companies disclosing these technologies, while it does not find significant results for the specific technologies' contribution to financial performance. In addition, the findings indicate that the market has positive expectations for digital technologies. At the same time, there is no significant evidence showing an increased financial performance by the companies disclosing the individual technologies. These findings contribute to the literature on the resource-based view by highlighting the need for capabilities to utilize the identified digital technologies and further contribute to the emerging technology trends amongst Norwegian firms.

Acknowledgments

This thesis is the final submission of our strategy major in the Master of Science in Business program at BI Norwegian Business School. After studying at BI for almost five years, we are looking forward to approaching new challenges using the theoretical and knowledge fundamentals from BI. This thesis has been out of the ordinary in terms of methodology. Thus, it has been challenging in many aspects, with programming and strategic theory working hand in hand to create this product. Writing this thesis is a process that has been challenging and demanding, through the high necessity of coordination and some autonomous working between the two students. Nevertheless, this period has been highly rewarding and created a new solid professional and friendly relationship.

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Abbreviations

AI - Artificial Intelligence

ML - Machine Learning

IoT - Internet of Things

IIoT - Industrial Internet of Things

IoS - Internet of Services

IoD - Internet of Data

IoP - Internet of People

AR - Augmented Reality

CPS - Cyber-Physical Systems

OLS - Ordinary Least Square

MLR - Multiple Linear Regression

BLUE - Best Linear Unbiased Estimator

EBIT - Earnings Before Interest and Tax

ROA - Return On Assets

ROE - Return On Equity

RBV - Resource-Based View

IBV - Intelligence-Based View

VRIN - Valuable Rare Inimitable Non-Substitutable

IT - Information Technologies

IS - Information Systems

IaaS - Infrastructure-as-a-Service

PaaS - Product-as-a-Service

MaaS - Manufacturing-as-a-Service

1. Introduction

Markets are becoming increasingly global, with new technology opening for new business models. Global competitiveness is fierce, and the previously less pressured domestic markets open to greater competition with the increased global competition (Sheth, 1986). With immense power, larger companies have emerged in the web-2.0 phase, led by tech giants such as Google, Apple, Facebook, and Amazon (Moore & Tambini, 2018). Technology is evolving and changing the business model as we know it (Tongur & Engwall, 2014). According to several researchers, a new industrial revolution is emerging (Ghobakhloo, 2018; Lasi et al., 2014). This revolution is popularly called; Industry 4.0. The revolution is led by modern digital technologies, described as the "*industrial internet*". A greater need for technological renewal is found through the enhanced sharing of data, and self-learning technologies create large changes in the economy and the firms' activities. Several countries have already acted toward industry 4.0, with the US, Germany, France, and China all having programs facilitating the new industrial period (Dalenogare et al., 2018).

By looking at firms in the Norwegian market, this paper seeks to explore how a firm's digital technology orientation affects its financial performance. Norway has a high-quality research base and a highly competitive startup scene based on technologies like *Big Data, Machine Learning*, and *IoT*, making it a fascinating country to analyze in terms of technology orientation (GlobalData, 2022). This investigation is done through a modern research approach, namely Web Scraping. In this study, the analysis is two-fold. Part one is an event study of the market's expectations of the identified digital technologies. This analysis is tested through a stock market reaction to announcements disclosing the 18 identified technologies. In the second part of the analysis, all the annual reports at Oslo Børs for the same technologies are completed through an MLR analysis programmed in Python. By combining these analyses, this paper hopes to prove that more technologically oriented firms perform better than those that do not appear to use these technologies. By doing so, the paper applies a resource-based theoretical perspective which, with its intangible aspects relating to technology, increases the firm performance and competitive advantages (Rodríguez & Rodríguez, 2005). Based on this, the paper investigates the following research question:

How is the digital technology orientation of firms listed in Norway influencing financial performance?

In this paper, *digital technology orientation* is defined as a company's disclosure of the digital technologies; *Artificial Intelligence (AI)*, *Machine Learning (ML)*, *Automation, Robotics, Simulation, Modeling, Internet of Things (IoT), Internet of Services (IoS), Internet of Data (IoD), Internet of People (IoP), Cloud Computing, Big Data, Blockchain, Cybersecurity, Augmented Reality, Additive Manufacturing, Cyber-Physical Systems (CPS), and Semantic Technologies*. Further, *financial performance* is reflected through both profitability ratios and stock market pricing; *EBIT margin, Return on Assets, Return on Equity,* and *Abnormal Return*. Here, financial performance is considered to capture the financial aspects of firm performance. By researching the above-stated questiontopic, we seek to findstate the essence magnitude of digital technologies'digitalization's influence on a firm's financial performance. We expect to find results indicating how firms should maneuver the digital sphere to perform better strategically. Following the resource-based view, this paper investigates digital tools as a resource and whether these tools may lead to a competitive advantage. In addition, the firm needs to continuously change to stay competitive, maintaining a high dynamic capability. By doing the research based on keywords to map the companies' digital profiles, we could match the digital profile of the firms to their performance.

2. Literature Review

The following literature review is divided into three sections. In the first section, industry 4.0 and digital technologies are defined to emphasize the technologies in focus when analyzing our research question. The second section investigates the link between the Research-based view (RBV) and digital technologies. Last, the third section unravels the technologies and their effect on financial performance.

2.1 Introduction to Industry 4.0 and Digital Technologies

Industry 4.0 is referred to as the fourth industrial revolution, through the increased usage of computers and automation in the production process, an event which later also was called the *industrial internet* (Ghobakhloo, 2018; Posada et al., 2015). The strategic roadmap to Industry 4.0, made by Ghobakhloo (2018), shows how companies can transition and keep up in a time of the newest industrial revolution by leveraging different digital technologies for the different types of companies.

Industry and manufacturing companies often have a typical value chain configuration. Thus, certain technologies aligning with the primary activities, inbound logistics, manufacturing, outbound logistics, marketing & sales, and services, would be considered central to the strategic roadmap to industry 4.0 (Ghobakhloo, 2018; Porter, 1985). In recent times the business model of Manufacturing as a Service (MaaS) has emerged, indicating that the days of manufacturing firms mainly delivering a product are fading. Instead, the Manufacturing and Product as a Service (Maas and PaaS) companies are increasing due to the production capacity and manufacturing itself being the primary good (Ghobakhloo, 2018; Tao & Qi, 2017). Building on this transition, firms may use different value configurations simultaneously, meaning that a manufacturer does not necessarily need to focus on the typical primary activities of a value chain company (Stabell & Fjeldstad, 1998). Amongst other industries with typical value chain companies, the pharmaceutical industry is an example of an industry where technology development needs a value shop logic. Simultaneously the distribution part of the pharmaceutical industry takes advantage of a value network logic (Fjeldstad & Snow, 2018). The need for multiple value configurations simultaneously makes for challenges in effectively integrating other configurations. In the strategic roadmap to industry 4.0 made by Ghobakhloo (2018), although made for a typical manufacturing company with a value chain configuration, the roadmap and technologies should also be applicable for more typical value shop and value network businesses due to the need to combine these configurations in several industries (Fjeldstad & Snow, 2018).

Industry 4.0 consists of several different technologies. Using an extensive literature review, going through 536 different articles, Ghobakhloo (2018) identified 14 technologies in a strategic roadmap to industry 4.0. The technologies defined are: *Automation and Industrial Robotics, Simulation and Modeling, Internet of Things (IoT), Internet of Services (IoS), Internet of Data (IoD), Internet of People (IoP), Cloud Computing, Big Data Analytics, Blockchain, Cybersecurity, Augmented Reality, Additive Manufacturing, Cyber-Physical Systems (CPS), and Semantic Technologies*. Therefore, industry 4.0, defined through their technology trends, gives a nice sample of the existing technologies firms could use. In addition, *Artificial Intelligence (AI)* and *Machine Learning (ML)*, together with the Blockchain and *IoT,* are the central digital technologies referred to throughout this paper (Kumar et al., 2019). The 16 technologies, with a total of 18 technologies, where simulation and modeling, and automation and industrial robotics, are separated into four separate technologies. Further, industrial robotics and big data analytics are disentangled as robotics and big data, to capture a larger application of the technologies. The 18 technologies will be further described and analyzed throughout this paper.

2.2 Theoretical Foundations

2.2.1 Digital Technologies and RBV Applicability

In the previous section, the different technologies have been identified. Ghobakhloo's (2018) technology trends are central to this thesis. However, the 12 design principles described in the paper are the key to using the identified technologies, making the strategic roadmap to industry 4.0, and therefore of high significance when implementing and utilizing the technology as a resource. Technology as a resource is fundamental to the strategic logic of investing in digital technologies, with RBV as one of the most central strategic perspectives used to analyze the implementation of technology (e.g., Aydiner et al., 2019; Lioukas et al., 2016; Mikalef et al., 2019; Rivard et al., 2006; Rodríguez & Rodríguez, 2005; Wiengarten et al., 2013; Wu et al., 2006). There is a development going on in the field of research with technology and RBV. Ghobakhloo (2018) touches upon the technologies but also the importance of applying them to make the technologies valuable, creating an interesting theoretical platform for this paper.

2.2.2 Brief History of RBV

Characterizing a firm as a bundle of resources is the foundation of the resource-based view (RBV). This theory is derived from the study by Penrose (1959) released in the book, *The Theory of the Growth of the Firm*. Penrose states that a firm's growth is controlled by its ability to optimize the usage of the available resources. These ideas were formalized by Barney (1991) as a theory by breaking down what facilitates a resource for the firm by including attributes, assets, capabilities, processes, knowledge, and know-how. Further, Barney defined utilizing of these resources, as a quest to gain a competitive advantage, as the principle of this theory (Rivard et al., 2006). Four conditions apply for a firm's particular set of resources to give a competitive advantage: valuable, scarce, inimitable, and non-substitutional (VRIN) (Barney, 1991). First, the resource needs to be *valuable*, improving efficiency and fulfilling the customers' needs. Second, with the factor of *rareness,* the resource should not be available for everyone since a resource that every company may utilize in the same way is not providing a competitive advantage for one singular firm. Third, *in-imitability* builds on the same principles, meaning that companies would be hindered from recreating them. One barrier to duplication is the information problem and the difficulty of identifying the source of a firm's success, this is a problem called causal ambiguity (Reed & Defillippi, 1990). Another blocker for duplication is subject to legal protections, such as patents. Lastly, to complete the VRIN conditions, access to similar resources or *substitutes* enables companies to implement similar strategies. Thus, non-substitutable is the last condition for a resource to give a competitive advantage (Rodriguez & Rodriguez, 2005; Barney, 1991). Other researchers claimed that the RBV has two main principles. First, the resource is heterogeneous, meaning they diverge from other firms' resources. Second, the resource should have immobility, meaning that it would be possessed for a longer time and is hard to imitate (Mata et al., 1995). The principles overlap and build a strong foundation for using resources, such as digital technology, to gain a competitive advantage.

2.2.3 RBV and Evidence of Digital Technologies Impact

Although high investments in information technologies (IT) are not a guarantee for increased financial performance, a study of IT and firm performance in supply chain companies showed that having IT had a positive effect. This is shown through companies with high levels of IT support proving more efficient than those with low levels of IT support (Rodriguez & Rodriguez, 2005). Several researchers have adopted a resource-based perspective to assess how the business value is affected by information technologies (Bharadwaj, 2000; Melville et al., 2004; Rivard et al., 2006; Wiengarten et al., 2013).

A further classification of resources is presented to investigate the role of technology in the resource-based view, namely tangible and intangible resources (Rodriguez & Rodriguez, 2005). Scholars like Itami & Roehl (1991) state that intangible resources are the most important for business success. Intangible resources are highly knowledge-intensive and include human, reputational, organizational, but also technological capital (Grant, 1991). Highly knowledge-intensive assets have a substantial part of tacit knowledge, which is difficult to codify due to the specificity and typical know-how competencies. A firm's ability to capture value from technology increases due to the specificity, making it hard for others to utilize the same technology, thereby hindering the market from perfectly imitating the technology investments (Kogut & Zander, 1993; Rodríguez & Rodríguez, 2005). The factors above are according to the aforementioned studies, stating that technology is a resource that is valuable, rare, and hard to imitate and substitute, thus completing Barney's (1991) VRIN conditions, showing that technology could indeed be a source of competitive advantage. Looking at the RBV from more recent studies, the research has developed over time with the evolution of technology. Aydiner et al., (2019) complete a systematic literature review investigating information systems (IS) and firm performance from a resource-based perspective and finds that competitors can easily imitate an information system.

Thus, the IS itself is not a source of competitive advantage but rather the capabilities of how to use them.

Numerous studies on firms' performance use technology as a resource (Bharadwaj, 2000; Gu & Jung, 2013; Wang et al., 2016). Further, several studies that adopt the resource-based view to assess the IT contribution to the firm performance study the relationship between the IT resources and the firm performance (Rivard et al., 2005). This study rather looks at digital technologies. Simultaneously, a recent study has found a significant increase in performance for Thai SME companies using big data, smart factories, and IoT (Haseeb et al., 2019).

2.2.4 Building Capabilities Through Implementing Technologies

Technology is described as hard to learn but also hard to imitate, meaning that codifying the technology knowledge may be advantageous for the firm. Still, if they manage to codify it, it will be easier to imitate their competitors (Kogut & Zander, 1993). The capabilities needed to run technologies require a high degree of tacit knowledge that can only be built by trial and error (Bell & Pavitt, 1995). A learning by trying method was found significant in terms of technology implementation when qualitative research showed that even though the implementation of one technology failed, it would help the company to achieve better in the next round and, in this way, help to build capabilities (Fleck, 1994)

Based on the complete literature review, technology is found of interest in terms of financial performance. Thus, this paper formalizes two major hypotheses:

a. *Disclosing one or more of the 18 identified digital technologies will not influence the stock price*

b. *Disclosing one or more of the 18 identified digital technologies will not influence the firm’s profitability*

The 18 identified technologies will be explained in detail in the next section. Some of the technologies will contribute similarly to firm performance, but all the technologies will be categorized so that the contribution to firm performance reflects the technologies' actual value.

2.3 Digital Technologies and Performance

Throughout this section, the different technologies will be elaborated with their respective contribution to the potential increase in performance for the user of the named technology. Table 1 below summarizes the technologies and their contribution to performance, and table 2 underneath displays the number of hits each technology has on google scholar. These findings are further elaborated in detail in the rest of this literature review.

Table 1. Technologies and contributions to performance

Technology	Contribution to performance	Source
AI	Customer segmentation, profitability	Syam & Sharma, 2018
	Efficiency, reduced time processing data	Davenport & Ronanki, 2018
	Targeted products, Efficiency, through correct data rapidly to decision-makers accurate offerings	Kumar et al., 2019
IoT	Efficiency, using data to increase performance	Mourtzis et al., 2016
	Product quality, data optimizing production parameters	Côrte-Real et al., 2017
	New product offerings, innovative data coordination systems	Marjani et al., 2017
IoS	New product offerings, Tesla inc., offers upgrades online	Ghobakhloo, 2018
IoP	Targeted products, customer insight	Ghobakhloo, 2018
Cloud Computing	Reduced cost, pay for access rather than building a new system	Sabi et al., 2016
	Efficiency, quality of service	Akter et al. 2020
Big Data	Market adaption, rapid insight	Hu et al., 2014
	Efficiency, tailored products, leveraging data	Babiceanu & Seker, 2016; Wang et al., 2016
Blockchain	Reduce cost, no need for intermediaries	Michelman, 2017
	New product offerings, more secure and transparent	Zheng et al., 2018
Cybersecurity	More customers, reliable reputation	Hasan et al., 2021
Augmented Reality	Efficiency, rapid and better training of employees	Abraham & Annunziata, 2017
	Better products, improve quality, and control management	Elia et al., 2016
	More customers, cross-selling, re/up-selling	Rauschnabel et al., 2019
Additive Manufacturing	Product quality, improved insight into the production	Goh et al., 2021
	Reduce costs, tailored products, efficiency, faster time to market	Lasi et al., 2014
Cyber-Physical Systems	Efficiency, enabled by principles and routines	Oztemel & Gursev, 2020

Table 2. Keyword Frequency for Technology Strings in Google Scholar

Digital technologies	# Total Hits	# After 2018	Development
Digital technology	623 000	47 700	7.7%
Artificial Intelligence	2 960 000	664 000	22.4%
Machine Learning	3 560 000	1 020 000	28.7%
Automation	5 180 000	600 000	11.6%
Robotics	2 480 000	275 000	11,1%
Simulation	6 320 000	1 560 000	24.7%
Modeling	6 340 000	1 450 000	22.9%
Internet of Things (IoT)	857 000	175 000	20.4%
Internet of Services (IoS)	8 850	4 170	47,1%
Internet of Data (IoD)	767	409	53.3%
Internet of People (IoP)	8 360	6 480	77.5%
Cloud Computing	890 000	150 000	16.9%
Big Data	1 520 000	605 000	39.8%
Blockchain	476 000	114 000	23.9%
Cybersecurity	419 000	66 900	16.0%
Augmented Reality	432 000	41 500	9.6%
Additive Manufacturing	308 000	88 500	28.7%
Cyber-Physical Systems	281 000	40 300	14.3%
Semantic Technologies	33 200	8 140	24.5%

Source: Team Analysis, Google Scholar as per 21.06.2022

2.3.1 Artificial Intelligence, Machine Learning, Automation, Robotics, Simulation, and Modelling

Artificial Intelligence (AI) is commonly defined as

"*a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Haenlein & Kaplan, 2019, p. 5).*

To make it even simpler, *a "categorization of AI as theory and computers able to complete tasks that usually are done by human intelligence"* (Mueller & Massaron, 2018, as cited in, Lichtenthaler, 2019, p. 12). Both definitions are quite open, meaning several of the defined digital technologies come under the umbrella of AI. Machine learning, natural language processing, and robotics are examples of applying the theory behind artificial intelligence (Lichtenthaler, 2019). Finally, *AI* is mentioned 2 960 000 times on google scholar and 664 000 times after 2018, meaning that 22.4% of all these mentions were published recently, making it a trending topic within academics (see table 2).

Machine Learning, *Automation, Robotics, Simulation,* and *Modeling* will not be described in their own chapter due to being applications of artificial intelligence and the effects of AI, similar to the abovementioned technologies, being covered in the next paragraph (Lichtenthaler, 2019). *Machine Learning* poses the question of how to build machines or programs that improves automatically with the experience (Jordan & Mitchell, 2015). Through *AI*, intelligent *Automation* has appeared. Intelligent automation is

"*application of AI in ways that can learn, adapt and improve over time to automate tasks that were formally undertaken by a human"*,

making for significant cost changes and applicable to the industrial scenery (Coombs et al., 2020, p. 1).

Finally, *Machine Learning, Automation, Robotics, Simulation*, and *Modeling* have respectively 3 560 000, 5 180 000, 2 480 000, 6 320 000 and 6 340 000 hits. After 2018, the technologies had respectively 1 020 000, 600 000, 275 000, 1 560 000, and 1 450 000 hits on google scholar. *Automation* and *Robotics* only have around 11% of the results since 2018, and the rest are between 23% and

29%, but they all have many hits in the last few years. Thus, currently, all the technologies are highly rated within the field of academics (see table 2).

Contribution to firm performance. The utilization of *AI* grew by 270% between 2015 and 2019, according to a report published by Gartner (2019) showing its increased popularity (Mikalef & Gupta, 2021). However, researchers like Brynjolfsson et al. (2018) point to implementation and restructuring lags as the reason why AI has yet to deliver its expected results.

"AI will not only impact our personal lives but also fundamentally transform how firms take decisions and interact with their external stakeholders" (Haenlein & Kaplan, 2019, p. 9).

Empirical studies of *AI* have shown how artificial intelligence has improved several key performance indicators at the organizational level (Mikalef & Gupta, 2021)For example, *AI* could lead to improved market share and better customer retainment by using the technology to gain better knowledge and improve the interaction with the more profitable customer segments (Syam & Sharma, 2018). Reducing bottlenecks and increasing efficiency by reducing the time to process data is another potential usage of *AI* to increase performance (Ivanov & Webster, 2017). An example is handling customer communication and legal and contractual obligations (Davenport & Ronanki, 2018). Further, *AI* could give better data and insight to key decision-makers, enabling them to make important strategic decisions about slicing costs, expanding the products or services, and providing more offerings to the customers (Kumar et al., 2019). Thus, *AI* has a large potential to increase firm performance through several key performance indicators, and two new sub-hypotheses for each of the disclosed technologies are formed:

1a) *Disclosing AI will not influence the stock price*
1b) *Disclosing AI will not influence the firm's profitability*

2a) *Disclosing machine learning in will not influence the stock price*
2b) *Disclosing machine learning will not influence the firm's profitability*

3a) *Disclosing automation will not influence the stock price*
3b) *Disclosing automation will not influence the firm's profitability*

4a) *Disclosing robotics will not influence the stock price*

4b) *Disclosing robotics will not influence the firm's profitability*

5a) *Disclosing simulation will not influence the stock price*

5b) *Disclosing simulation will not influence the firm's profitability*

6a) *Disclosing modeling will not influence the stock price*

6b) *Disclosing modeling will not influence the firm's profitability*

2.3.2 Internet of Things (IoT) and Internet of Data (IoD)

Internet of Things (IoT) is a technology that enables communication, coordination, and sharing formation between physical objects (Al-Fuqaha et al., 2015). Therefore, IoT allows things, people, and processes to be connected anyplace at any time with anything and anyone connected to the technology by using any path/network and any service (Côrte-Real et al., 2020). In the context of Industry 4.0, IoT is commonly referred to as the industrial internet of things (IIoT), addressing the industrial use of *IoT* (Wang et al., 2016). It is described as one of the building blocks of Industry 4.0 (Liao et al., 2017). Further, IIOT not exclusively refers to networks of physical objects in the industry but also digital representations of products, processes, and manufacturing infrastructures (Ghobakhloo, 2018). The process of data acquisition and transmission in IoT architecture usually consists of three layers, namely, device (doing the sensing), connection (providing the network), and application (M. Chen et al., 2014). IoT hardware such as RFID, Near Field Communication (NFC), and sensor networks, already exist and are built upon these layers. The technology can be used across different industries, like healthcare and social applications, in addition to logistics and smart infrastructure (Whitmore et al., 2015). Further, the technology is an important source of big data and is applicable for other digital technologies like *Automation, Blockchain,* and *Robotics*, making it an important technology and source of data (Côrte-Real et al., 2020; Makhdoom et al., 2019; Whitmore et al., 2015). Finally, the technology has been mentioned 857 000 times and 175 000 times since 2018 on google scholar, making for 20.4% of the total hits (see table 2). This indicates that technology has also been a popular research topic for academics in recent years.

Internet of Data (IoD) primary application is to increase the efficiency of the methods to transfer data, store it, and manage and process it in the IoT environment (Anderl, 2015). IoD is in many ways an extension of the IoT and is therefore described in the same section of this paper (Fan et al., 2012). The technology would help data entities with identification and be inventoried in the system needed, making virtual tags for the data activities and data vitalization so that it can be collected. Due to *IoD* and the described process, the companies can enjoy the benefits of data tracing, identification, and virtualization by using another digital technology, namely, big data analytics (Ghobakhloo et al., 2018). Finally, the technology has been mentioned only 767 times on google scholar, and 409 since 2018. A small number compared to the other technologies, but with 53.3% since 2018, it is at least not shrinking, although not the most popular amongst academics.

Contribution to firm performance. The utilization of *IoT* opens new paths for companies to create business value. Data-driven strategies will help firms to increase performance by using the data created by the *IoT* and leveraging it to increase their performance (Mourtzis et al., 2016). An example of leveraging *IoT* to increase performance is when Kaeser Compressors created a new business model by selling metric cubits of air rather than selling equipment by applying analytics to IoT. Another example is Trenitalia, reducing maintenance costs by 8% per year, equalling 130 million euros. By using IIOT-enabled factory equipment, the equipment could communicate with data parameters like temperature, and then use this data to optimize performance by dynamically changing the equipment settings (Côrte-Real et al., 2020; Marjani et al., 2017). Furthermore, communication between devices becomes possible by connecting mobile devices, transportation facilities, public facilities, and home appliances, through channels like Bluetooth, WiFi, ZigBee, and GSM. *IoT* opens for innovations within supply chains, transportation, agriculture, retail and logistics, healthcare, and smart cities (Marjani et al., 2017). Thus, *IoT* and *IoD* have a large potential of increasing firm performance through several key performance indicators, and two new sub-hypotheses for each of the disclosed technologies are formed:

7a) *Disclosing IoT will not influence the stock price*

7b) *Disclosing IoT will not influence increase the firm's profitability*

8a) Disclos*ing IoD will not influence the stock price*

8b) *Disclosing IoD will not influence the firm's profitability*

2.3.3 Internet of Services (IoS)

Internet of Services (IoS) has Product-as-a-Service (PaaS) as a business model materialized by the use of the internet (Ghobakhloo, 2018). IoS consists of the service itself, participants, service infrastructure, and the business models. Services are combined into new value-added services by numerous suppliers. The new value-added services, typical PaaS, are communicated to both users and consumers, and the service is accessed through numerous channels (Buxmann et al., 2009, p. 341, as cited in Hermann et al., 2015). This concept opens to creating larger value-added networks where factories could offer product technologies, rather than production types. These technologies could be offered through the *IoS* (Scheer, 2013). Finally, the technology has been mentioned 8 850 times on google scholar, and 4 170 since 2018. A small number compared to the other technologies. Still, with 47,1% since 2018, it has a significant percentage of the hits in recent years, even though the technology has not been largely popular amongst academics, compared to the likes of *AI* and *IoT* (see table 2).

Utilization. IoS has been implemented as a new production control for the automotive industry in Germany. A project called SMART FACE is based on service-oriented architecture. *IoS* created an opportunity for using modular assembly stations that could be modified or expanded flexibly. Automated guided vehicles provide transportation between stations. An autonomous mapping of working steps was utilized, through the vehicle bodies knowing their customer-specific configurations, making them able to compose the required process and autonomously navigate through the production (Hermann et al., 2015). Tesla Inc is another example of a company using data to offer purchasable system upgrades through the internet. *IoS* is, therefore, a digital technology that can offer a supplementary service and cultivate an additional source of income, which could lead to increased revenue (Ghobakhloo, 2018). Thus, *IoS* has a large potential to increase firm performance through several key performance indicators, and two new sub-hypotheses for the technology have been developed:

9a) *Disclosing IoS will not influence the stock price*

9b) *Disclosing IoS will not influence the firm's profitability*

2.3.4 Internet of People (IoP)

Internet of People (IoP) is concerned with a complex socio-technical system where the users are active elements of the internet. Users and their personal devices become part of a system (Conti et al., 2017). IoP consists of an infrastructure of social devices and People as a Service (PeaaS). Social devices, like smartphones, are used to improve proactive capabilities to coordinate the devices' interactions with other devices linked to the IoT. On the other hand, PeaaS only indirectly uses people's personal devices. People owning the device can execute what they intend, but with opportunities like providing their sociological profile online, they provide their feelings and interest online, through the social media (Miranda et al., 2015). A central thought for IoP is that data is collected to give better offerings to the users (Conti & Passarella, 2018). Finally, *IoP* is like its sibling technologies *IoS* and *IoD* not highly cited with only 8 360 total hits, although 6 460 being 77.5% of them since 2018, the largest percentage of the citations after 2018 of all the technologies, although with few citations compared to several other technologies (see table 2).

Contribution to firm performance. The data provided by the individual user's virtual communication can be used to give a reflection of real human sentiment. By computing and simulating a comprehensive set of data collected from the users in the IoP environment, companies can predict market trends to a larger extent. Through data on the consumers' buying patterns and purchase triggers, they can predict actionable results and tailor the offerings to the individual user (Ghobakhloo, 2018). Thus, *IoP* has a large potential of increasing firm performance through several key performance indicators, and two new sub-hypotheses for the technology have been developed:

10a) *Disclosing IoP will not influence the stock price*
10b) *Disclosing IoP will not influence the firm's profitability*

2.3.5 Cloud Computing

Cloud Computing could be defined as a computational model that can process on-demand access to networks with shared resources, like hardware or software. Some factors are common in cloud computing, firstly, the pay-per-use business model, secondly, an interface that is built upon self-service principles where the resources are visualized, and finally, the storage in the cloud is elastic and is often perceived as an infinite resource (Avram, 2014). The technology has emerged due to three major trends within the field of computing systems: service orientation, standardization, and virtualization. Further, three types of different services are provided through this digital technology: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and finally, Software as a service (SaaS) (Akter et al., 2020). Furthermore, cloud computing has been described as a revolutionary technology, which has transformed the location of computing and the production of tools for business processes (Kushida et al., 2015). Finally, *Cloud Computing* is a technology trend with 890 000 hits, with 150 000 of them being since 2018, making for a percentage of 16.9%, making it a technology similarly popular for academics compared to the average popularity of the other defined digital technologies.

Contribution to firm performance. Cloud Computing is beneficial since the access is customizable with minimal effort required from the service provider (Bhushan & Gupta, 2018). The availability of this technology means that the company can get highly scalable computing systems (Wang et al., 2020). Therefore, the cost of having a global business and expanding is minimized through cloud computing technology, as companies could use and pay for the cloud services according to their needs (Sabi et al., 2016). Microsoft reported that its net income grew by 36% due to its cloud computing business model, with programs like Azure, in the last quarter of 2019 (Duffy, 2020). In a literature review, Akter et al. (2020) list different research showing that increased efficiency, increased quality of service, improved operations, and more digitalization, are happening due to cloud computing technology. Thus, *Cloud Computing* has a large potential to increase firm performance through several key performance indicators, and two new sub-hypotheses for the technology is developed:

11a) *Disclosing Cloud Computing will not influence the stock price*

11b) *Disclosing Cloud Computing will not influence the firm's profitability*

2.3.6 Big Data

Big Data Analytics has been described as "*a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high-velocity capture, discovery and/or analysis*" (Mikalef et al., 2018 as cited by Mikalef et al., 2019, p. 262). *Big Data Analytics* provides firms a better opportunity to sense emerging opportunities and threats, facilitate critical insight, and adapt to the best necessary trends based on their competitive environment (H. Chen et al., 2012). Therefore, the main contribution to the firm's competitiveness by using big data analytics comes through better-informed decision-making (Abbasi et al., 2016; Mikalef et al., 2019). Big Data has 1 520 000 hits, with 605 000 of them being since 2018, making up for 39.8% of the hits, indicating that it is a popular digital technology amongst academics also in recent times (see table 2).

Contribution to firm performance. Firms have moved towards a big data analytics approach to identify insights and upcoming trends more rapidly for immediate decision-making and sustain competitiveness (Hu et al., 2014). Asset efficiency, improved customization of products to the customers' needs, and proactive and predictive maintenance are some direct effects of using big data analytics (Babiceanu & Seker, 2016, Wang et al., 2016). However, it has been shown that big data investments take some time to pay off (Pappas et al., 2018; Wamba et al., 2017). Overall, by implementing big data five to six percent higher profitability is expected (Akter et al., 2020). On the other hand, some recent studies stated that many companies fail to capture value through their big data investments (Popovič et al., 2018; Wamba et al., 2017). Thus, big data has a large potential to increase firm performance through several key performance indicators, and two new sub-hypotheses for the technology have been developed:

12a) *Disclosing Big Data will not influence the stock price*
12b) *Disclosing Big Data will not influence the firm's profitability*

2.3.7 Blockchain

Blockchain is a technology utilizing an open-source distributed database giving value by using advanced cryptography (Tapscott & Kirkland, 2016, as cited in Akter et al., 2020). Blockchain is based on five principles determining the operation of this digital technology, namely: Irreversibility of records, computational logic, transparency with pseudonymity, distributed database, and finally, peer-to-peer networks (Iansiti & Lakhani, 2017). A *Blockchain* has an architecture consisting of a continuous, sequential chain of blocks, which holds typical ledger records. The decentralized ledger technology, that blockchain is, is maintained by peer-to-peer networks, meaning that it is owned by the network, not one singular authority. The user cannot lose control over their digital identities, even if they lose access, while it is also tamper-resistant (Dunphy & Petitcolas, 2018). Decentralizing the records implies that no single entity has control or can make changes without following a protocol most of the users have to agree upon after authentication of themselves through the cryptography algorithms blockchain consists of (Casey & Vigna, 2018; The Economist, 2015). In the scientific community, blockchain is believed to be essential to Industry 4.0, due to the technology allowing smart devices to perform secure, transparent, fast, and frictionless transactions autonomously in the *IoT* environment (Devezas et al., 2016; Sikorski et al., 2017). Finally, *Blockchain* is a technology trend with 476 000 hits on google scholar, with 114 000 of them, or 23.9% of the hits being after 2018, making it a popular digital technology amongst academics, although not as popular as some of the other identified digital technologies (see table 2).

Contribution to firm performance. Blockchain platforms are typically un-hackable, making them highly secure (Akter et al., 2020). Cryptocurrency, with the specific currency, Bitcoin, is one of the most popular blockchain applications (Kumar et al., 2019). While cryptocurrency has been a popular application of the technology, blockchain application is not limited to financial services but can be used for any type of digitized transfer of information (Ghobakhloo, 2018). Blockchain has more advantages than decentralization. Three characteristics of blockchain are also important: persistency, anonymity, and audibility. While blockchain is persistent in using decentralization and technology factors to capture falsifications, its anonymity enables people to generate as many addresses as they want without real identity exposure. Finally, audibility enables the users to track and trace transactions done through blockchain technology using the distributed network (Zheng et al., 2018). Based on the traits described above, it can reduce costs, by removing the cost of intermediaries, when rather using blockchain technology (Michelman, 2017). Thus, *Blockchain* technologies have a large potential to increase firm performance through several key performance indicators, and two new sub-hypotheses for the technology have been developed:

13a) *Disclosing Blockchain will not influence the stock price*

13b) *Disclosing Blockchain will not influence the firm's profitability*

2.3.8 Cybersecurity

Cybersecurity and information security are two terms that often get mixed up. *Cybersecurity* not only protects the traditional resource as information security does but also secures the other assets, like humans. Further, some scenarios of cases different from those of information security are listed: cyber bullying, unauthorized access to smart homes and devices, digital media in the form of movies and music, and finally cyber terrorism targeting control over the central infrastructure in a country. These are examples where information is not the ultimate target (von Solms & van Niekerk, 2013). Finally, *Cybersecurity* is a digital technology with 419 000 hits on google scholar, and 66 900 of them, making up 16% since 2018. It is therefore not like some of the other technologies and is decreasing slightly in popularity amongst researchers compared to other digital technology trends.

Contribution to firm performance. Cybersecurity could create value by protecting the resources that create value in the firm, thereby, securing that unauthorized actors do not utilize a firm's most valuable assets. Examples of these resources are confidentiality, integrity, and availability of information (Whitman & Mattord, 2021). A study made by Cisco (2016) showed that cybersecurity would protect 5.3 trillion US dollars until 2026. On the one hand, in the industry 4.0, there are no doubts about many devices being connected, providing valuable data for the businesses to use to make important decisions and actions, if this data is not secure, the consequences could be significant (Mehnen et al., 2017). Further, studies like Hasan et al., (2021) find that increased cybersecurity provides improved sales and profitability, a competitive advantage, a well-perceived image, and a good reputation. On the other hand, a report, based on a survey with over 2400 IT and business decision-makers, states that 70% of *Automation* initiatives are hindered by security concerns (MuleSoft, 2021). *Cloud Computing* faces the same security concerns (Rebollo et al., 2015). Thus, *Cybersecurity* has a large potential of increasing firm performance through several key performance indicators, and two new sub-hypotheses for the technology are developed:

14a) *Disclosing Cybersecurity will not influence the stock price*
14b) *Disclosing Cybersecurity will not influence the firm's profitability*

2.3.9 Augmented Reality

Augmented Reality (AR) is a technology that allows the visualization of computer graphics appearing in the physical environment (Yew et al., 2016). *AR* is a technology with the opportunity to provide people with 3-D relevant information to their work, which could be placed in a real environment, like the workspace of a company, for a specific task completed in the workspace (Azuma, 1997). Therefore, *AR* could be a valuable tool, providing a guide to a complex case unfamiliar to the user (Borsci et al., 2015). The technology can be used in many tasks, e.g., planning, design, assessments, and training (Wang et al., 2016). Smart glasses in one way of providing *AR*, providing information through wearable glasses (Abraham & Annunziata, 2017). Finally, augmented reality is a technology found of interest within the scientific community with a total of 308 000 hits, where 88 500, making up 28.7% are found from 2018 until 23.06.2022. It is therefore not the most popular technology amongst researchers, but with a quite high percentage of the hits from recent studies (see table 2).

Contribution to firm performance. AR is by now already improving workers' performance. *AR* is already used in manufacturing, warehouses, and field service environments. The technology is actively increasing the worker's performance by enabling them to complete tasks, even without prior training, making them more skilled and efficient (Abraham & Annunziata, 2017). Product design and quality and control management are other technology applications (Elia et al., 2016). Nee et al., (2012) concluded that in industries, the limited understanding of issues related to human factors would be likely to hinder the spread of *AR*. On the other hand, recent studies showed that marketing through *AR* apps, like the popular game Pokemon Go, improves the commercial's reception. Further, some researchers believe that AR could be used for cross-selling, up-selling, and re-service purposes, potentially providing the companies with even more customers (Rauschnabel et al., 2019). Thus, AR has a large potential to increase firm performance through several key performance indicators, and two new sub-hypothesis for the technology have been developed:

15a) *Disclosing Augmented Reality will not influence the stock price*
15b) *Disclosing Augmented Reality will not influence the firm's profitability*

2.3.10 Additive Manufacturing

Additive Manufacturing (AM) is a process in manufacturing that is a technique where the melting of thin layers of material on top of each other, based on geometrical instructions suggested by Computer-Aided Design (CAD) modules (Esmaeilian et al., 2016). The technology has seen development in recent years with the technology being used to produce products in various materials, such as plastic, metal, concrete, clothing, and food (Dilberoglu et al., 2017). In addition, *AM* can be used in different manufacturing processes, such as production planning and control, product design, and maintenance. Thus, it is not necessarily only for production, but could also be used as a service (Elia et al., 2016). Finally, additive manufacturing is a technology found of interest within the scientific community with a total of 432 000 hits, where 41 500, making 9.6% are found from 2018 until 23.06.2022. It is therefore not the most popular technology amongst researchers, but with a quite high percentage of the hits from recent studies (see table 2).

Contribution to firm performance. By combining *AM* with machine learning, one could get more insight into the created products and increase the quality of the products making them even stronger (Goh et al., 2021). The process is deemed a bit slow for mass production of products, thus, giving high costs in these cases (Dilberouglu et al., 2017). On the other hand, *AM* could increase the speed of production, give a more significant manufacturing design freedom, and reduce supply chain costs, through fewer materials used. If given smaller production samples, it could also give supply chain reductions, and speed up the prototyping phase, potentially giving products a faster time to market (Lasi et al., 2014). Thus, additive manufacturing has a large potential to increase firm performance through several key performance indicators, and two new sub-hypotheses for the technology have been developed:

16a) *Disclosing Additive Manufacturing will not influence the stock price*
16b) *Disclosing Additive Manufacturing will not influence the firm's profitability*

2.3.11 Cyber-Physical Systems

Cyber-Physical Systems (CPS) is a technology enabling the operations between physical assets and computational capabilities (Lee et al., 2015). Computer-based algorithms control and monitor *CPS* and relate to its user through the internet. For example, a smart production line could be considered a *CPS* (Ghobakhloo, 2018). *CPS* performs different activities within manufacturing; Process monitoring, Applicability in different domains to generate a larger system, integration between different disciplines in different domains, effectively handling dependability, user interaction, performance monitoring in real-time, live configuration, deployment, and decommissioning, decision-making distributions of interconnected communications. Finally, *Cyber-Physical Systems* is a technology of interest amongst researchers with 281 000 hits on google scholar. Of these, 14.3% were found from 2018 with a total of 40 300 hits, showing that it is a researched technology, although not as much as some of the other defined digital technologies (see table 2).

Contribution to firm performance. CPS provides easier access to information, proactive maintenance, and decision-making based on predefined principles and optimization routines. Through combining two important elements *IoT/IoS* combined with a virtual environment created to project the real world, the *CPS* could give vast benefits in the utilization of resources and productivity improvements. On the other hand, there are security problems concerning technology. It is highly disruptive, and potentially a source of immense value, but with new value contributions, it is also a security concern (Oztemel & Gursev, 2020). Thus, *CPS* has a large potential to increase firm performance through several key performance indicators, and two new sub-hypotheses for the technology have been developed:

17a) *Disclosing Cyber-Physical Systems will not influence the stock price*

17b) *Disclosing Cyber-Physical Systems will not influence the firm's profitability*

2.3.12 Semantic Technologies

Semantic Technologies are technologies used to process and use background knowledge and connect different data streams to make valid reasoning. The technology could handle multiple data streams simultaneously and be combined with event processing to detect critical situations before they happen. This technology has several advantages, and the term ontology, a major part of the technology itself, is central to these advantages. Ontology is based on: Firstly, structure, being where the technology facilitates operability in-between events published by different sources, creating a common understanding of the event in question. Secondly, formal is giving an explicit representation of the event by providing verification, gap analysis, and justification. Lastly, enabling inference creates extra power and capabilities to make valid reasoning (Schneider & Xhafa, 2022). Finally, *Semantic Technologies* has only 33 200 hits on google scholar, with 8 140 hits and 24.5% of these after 2018, making it less popular compared to other digital technologies, but still significantly used within research (see table 2).

Contribution to firm performance. Semantic Technologies can help provide a common communication for exchanging information between different smart components and devices (Janev & Vraneš, 2011). For example, IoT offers devices to communicate with each other. Still, the monitoring and extraction of the communication between the devices can only be done if they are communicating in the same way, and often by the same manufacturer, making the *IoT* more flexible and adaptable to the individual company's needs (Ghobakhloo, 2018). Thus, *Semantic Technologies* have a large potential of increasing firm performance through several key performance indicators, and two new sub-hypotheses for the technology is developed:

18a) *Disclosing Semantic Technologies will not influence the stock price*

18b) *Disclosing Semantic Technologies will not influence the firm's profitability*

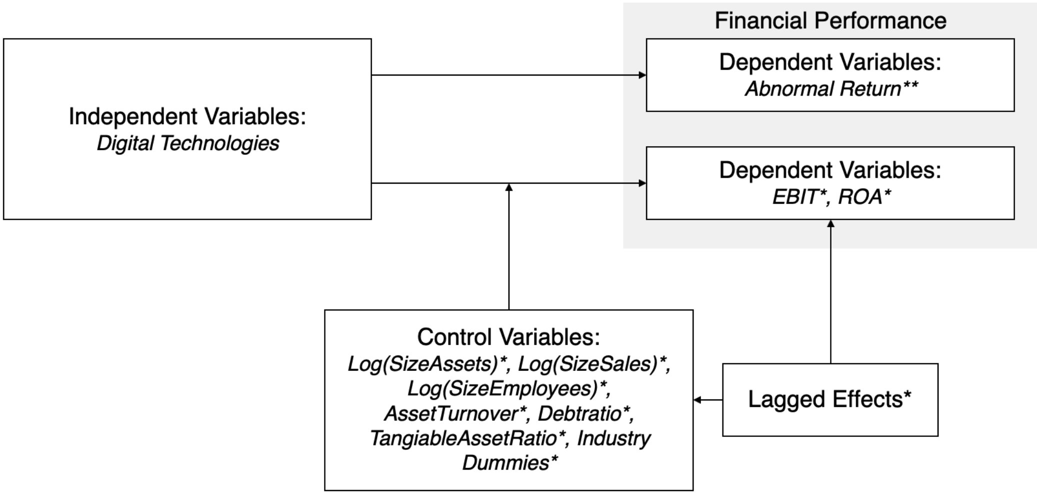
3. Methodology

In this paper, we utilize a deductive research approach, by forming hypotheses based on established theories from the literature on strategy and analyzing their validity by fitting a best linear unbiased estimator (BLUE) (Wooldridge, 2015). This estimator is fitted to indicate relationships between numerical proxies for digital technology orientation as a source of increased performance. A quantitative approach is used to analyze the Norwegian market to look at how this technology gives advantages to its users, specifically corporate users. With a modern approach to strategy, a modern research method felt appropriate. A frequency-based text analysis of listed Norwegian companies was created and employed through programming in python. Antweiler & Frank (2004) investigated announcements through text analysis and showed a significant effect between announcements and stock price. This effect reflects the market's perception of the message. An analysis of the market's perceived meaning of digital technologies and the actual increased performance and financial results coming from the technology is the topic of investigation.

The analysis is based on both primary data and secondary data. Primary data is collected when secondary data is unavailable. This paper indicates a relationship between financial performance and company-specific digital technology orientation on Oslo Børs. The latter requires a less traditional data collection method, and we could not find applicable secondary data material. Therefore, a great amount of effort was put into creating a program for data mining, a proxy for digital technology orientation that could further be analyzed to indicate the hypothesized relationships.

The effects of using and implementing digital technologies are interesting if they provide for increased financial performance. The analysis is two folded to get a complete overview of the digital technologies and financial performance. First, is an analysis based on all the annual reports, comparing the companies disclosing digital technologies with those that are not. Then, estimating the effect of digital technologies on financial return ratios indicates how digital technologies affect a firm's financial performance. Secondly, these effects are analyzed by using the keywords defined by Ghobakhloo (2018) through all the Norwegian listed companies' announcements to observe the effect these mentions have on their respective stock prices. These two analyses will give an overall insight into the digital technologies' effect on financial performance.

Figure 1. Regression analysis model



Source: Team Analysis

3.1 Event Study of Digital Technology Announcements

The *stock market reaction analysis* is conducted as an event study. An event study is a study where data from the financial markets are utilized to measure the impact of an event and its effect on the value of a firm. Two factors are important when completing an event study: first, to define the event of interest, and second, to define what time intervals to use to check for abnormality in prices. Announcements are a common form of event (MacKinlay, 1997). The event study methodology has been suggested to be a powerful tool for assessing the business performance of investments in digital technologies (Im et al., 2001).

Further, event studies can support the relationship between digital technology investments and performance, where accounting-based measures have been criticized for being inadequate (McWilliams & Siegel, 1997). In this study, the special event measured is the announcements disclosing one of the pre-defined digital technology keywords, with a control group measuring the reaction of a random event announcement. An event window is defined to capture the abnormal return of stock on the day of the announcement. Because the event should have information content related to the digital technologies, the abnormal return of a stock should be observed (Im et al., 2001). For an event day t the stock market reaction is calculated as:

$$SMR_{it} = R_{it} - R_{mt},$$

where:

$$R_{it} = P_{it}/P_{it-1}, \quad \text{and} \quad R_{mt} = P_{mt}/P_{mt-1},$$

where SMR, R, and P, are the stock market reaction, return, and price, respectively, for i company and m market. The regression will further estimate the abnormal return effect over the normal return. Research bases this assumption on the efficient market hypothesis (Fama, 1970). Further, if rational actors value both intangible and tangible assets of the digital technologies, the stock market reaction should reflect the technologies' true contribution in increased variety, timeliness, and quality, and not just cost reduction (Brynjolfsson & Yang, 1996). Occasionally, announcements are published after or close to the closing of the market. Therefore, a two-day window is defined.

Further, an adjustment window is set to capture a slower market efficiency effect in the five days after the event. An anticipation window is defined to control for effects from insider information or other public disclosures relating to the event in the five preceding days. Finally, the estimation window is set to capture the normal market return of the stock as a benchmark for the abnormal return of the announcement. The time intervals were set to a total of 135 days, five days after the event as the adjustment window, one or two days as the event window depending on the time of the announcement, 5-6 days before the event as the anticipation window, and 123 days before the anticipation window as the estimation window (See figure 2., MacKinlay, 1997).

Figure 2. Time windows

Estimation	Anticipation	Event	Adjustment
123 days	5-6 days	1-2 days	5 days
135 days			

Source: Team Analysis

3.2 Study of Digital Technology's Effect on Profitability

An empirical study sets out to analyze the cause-and-effect relationships in a set of observed variables. In general, two types of variables are defined and observed. First, a dependent variable, or response variable, is dependent on the other variables in the relationship and is often denoted as Y. Second, independent variables, or explanatory variables, are defined as explaining an effect in the dependent variable. Independent variables are assumed not to be influenced by the other variables, hence independent, and are commonly denoted as X. Further, independent variables can be categorized either as the variables under consideration or as control variables for explaining established relationships (Wooldridge, 2015). After defining the variables, a regression model is fitted to estimate their relationships as a linear function of the independent variables on the dependent variable. The latter can be simplified as:

$$\boldsymbol{Y = \beta_0 + \beta_1 X + \varepsilon_i}$$

Where, Y is the dependent variable, β_0 and β_1 are the estimated constant and coefficient, X is the independent variable, and ε_i is the error term.

3.3 Keyword Frequency

Independent variables in both the stock market reaction and annual report analysis are based on a keyword frequency investigation. A keyword frequency approach is implemented to quantify proxies for the digital technology orientation in this paper. The frequency approach is used due to measurement problems for the application of digital technologies. Measurement problems often stem from the difficulty of measuring multidimensional constructs with unclear definitions (Waddock & Graves, 1997). This paper would be superficial if an unbiased application of digital technologies could easily be quantified, but as this is not the case, a more creative method was adopted. Although the method of text analysis is less popular, research using text to create numeric proxies for phenomena is far from rare. Keyword frequency is often used as an indicator of trends within research (e.g., Lu et al., 2021). Further, keyword frequency is used in technology-related patent analyses (e.g., Joung & Kim, 2017). Text analysis on the frequency of negative wording has also been used to predict companies' financial performance

(Tetlock et al., 2008). This paper uses keyword frequency as an indicator of trends within technology for company announcements. The identified technologies (see table 3) are searched for as strings to identify the frequency of the different keywords to indicate a company's orientation to different technology trends. Annual reports and company announcements were used as text material to further create the proxy for companies' digital technology orientation. Also, Google Scholar was used when assessing the popularity of the different technology trends within research to capture the largest sample of observations, and to compare the different technology trends' popularity within research (Martín-Martín et al., 2018).

Table 3. Strings For the Identified Digital Technologies

Technologies	Strings
Blockchain	'blockchain' or 'Blockchain'
IoS	'IoS' or 'Internet of Services'
IoT	IoT' or 'Internet of Things'
IoP	'IoP' or 'Internet of People'
IoD	'IoD' or 'Internet of Data'
Automation	'automation' or 'Automation'
Cybersecurity	'cybersecurity' or 'Cybersecurity'
Simulation	simulation' or 'Simulation'
Cyber-Physical Systems	Cyber-physical systems' or 'cyber-physical systems'
Augmented Reality	AR' or 'Augmented reality' or 'augmented reality' or 'Augmented Reality'
AI	AI' or 'artificial intelligence' or 'Artificial intelligence' or 'Artificial Intelligence'
ML	'ML' or 'Machine learning' or 'machine learning' or 'Machine Learning'
Robotics	'industrial robotics' or 'Industrial robotics' or 'industrial robotic' or 'Industrial robotic'
Modeling	'Modeling techniques' or 'modeling techniques'
Semantic	Semantic technologies' or 'Semantic technology' or 'semantic technology' or 'semantic technologies'
Additive Manufacturing	'Additive manufacturing' or 'additive manufacturing'
Cloud Computing	Cloud computing' or 'cloud computing'
Big Data	'Big data' or 'Big Data' or 'big data'

3.4 Text Mining and Analysis in Python

Both analyses were administered through the *JupyterLab 3.0.14* environment running Python, managed through the graphical user interface (GUI) *Anaconda Navigator 2.0.4*. A large collection of packages for python were applied throughout the process of data collection, curation, and analysis. The process started with scraping the text from announcements and annual reports.

For scraping the announcements from the Newsweb platform, the script *Pyckaxe* was created and employed. *Pyckaxe* was formed as multiple loops to run through the indexed announcement IDs through a *Selenium webdriver* and temporarily extract and analyze the content for the digital technologies for each announcement using the *Nltk* package, before storing the relevant information in a csv (NLTK, 2022, Selenium, 2021). Because the content needed to be loaded for each announcement and to avoid violating inbuild rate limits, a pause of 1 second was constructed for each announcement. Therefore, the total time for running the script through 216 511 announcements was over 60 hours. The method of scraping the announcements was approved by Oslo Børs over the phone. Further, *MeltingPyt* structured the data collected in one large data frame, before removing failed observations and storing the clean data in a csv file. Next, *Pryceaxe* was used to collect historical prices for the stock market reaction window, for each technology found, utilizing the *YFinance* package, and further matching the prices with the return on a benchmark index on Oslo Børs (Aroussi, n.d.). Based on the relative date of the prices, the script gives the data a dummy variable for the different windows, before saving the data in a new csv file. *Casting* was then employed to go through the new csv file, collecting the relevant data and structuring it again with dummy variables for both digital technologies and time windows. Lastly, the *RegressionStockmarketReaction* script, imports the collected data and utilizes packages from *Matplotlib, Statsmodel,* and *Linearmodels* to run statistical tests and estimators (Matplotlib, n.d.; Seabold & Perktold, 2010; Sheppard, n.d.).

The annual report analysis included a similar script as the *Pyckaxe*, *Pydfaxe*, but did not include scraping. Because annual reports were not freely available in one online directory, the reports had to be downloaded individually from each company's webpage. Further, the analysis looped through the pdfs in the file directory by number for year and company name, using the *Glob* and *OS* packages, before reading the pdfs through the *Fitz* package and storing the number of each trend found in a csv file (Python, n.d.b, n.d.a; ReadtheDocs, n.d.). Further, the *Pydfaxe* runs through the data collected from the PDFs for each of the companies and years and merges the findings with the financial information collected from the

Compustats database, before giving each observation dummy variables for industry and digital technologies. Lastly, the *RegressionAnnualReports* is employed to run statistical tests and estimators from the *Matplotlib, Statsmodel*, and *Linearmodels* packages to analyze its relationships (Matplotlib, n.d.; Seabold & Perktold, 2010; Sheppard, n.d.).

The packages *Csv, Nympy* and *Pandas* are utilized throughout the scripts for reading and managing the data (*Python, n.d.c, Numpy, n.d.; Pandas, n.d.).*

3.5 Sample & Data

Primarily, two different types of data were gathered, one textual from company publications and one financial. The company information and related textual data were gathered from various Euronext records, as well as company websites. For the textual company-related publications, two different data extractions and analyses were completed: one with annual reports, and the other with the company announcements.

3.5.1 Sample for Annual Report Analysis

First, the annual reports were gathered through a selection of companies based on one main characteristic, being a listed company on the Norwegian stock exchange, Oslo Børs. The filtration was done to remove companies listed on Euronext Growth and Expand, due to many lacking the history and size to see the wanted effects on a company's performance based on their digital technology orientation. The companies included in this exchange are often smaller, thus, more likely to be newly established and have more incentives to exploit information technologies, and since the analysis was to examine the effect of digital technologies over time, these companies were not as interesting (Brynjolfsson, 1994). In total, there were 209 company stocks listed on Oslo Børs as of 21.01.2021 (Euronext, 2022b).

Of these, annual reports from the 201 different companies were downloaded due to 5 companies being too new, and 3 being the same company listed twice with a different value on the different types of stocks, A and B type. A time span of 7 years, from 2020 to 2014, was determined for the extraction of annual reports. This timespan was chosen for two reasons. First, many companies did not have annual reports dating further back. Second, to have a large enough timeframe to see the changes in performance over time and the actual effects of the digital technology orientation. In total this resulted in 1169 annual reports manually downloaded, to gain the wanted insight.

Further, financial data was gathered from the Fundamentals Annual Global Compustat database, provided by S&P Global Market Intelligence through the Wharton Research Data Services (wrds) (Compustat Global, n.d.). The database was accessed through authorization from a BI business school representative after application. The financials were extracted based on a list of International Securities Identification Numbers (ISIN) for the 201 companies and later merged with the data for company information and digital technology findings from the annual reports. After scrubbing the data for errors and incomplete entries, the sample included 183 companies. Further, the data included only companies with three or more observations in each panel. Limiting the time series is a conflicting task, as more balanced panels and fuller samples are both more robust and contradictory. Therefore, a golden middle way is adopted. The final sample included 153 companies with 911 observations. The effect of omitting data is considered in the section about *internal validity*.

3.5.2 Sample for Stock Market Reaction Analysis

In the second analysis, the announcements of all listed companies are up for investigation. All announcements containing one of the digital technology keywords originating from Ghobakhloo (2018) and (Kumar et al., 2019), and a control group of similar size, are gathered by programming in python and scraping data from Oslo Børs' announcement site Newsweb (Oslo Børs, n.d.). A total of 212 989 announcements were scraped, where 5676 announcements, 2.7%, were unavailable due to Oslo Børs having removed the announcements for an undisclosed reason. The analysis was set to start with the more recent announcements in 2022 and work its way back chronologically. When getting to 2014, the rate of available announcements and the rate of keywords disclosed decreased, and the sample was limited to from 2014 up until 2022. In this sample, Euronext Growth and Expand were also included. Of these announcements, 1 423 disclosed one of the keywords and had available price data, and 1 728 were randomly collected as the control group with available financial data. The randomization for the control group was done by only collecting announcements with IDs ending on the number 42 or 13. The IDs are ordered chronologically for the announcements through the period and, therefore, should carry no selection bias. Since the longer-term financial effects are in focus in the other analysis, the market's and shareholders' expectations connected to the keywords are at the center of this analysis. Further, the announcements were then checked against stock market reaction using the YFinance package for python and Euronext OSEBX GR historical prices (Euronext, n.d.), extracting closing prices for the 135-day window to check the isolated effect of the digital technology announcement. After the extraction, the final sample included 425 519 available prices for announcements disclosing the keywords and the control group.

3.6 Measures

3.6.1 Dependent Variables

Stock Market Reaction Analysis. The dependent variables in the stock market reaction analysis are set to the abnormal return of the stocks. The return of a stock is measured as the change in stock price from the closing price on one day divided by the closing price of the preceding day. Further, the abnormal return is estimated using a marked model to estimate the event effect of stock while controlling for the market return (MacKinlay, 1997).

$$\boldsymbol{AR_{st} = R_{st}, - E(R_{st}|X_t)}$$

Here, AR_{st} is the abnormal return, R_{st} is the actual return, and $E(R_{st}|X_t)$ is the expected normal return of a share (s), on a specific time, (t). For the statistical model, we impose an assumption of multivariate normal and independent distribution through time. MacKinlay (1997) states that although the assumption is strong, problems rarely occur as the normal return model is robust to deviations from the assumption.

Annual Report Analysis. The dependent variable in the Annual Report Analysis is financial performance. In line with a heavily cited article by Waddock & Graves (1997) employing a similar method, financial performance is estimated by three ratios, return on assets (ROA), return on equity (ROE), and return on revenue, also called operational margin or earnings before interest and tax margin (EBIT). The latter is a small deviation from the return on sales (ROS) used by Waddock and Graves (1997), stemming from the lack of available financials for sales. Further, *EBIT* is used as a proxy for return to capture the operational profitability and avoid differences in tax and interest. Share price-based variables like price to book (P/B), reflecting the market value of a listed stock divided by the reported value of its assets, could also be employed. P/B, as an example, is a ratio reflecting the market's predictions for future valuation and can give insights related to the stock market's sentiment related to different technologies. Because this effect is measured more directly in the stock market reaction analysis, share price-based dependent variables are omitted.

3.6.2 Independent Variables

For both analyses, the defined digital technologies were used as independent variables, included in the sample by using the strings defined in table 3 to search for the digital technologies.

Stock Market Reaction Analysis. The independent variables for the stock market reaction are structured as dummy variables for each time window and digital technology. The dummy variables are denoted as boolean values 1 and 0. For the time windows, three different dummy variables are used to indicate that the stock returns are in either the anticipation window, the event window, or the adjustment window. Further, the same mechanism is applied for dummy variables representing digital technologies. For most of the estimations, a dummy is applied by multiplying the event window dummy with a digital technology dummy to create a dummy for the event of a specific technology. Further, the estimations of the aggregated technologies, and the control group, are fitted by including all event dummy variables.

Annual Report Analysis. The independent variables in the annual report analysis are based on the identified digital technologies. The digital technology independent variables are fitted to give insights into the relative effectiveness of a company's orientation towards digital technologies. Due to the lack of available numerical material for digital technology use and orientation, a proxy is built from the disclosing of technologies in companies' annual reports. Further, there are primarily two types of independent variables for this analysis. First, a variable for the total number of times any of the technologies are disclosed for a given annual report, coined the aggregated technologies, to give insights into the effect of digital technologies in general on financial performance. Second, the number of times a specific technology is disclosed for a given annual report to give insights into the effect of the specific technology on financial performance. Further, independent variables are transformed into quadratic variables to estimate the quadratic relationships with financial performance. Also, the mentioned independent variables are employed with three degrees of negative lag, zero years, one year, and two years. The negative lag is used to check the delayed effect of digital technology on financial performance as one can does not expect the performance realization to be instantaneous.

3.6.3 Control Variables

Stock Market Reaction Analysis. Other than the fixed entity effects in the regression, no additional control variables are employed in the stock market reaction analysis. The time-series data control for the normally expected effect in the estimation window and the fixed entity effects account for differences between companies. To further control for the effects of announcements in general, a control group is randomly selected and estimated to check the effect of the events without technology disclosure.

Annual Report Analysis. The control variables in the annual report analysis are based on additional independent variables that have a known explanatory effect on financial performance. These are included to control for effects that stem from established relationships other than the independent variables under consideration. In line with research on financial performance Waddock & Graves, 1997, we set out to implement control variables for size, *Log(SizeAssets); Log(SizeSales); Log(SizeEmployees)*, risk; *Debtratio*, and industry dummies (see table 7.). First, size values are calculated from the logarithm of total assets, the logarithm of employees, and the logarithm of revenue (Waddock & Graves, 1997). Logarithm is used to create a more normally distributed value for the variables to balance the effect of the extremes. Second, a leverage ratio is employed as a proxy for the risk of the company. The leverage ratio is calculated as total debt on total assets. Third, dummy variables based on ranges of Standard Industrial Classification (SIC) codes are included to capture the differences in financial performance by industry. The largest industry dummy, *Miningconstruction*, is not included in the models to avoid the dummy variable trap. In addition, asset turnover; *AssetTurnover,* and proportion of tangible assets; *TangibleAssetRatio*, are included in line with Pouraghajan et al., (2012) findings of capital structure on financial performance. Asset turnover is calculated as total revenue on total assets, to describe the efficiency of a company's assets in creating revenue. The proportion of tangible assets is calculated as tangible assets on total assets, to show the differences in the companies' asset bases. Lastly, fixed time effects are incorporated to control for the annual market-related differences in financial performance.

3.7 Validity

3.7.1 External Validity

External validity is a term referring to whether the findings, such as the ones in this paper, are generalizable to different settings (Calder et al., 1982). The data mining is done through text analysis, also by other researchers, a method used to capture the digital technology orientation and further estimate its effect on the financial performance (Dos Santos et al., 1993). Further, the research supports the use of the resource-based view and technology with 203 000 hits on this phenomenon on google scholar as of 21.06.2022. The theory has by some researchers been criticized, because the capability and intangible assets are the only resources to give a sustainable competitive advantage and that the technology itself is not enough (Akter et al., 2020; Kogut & Zander, 1993; Mikalef et al., 2019; Rodríguez & Rodríguez, 2005). This research seeks to analyze the impact technology has on firm performance, showing the potential strength and weaknesses some of the technologies have on firm performance. The scope and large set of data in the analysis strengthen the generalizability to other settings. Although not all capabilities and aspects of technology usage are found through this research, the research is indeed giving some indications on the technologies' impact on firm performance. The generalizability of this research to other settings, although advantageous, is not necessary for the research to be externally valid, since this is a single study (Calder et al., 1982).

3.7.2 Internal Validity

Internal validity is a term referring to what degree the independent variables are responsible for the abnormal activity found in the dependent variable (Calder et al., 1982). In general, there are indications for research that is not experimental to gain high internal validity. In this research, there are primarily four main factors reducing the internal validity.

First, these analyses are completed solely on to what degree Norwegian companies have an orientation towards technology. This makes for the exclusion of other companies internationally, potentially having other sets of capabilities. Thus, it could be argued that the generalizability of technology usage in terms of performance is not generalizable to other countries. Further, the Norwegian stakeholders might be more interested in technology and have different expectations than other countries, and, therefore, there could be a sample selection bias. Another analysis done through a couple of other reference groups in other countries could be beneficial to find if the results would be similar.

Second, the timeframe for the analyses is set to the years from 2014 up until now and may therefore include a selection bias. The timeframe was limited primarily due to the availability of data and is considered relatively extensive, but companies' orientation to technology is ever-changing. The different digital technologies analyzed in this paper can be at various stages in their life cycle and have various effects on different industries. Therefore, the generalizability of the findings is reduced, and the findings should be considered as a snapshot of the market with indicative results at best.

Third, the data for some of the observations in the sample are unavailable. The observations for the unavailable data therefore must be omitted. The omitted data can impose a bias on the sample distribution, where the sample can be skewed toward companies with a longer history of financial reporting. This is a problem if the omitted observations have similar characteristics because the remaining sample would no longer reflect the population. The possible sample bias for companies with a longer history of financial reporting should be considered when interpreting the findings.

Last, the firm's orientation, measured through their own disclosing of the digital technologies, could vary significantly. Hence, the real effect of using technologies may not be completely grasped due to companies disclosing the technologies to a different degree.

We could not find, nor did we expect to find, a common practice amongst firms regarding how to define technologies or use the terminology. The same uncertainty exists as to what extent it is normal for companies to announce which technologies they are affiliated with publicly. Further, the disclosing of digital technology lacks a clear factor for how and to what extent the technologies are used.

As previously mentioned in the literature review, research on the topic is often positive to the use of digital technologies even though less quantitative evidence is published. The limited availability of numeric data for the application of different digital technologies creates the need to estimate their digital technology orientation, although the validity of the findings might be biased. This paper establishes an indicative relationship to raise the compounded evidence on the phenomenon even further.

3.7.3 Construct Validity

Construct validity refers to whether the variables fitted in a test can be used to observe the theoretical construct, in this case, financial performance (Calder et al., 1982). Various phenomena's effects on financial performance are a heavily researched topic. Primarily, financial performance can be divided into market-based variables and accounting-based variables. The market-based variables are used to indicate the market's expectations of a specific company in the future, and the accounting-based variables to indicate the relative realized operational effectiveness.

For the stock market reaction analysis, the abnormal return of a stock is used to measure the market's expectations of the company with a specific digital technology. The validity of the stock market reaction as a proxy for financial performance is tautological in that financial performance can be defined as stock return. Further, the implications of market-based financial performance on the future success of a company are more unclear. Here, the assumption of market efficiency is held. The market efficiency hypothesis describes the pricing of stocks in a market as efficient with more rational actors considering and acting on all available information (Fama, 1970). The hypothesis has been the source of much debate, with the behavioral side of economics arguing that the agents have limitations in knowledge and computation and therefore have merely bounded rationality (Simon, 1990). The latter would imply that stock price-related variables are less valid for measuring the future success of a company, but its validity as a proxy for financial performance would be upheld due to its tautological nature.

For the annual report analysis, return ratios are employed as proxies for profitability-related financial performance. The degree of profitability can be understood as a company's ability to compete in resource application and allocation. In the case of digital technologies, increased profitability can indicate a company's realized efficiency effects related to the technology. A problem regarding digital technologies' effect on profitability can be the delay in profit realization. The delay can vary for different companies and technologies and, therefore, reduce the validity. The lagged dependent variables for profitability set out to capture the delayed realization but simultaneously increase the distance in time from the estimation of the digital technology orientation. The latter can decrease the validity of the findings because the increased distance in time can include more influence from other unobserved variables. Based on the inclusion of multiple control variables and that better-unbiased proxies for digital technology orientation are lacking, the findings are considered valuable and valid for their purpose of building indicative findings for an emerging topic.

3.8 Descriptive Statistics

3.8.1. Annual Report Analysis Independent variables

For the annual report analysis, a multitude of independent variables are employed. First, a statistical description of the number of digital technologies is presented in table 4. We can see that the highest number of observations is for the Number of Internet of Things, denoted as *Noiot*, with a total of 72 observations, followed by AI, denoted as *Noai,* with 51 observations.

Table 4. Observations Per Technology.

	Count	Mean	Std	Min	0,25	0,50	0,75	Max
Noblockchain	911,00	0,02	0,20	0,00	0,00	0,00	0,00	5,00
Noios	911,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Noai	911,00	0,61	3,35	0,00	0,00	0,00	0,00	51,00
Noiot	911,00	0,57	4,15	0,00	0,00	0,00	0,00	72,00
Noiop	911,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Noiod	911,00	0,00	0,08	0,00	0,00	0,00	0,00	2,00
Noar	911,00	0,03	0,37	0,00	0,00	0,00	0,00	6,00
Noautomation	911,00	0,67	1,91	0,00	0,00	0,00	0,00	24,00
Nocybersecurity	911,00	0,13	0,92	0,00	0,00	0,00	0,00	20,00
Nosimulation	911,00	0,19	0,71	0,00	0,00	0,00	0,00	8,00
Nocps	911,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Noml	911,00	0,24	1,15	0,00	0,00	0,00	0,00	17,00
Norobotics	911,00	0,13	0,89	0,00	0,00	0,00	0,00	17,00
Nomodeling	911,00	0,05	0,27	0,00	0,00	0,00	0,00	3,00
Nosemantic	911,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Noadditive	911,00	0,00	0,05	0,00	0,00	0,00	0,00	1,00
Nocloud	911,00	0,05	0,39	0,00	0,00	0,00	0,00	6,00
Nobigdata	911,00	0,11	0,52	0,00	0,00	0,00	0,00	11,00

Year	Observations
2020	150
2019	150
2018	148
2017	141
2016	124
2015	112
2014	86
SUM:	911

Observations per year are shown in table 5 to the right. With more recent reports, it is not surprising that the observations from 2020 and 2019 are the largest. More surprising might be the decrease in the growth of companies disclosing digital technologies in later years. Still, this stable number of observations makes for an interesting analysis.

Further, table 6 below shows the development of the independent variables, namely the digital technologies disclosed, per year. The number of trends each year increases, especially for *AI, IoT, Automation, Cybersecurity, Machine Learning,* and *Big Data*. While most of the other technologies have a quite similar number of observations in 2014 as 2020, modeling is the only technology with a negative development from 3% to 1% of the observations per year.

Table 6. Observations Per Technology Per Year Development

	2014	2015	2016	2017	2018	2019	2020
Blockchain	0%	0%	1%	1%	1%	1%	3%
Ai	1%	2%	6%	14%	16%	19%	20%
Iot	2%	4%	5%	6%	7%	7%	7%
Iod	0%	0%	0%	0%	0%	1%	1%
Ar	0%	0%	0%	2%	3%	1%	3%
Automation	16%	23%	23%	24%	24%	28%	28%
Cybersecurity	2%	1%	2%	3%	5%	7%	11%
Simulation	13%	10%	8%	10%	11%	11%	12%
Ml	0%	3%	6%	11%	14%	15%	13%
Robotics	1%	2%	4%	5%	5%	8%	5%
Modeling	3%	4%	2%	6%	5%	3%	1%
Additive	0%	0%	0%	0%	0%	0%	1%
Cloud	1%	3%	2%	3%	3%	3%	3%
Bigdata	2%	3%	11%	9%	9%	5%	11%

3.8.2. Annual Report Analysis Control Variables

Industry dummies, used as control variables, are observed in table 7, displaying the observations per industry dummy. Although Mining and construction is the most observed category, bank and financials are following closely, showing that the observed companies include several value configuration businesses, and not only the typical industry business.

Industry	Observations
Miningconstruction	194
Foodtextileapparel	40
Forestpaperpublishing	30
Chemicalspharma	61
Refiningrubberplastic	10
Containerssteelheavy	34
Computersautosaerospace	94
Transportation	104
Telephoneutilities	31
Wholesaleretail	34
Bankfinancial	188
Otherservices	70
Administrationandother	21
SUM:	911

Further, table 8 describes the count of observations: the mean and standard deviation (Std), the minimum (min) and maximum (max), and the 25th, 50th (median), and 75th percentile of the other control variable values. This shows that the *EBIT* control variable is highly influenced by the large minimum outlier. The same goes for *ROE*, but this variable was not used in the analysis due to the poor fit of the model.

Table 8. Control and Dependent Variables Count of Observations

	Count	Mean	Std	Min	0,25	0,50	0,75	Max
EBIT	911,00	-294,47	3747,41	-75000,00	1,52	8,73	25,22	94,99
ROA	911,00	1,93	16,35	-155,79	0,65	3,31	7,68	39,25
ROE	911,00	1,66	255,07	-7537,50	2,95	14,10	25,01	241,97
Log(SizeAssets)	911,00	3,54	0,98	1,11	2,84	3,52	4,24	6,41
Log(SizeSales)	911,00	3,04	0,99	-1,00	2,41	3,05	3,68	5,78
Log(SizeEmployees)	911,00	-0,25	0,86	-2,70	-0,87	-0,21	0,34	1,58
AssetTurnover	911,00	58,75	54,61	0,01	13,70	45,27	90,18	325,90
Debtratio	911,00	23,30	19,32	0,00	7,16	19,92	34,89	115,48
TangibleAssetRatio	911,00	86,72	17,80	10,80	77,45	94,93	99,91	100,00

Further, for the control variables, table 9 shows how many times the technologies are mentioned in each defined industry category relative to the total observations. This table gives a unique insight into which industries are using which technologies, which is very interesting regarding the industries' specific digital technology capabilities. Bank financial with a large degree of mentions in automation is found quite interesting, while typical value chain industries like *containersteelheavy* and *foodtextileapparel* surprisingly score higher in this genre. Further, the use of AI in *wholesaleretail* and *otherservices* is also a finding that sticks out in terms of results.

Table 9. Digital Technology Observations Per Industry

	Number of digital trends for each industry (in percent)													
	Blockchain	Ai	Iot	Iod	Ar	Automation	Cybersecurity	Simulation	Ml	Robotics	Modeling	Additive	Cloud	Bigdata
Miningconstruction	1 %	9 %	3 %	0 %	1 %	30 %	25 %	28 %	10 %	8 %	9 %	0 %	5 %	4 %
Foodtextileapparel	13 %	70 %	23 %	0 %	0 %	160 %	3 %	3 %	88 %	10 %	15 %	0 %	3 %	55 %
Forestpaperpublishing	3 %	37 %	0 %	0 %	0 %	7 %	30 %	0 %	13 %	0 %	0 %	0 %	0 %	3 %
Chemicalspharma	2 %	10 %	0 %	2 %	0 %	23 %	0 %	5 %	3 %	0 %	11 %	2 %	0 %	7 %
Refiningrubberplastic	0 %	0 %	70 %	0 %	0 %	30 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	10 %
Containerssteelheavy	0 %	41 %	0 %	0 %	0 %	179 %	0 %	32 %	9 %	24 %	18 %	0 %	0 %	6 %
Computersautosaerospace	0 %	27 %	353 %	3 %	22 %	141 %	31 %	62 %	10 %	44 %	0 %	0 %	2 %	9 %
Transportation	2 %	19 %	0 %	0 %	0 %	52 %	9 %	8 %	5 %	1 %	4 %	0 %	1 %	4 %
Telephoneutilities	0 %	106 %	229 %	0 %	0 %	58 %	19 %	23 %	19 %	52 %	0 %	0 %	0 %	26 %
Wholesaleretail	0 %	109 %	9 %	0 %	0 %	97 %	9 %	6 %	44 %	44 %	0 %	3 %	21 %	26 %
Bankfinancial	2 %	26 %	0 %	0 %	0 %	93 %	10 %	28 %	10 %	3 %	0 %	0 %	0 %	10 %
Otherservices	4 %	464 %	127 %	0 %	11 %	86 %	11 %	13 %	151 %	17 %	0 %	0 %	33 %	33 %
Administrationandother	0 %	10 %	0 %	0 %	0 %	10 %	0 %	0 %	0 %	5 %	0 %	0 %	0 %	5 %
SUM:	2 %	68 %	66 %	1 %	4 %	71 %	15 %	22 %	27 %	15 %	5 %	0 %	6 %	12 %

3.9 Multicollinearity

Table 10 shows how all the variables in the annual report analysis are correlated. The correlation matrix is primarily used to inspect the collinearity between the independent variables in a sample. Collinearity describes the degree to which two variables explain similar linear effects. Therefore, excessive correlation can render the reliability of the independent variables' explanatory power in a regression model weak. Most strikingly, we can see that the control variables for size, *Log(SizeAssets)*, *Log(SizeSales)* and *Log(SizeEmployees)*, are highly correlated at, 0.54 for *Log(SizeAssets)* and *Log(SizeEmployees)*, 0.76 for *Log(SizeEmployees*) and *Log(SizeSales)*, and 0.82 for *Log(SizeAssets)* and *Log(SizeSales)*. We consider these correlations too high and further omit *Log(SizeAssets)* and *Log(SizeEmployees)* from the model. *Log(SizeSales)* is kept because it has the highest correlation with the two other size variables and thus represents the best proxy for the omitted variables. Further, the highest correlation among the independent variables is between the industry dummy variables for other service firms with *AssetTurnover* and *TangibleAssets*, at 0.40 and -0.40, respectively. This level of collinearity is considered acceptable.

Further, a test for variance inflation factor (VIF) was calculated. A VIF test is a diagnostics tool for multicollinearity that calculates the R-squared from a regression of all predictors on one predictor. It differs from the correlation matrix in that it calculates the collinearity of multiple variables instead of pairwise. A high VIF is primarily a problem for the independent variables of interest, explanatory variables, and not the control variables (Allison, 2012). For the explanatory variables in the annual report analysis, the highest calculated VIF was 2.356354 for the number of machine learning disclosures, *Noml*. This is not considered a problematic VIF, and therefore the degree of multicollinearity was acceptable (Allison, 2012).

Table 10. Correlation matrix for all variables in the annual report analysis

	ROA	EBIT	Log(SizeAssets)	Log(SizeSales)	Log(SizeEmployees)	AssetTurnover	Debtratio	TangibleAssetRatio
ROA	1,00							
EBIT	0,21	1,00						
Log(SizeAssets)	0,27	0,07	1,00					
Log(SizeSales)	0,44	0,29	0,82	1,00				
Log(SizeEmployees)	0,26	0,10	0,54	0,76	1,00			
AssetTurnover	0,23	0,09	-0,27	0,22	0,26	1,00		
Debtratio	0,07	0,09	0,18	0,05	0,07	-0,34	1,00	
TangibleAssetRatio	-0,04	-0,04	0,16	-0,08	-0,18	-0,31	0,22	1,00
Miningconstruction	-0,06	-0,01	-0,27	-0,26	-0,05	-0,11	0,09	-0,04
Foodtextileapparel	0,13	0,02	0,10	0,18	0,12	0,06	-0,04	-0,11
Forestpaperpublishing	0,04	0,01	0,03	0,11	0,10	0,11	-0,08	-0,07
Chemicalspharma	-0,13	-0,04	-0,11	-0,08	-0,08	0,00	-0,11	0,03
Refiningrubberplastic	0,02	0,01	0,14	0,16	0,14	-0,01	0,00	-0,01
Containerssteelheavy	0,04	0,02	0,03	0,11	0,07	0,10	-0,08	-0,04
Computersautosaerospace	-0,24	-0,11	-0,28	-0,23	-0,13	0,15	-0,16	0,03
Transportation	0,01	0,03	-0,04	-0,05	0,00	-0,12	0,27	0,24
Telephoneutilities	0,07	0,02	0,06	0,10	0,03	0,07	0,05	-0,03
Wholesaleretail	0,06	0,02	0,05	0,16	0,14	0,26	-0,01	-0,28
Bankfinancial	0,08	0,02	0,20	0,14	0,00	-0,17	-0,03	0,14
Administrationandother	0,02	0,01	0,18	0,21	0,22	-0,03	0,04	-0,03
Otherservices	0,10	0,02	-0,22	-0,05	0,01	0,40	-0,15	-0,40
Noblockchain	0,02	0,01	0,00	0,03	0,07	0,05	0,00	0,00
Noios	nan	nan	nan	nan	nan	nan	nan	nan
Noai	0,07	0,01	-0,09	-0,01	-0,01	0,20	-0,10	-0,05
Noiot	-0,01	0,00	-0,08	-0,03	0,04	0,10	-0,10	-0,04
Noiop	nan	nan	nan	nan	nan	nan	nan	nan
Noiod	-0,39	-0,31	-0,07	-0,17	-0,05	-0,06	-0,06	0,00
Noar	-0,13	-0,06	-0,10	-0,17	-0,09	-0,01	-0,09	0,03
Noautomation	0,07	0,03	0,12	0,20	0,22	0,10	-0,07	-0,03
Nocybersecurity	-0,06	0,01	-0,04	-0,03	0,01	-0,02	0,02	-0,11
Nosimulation	0,07	0,02	0,17	0,22	0,22	0,04	-0,08	0,02
Nocps	nan	nan	nan	nan	nan	nan	nan	nan
Noml	0,10	0,02	-0,07	0,01	0,04	0,18	-0,09	-0,12
Norobotics	0,02	0,01	0,05	0,10	0,10	0,05	-0,05	-0,09
Nomodeling	-0,02	0,01	0,05	0,07	0,08	-0,02	0,00	0,00
Nosemantic	nan	nan	nan	nan	nan	nan	nan	nan
Noadditive	0,00	0,00	0,04	0,07	0,07	0,03	0,00	0,00
Nocloud	0,01	0,01	-0,01	0,06	0,08	0,20	-0,05	-0,12
Nobigdata	0,07	0,02	0,03	0,11	0,12	0,13	-0,03	-0,13

3.10 Statistical Models

When deciding on the Best Linear Unbiased Estimator (BLUE), the Gauss-Markov assumptions need to be validated for cross-sectional multiple linear regression models (MLR) (Wooldridge, 2015).

The first assumption states that the parameters in the regression must be linear. The parameters are the coefficients in the regression that indicate the relationship between the dependent variables and independent variables. The model with linear parameters can be written as:

$$Y = B_0 + B_1X_1 + B_2X_2 + \ldots + B_xX_x + U,$$

where Y is the dependent variables, X is the independent variables, U is the disturbance term, and B is the constant parameters or coefficients (Wooldridge, 2015). From the figures 11 and 13-18 on regression output for the stock market reaction and the annual report analysis, we can see that all parameters are linear because none of the coefficients are functions. Also, the models employed are by design estimating linear parameters. Therefore, we can conclude that MLR 1 is upheld.

The second assumption describes the need for the sample to be randomly selected. A randomly selected sample should include a portion of observations randomly drawn from a population to create a representative sample (Wooldridge, 2015). As the samples in the annual report analysis initially include the whole available population within a set timeframe, the need for a representative sample is met. After limiting the sample to include a minimum of three years of observations for each company and removing observations lacking data points, the final sample can be biased. For the stock market reaction analysis, the sample includes randomly selected observations from the population for the control group and the whole population of available announcements for the digital technology group within the same timeframe. We assume MLR 2 to be met, but the potential biases imposed due to data availability must be considered.

The third assumption states that none of the independent variables should be constant, and none should have an exact linear relationship. If two or more independent variables have an exact linear relationship, the model includes perfect collinearity, and cannot be estimated by an OLS (Wooldridge, 2015). Because the digital technologies in both analyses can be expected to have collinearity, the variables are fitted in individual regression models, to avoid violating the assumption of perfect collinearity. After inspecting the data sets and the regression outputs, we can see that none of the models are fitted with constant variables or include independent variables with an exact linear relationship. Assumption MLR 3 is considered upheld.

The fourth assumption is concerned with the error term having an expected value of zero, coined the zero conditional mean. This can be illustrated as:

$$E(U|X_1,X_2,...,X_x) = 0$$

where $E(U|X_1,X_2,...,X_x)$ is the expected error term (U) of the independent variables (X_x) in the model. The zero conditional means include that the independent variables, or explanatory variables, should be exogenous. A variable is exogenous when the covariance with the error term is zero and endogenous otherwise (Wooldridge, 2015). To test our models for endogeneity, we perform a Hausman-Test. The Hausman-Test is used to compare estimates to check if the difference is within a reasonable range based on the sampling errors (Hausman, 1978, as cited in Wooldridge, 2015). In the annual report analysis, we find the models for both dependent variables to be insignificant and, therefore, the independent variables to be exogenous. In the stock market reaction analysis, we find the models to be insignificant and the independent variables to be exogenous. Therefore, the assumption MLR 4 is considered upheld.

The fifth assumption raises the issue of homoscedasticity in the model. Homoscedasticity describes the variance of the unobserved error not depending on the independent variables in the model. If the variance changes for any of the values in the independent variables, heteroscedasticity is present (Wooldridge, 2015). The presence of heteroscedasticity is inspected both visually and by performing a White-Test and Breusch-Pagan-Test. The White-Test is intended to check for heteroscedasticity that renders the OLS standard errors and test statistics invalid by adding squares and cross products of all predictors to check for the non-linear heteroscedasticity (White, 1980, as cited in Wooldridge, 2015). The Breusch-Pagan-Test is another test to check for heteroscedasticity. It is different from the White-Test as it does not include the cross-terms and original squared variables and is more appropriate to check for linear forms of heteroscedasticity (Breusch & Pagan, 1979, as cited in Wooldridge, 2015). Both tests are performed for the models in the annual report analysis, and no significant heteroscedasticity is found. For the stock market reaction analysis, heteroscedasticity is present in some of the models, and the assumption of homoscedasticity is violated. To retain the OLS estimator as BLUE for the stock market reaction analysis, heteroscedasticity-robust standard errors are fitted (White, 1980, as cited in Wooldridge, 2015). These robust standard errors can reduce the significance of variables in a model but are needed to keep a rigid analysis. The MLR 5 assumption is considered upheld.

Further, we test the analysis for serial correlation, also called autocorrelation. Autocorrelation can be described as the correlation among values of a variable at a point in time and the lagged value of the same variable at a different point in time. To test for autocorrelation, a Durbin-Watson-Test is employed. The Durbin-Watson test checks the correlation among residuals over different time periods from a regression analysis. Autocorrelation can lead to more significant predictors due to underestimation of the standard errors (Durbin & Watson, 1950, as cited in Wooldridge, 2015). This can be more typical for the analysis of financial data as some values (e.g., assets, employees) are more constant over time. Some positive autocorrelation was identified in the annual report models and some negative in the stock market reaction models. The degree of autocorrelation is considered relatively small but should be considered when interpreting the findings.

Stock market reaction analysis. An ordinary least squares (OLS) regression for panel data with heteroscedasticity robust standard errors and fixed effects (FE) for entities was fitted to analyze the balanced cross-sectional times series data in the stock market reaction analysis. The data is balanced because all entities contain observations for the whole time series. Further, the data is panel data because it contains data for multiple companies for each time series. The estimation is employed on dummy variables for the independent variables, and can be simplified as:

$$\boldsymbol{Y_i = \beta_0 + \beta_1 D_i + u_i,}$$

where D is a binary dummy variable instead of a scalar variable X.

Annual report analysis. A quadratic ordinary least square (OLS) estimator with fixed effects (FE) for the time was fitted to analyze the unbalanced cross-sectional time-series data in the annual report analysis. The data is unbalanced because the sample includes various numbers of years for the companies, with a minimum of 3 and a maximum of 7 years. Further, the data is a cross-sectional time series because it observes a set of years for each company. The OLS was fitted for panel data with FE to control for the specific time characteristics. The quadratic term was fitted after visually inspecting the output from the first-degree estimation and suspecting the presence of curvature.

4. Findings

Tables 11-18 summarize the analyses' results from the annual report and the stock market reaction. The analyses are a bit different given that there is only one dependent variable in the stock market analysis, namely the abnormal return, while there is both *EBIT* and *ROA* in the annual report analysis. The estimation for *ROE* was originally included in the annual report analysis but resulted in a bad fit for the model and was not included in the findings. Further, measuring the lagged effects in the annual report analysis makes this analysis more extensive compared to the stock market reaction analysis. Since both analyses are estimated as regression models, they follow some of the same principles and thus will be commented on somewhat similarly. First, if the coefficient differs from zero, the null hypothesis would be rejected. This implies that the p-value is small enough for the test to be valid. In this case, less than 0.10, therefore, each technology will be described both with the coefficient and p-value. Finally, the R-squared and shape of the MLR graph output will be described for the annual report analysis to lay the foundations for a thorough discussion of the findings.

4.1 Findings Stock Market Reaction Analysis

Table 11 reports the output from the statistical analysis of the stock market reaction to the identified digital technologies. The table presents the effect digital technologies have on the stock price. The R-squared indicates how much of the variation in the dependent variables, the stock price, is explained by the independent variables, here represented by the technologies. For the stock market reaction analysis, the R-squared is lower than 0,01. The low R-squared is expected because the analysis contains only one binary dummy variable for every panel of 135 observations and are not considered a problem. The constants have a high significance with at least a 99% confidence interval, and a value of around 0.3, for all the digital technologies. Further, there is naturally no increase in stock price when investigating the results of the technologies not being disclosed in the announcements, thus, the null hypothesis could not be rejected in these cases. If there is a significant increase in stock price after disclosing one of the technologies, the null hypothesis will be rejected and replaced by an alternative hypothesis, namely, that the stock price will go up. On the other hand, if the null hypothesis holds, and cannot be rejected, the assumption of increased stock price based on the disclosing of digital technologies is rejected.

4.1.1 Digital Technologies Hypotheses

Hypothesis a stated that disclosing *the aggregated technologies* will have no influence on the stock price. The coefficient is 0.0222 for the dummy in the event window, found when disclosing at least one of the 18 technologies in the announcements. The standard error of this event is 0.0075. Further, a p-value of 0.003 gives a significance for at least a 99% confidence interval, making for a low probability of type 1 errors in the data. Further, the constant, representing the normal return of the stocks, has a coefficient of 0.003 and is significant at a 99% level. Therefore, the null hypothesis is rejected.

Further, some of the 18 technology trends were not disclosed in any of the announcements. Therefore, the "a hypothesis" of the digital technologies; Robotics*, Modeling, IoD, IoS, IoP, Cloud Computing, CPS,* and *Semantic Technologies,* could not be rejected.

Some digital technologies do not obtain robust enough results in the analyses to draw significant conclusions, as reflected by obtaining a p-value larger than 0.10. Therefore, the "a hypothesis" of technologies; *AI, Machine Learning, Automation, Simulation, Big Data, Cybersecurity, Augmented Reality,* and *Additive Manufacturing* cannot be rejected.

On the other hand, hypothesis 13a, representing *Blockchain,* shows a positive effect on stock price after disclosing the respective technologies with a significance of 99%, visualized by all of them having a p-value of under 0.01. The p-value that the results found regarding these digital technologies are robust. Blockchain has a coefficient for the dummy in the event window of 0.052 when disclosing Blockchain and a standard error of 0.0195. Further, the constant, representing the normal return of the stocks, has a coefficient of 0.0033 and is significant at a 99% level. The coefficient value is unequal to zero, meaning that the abnormal return of the stock is expected to increase by 5.2% if blockchain is disclosed, and all the connecting null hypotheses are rejected.

Finally, hypothesis 7a, representing *IoT* is significant at a 90% confidence level with a coefficient of 0.0587 and a standard error of 0.0315, meaning that disclosing IoT will give an expected increase in abnormal return of 5.87%. Further, the constant, representing the normal return of the stocks, has a coefficient of 0.0032 and is significant at a 99% level. Therefore, also this hypothesis is rejected, even though not being on the same significance level as blockchain.

For the randomized control group, the coefficient for the event reaction is -0.0058, with a standard error of 0.0056, and is not significant at any of the levels with a P-value of 0.2971. Further, the constant is neither significant at any of the levels and has a coefficient of 0.0071. This further indicates that the findings for the other technologies are not due to the general effects of announcements.

Table 11. OLS Results Stock Market Reaction Analysis

Technology	Abnormal Return	Constant
Aggregated Technologies	0.0222*** (0.0075)	0.003*** (0.0004)
AI	0.0182 (0.0261)	0.0033*** (0.0004)
Machine Learning	0.0088 (0.0183)	0.0034*** (0.0004)
Automation	0.0056 (0.0035)	0.0034*** (0.0004)
Robotics	N/A	N/A
Simulation	0.0385 (0.0280)	0.0034*** (0.0004)
Modeling	N/A	N/A
Internet of Things (IoT)	0.0587* (0.0315)	0.0032*** (0.0004)
Internet of Services (IoS)	N/A	N/A
Internet of Data (IoD)	N/A	N/A
Internet of People (IoP)	N/A	N/A
Cloud Computing	N/A	N/A
Big Data	-0.0084 (0.0110)	0.0034*** (0.0004)
Blockchain	0.0520*** (0.0195)	0.0033*** (0.0004)
Cybersecurity	0.0040 (0.0128)	0.0034*** (0.0004)
Augmented Reality	-0.0075 (0.0066)	0.0034*** (0.0004)
Additive Manufacturing	0.1854 (0.1475)	0.0034*** (0.0004)
Cyber-Physical Systems	N/A	N/A
Semantic Technologies	N/A	N/A
Control group	-0.0058 (0.0056)	0.0071 (0.1174)

Note. Standard errors are noted in brackets behind each coefficient. The* indicates the p-values; *= p< 0.1, **= p<0.05, ***= p<0.01

4.2 Findings Annual Report Analysis

Table 13-18 below reports the statistical analyses of *the Aggregated Technologies*, *AI, Machine Learning, Automation, Simulation,* and *Big Data*, effect on financial performance through the dependent variables, *EBIT* and *ROA*. The tables present the results of the effect these results have on the firm's financial performance, both looking at the six technologies without a lag, with a one-year lag, and a two-year lag. The constants are all significant with a 99% confidence interval. Adding on, the dependent variables of *Log(SizeSales), AssetTurnover,* and *DebtRatio* are all significant at least on a 95% level, and mostly at a 99% level for the six different categories of trends in this analysis. Various industry categories hold a high significance with a variation depending on which technology and industry category is up for investigation. This indicates a good fit for the model.

The R-square values (see Table 100) indicate how much of the variation in the dependent variable, in this analysis the *EBIT* and *ROA*, are explained by the independent variables. For the analysis using *EBIT* as a dependent variable, the R-squared is 0.11 on average for all the technology trends in the three different time lags. On the other hand, the analysis using *ROA* as a dependent variable gave R-squared values around 0.28 for all the technology trends in all the three-time lags, although both of the dependent variable analyses had a small increase in the R squared from no lag to the 2 years lag. Therefore, the R-squared indicate a low to moderate goodness of fit for the independent variables on the *EBIT* and *ROA* variables.

Finally, *EBIT* as a dependent variable gave a U-shaped expected effect for all the technology trends in all three different time frames. In the analysis with *ROA* as a dependent variable, the output consisted of mostly U-shaped effect outputs as well, but the *AI* and *ML* variables were inverted U-shaped for the analysis without a lag and with a one-year lag. The U shape could give an indication of the influence of the independent variables, namely the technologies, being larger either with fewer mentions or many.

Table 12. R^2 For All the Technology Trends

Analysis	Aggregated technologies	AI	ML	Automation	Simulation	Bigdata
EBIT no lag	0.1118	0.1113	0.1099	0.1106	0.1127	0.1100
ROA no lag	0.2837	0.2764	0.2779	0.2755	0.2759	0.2758
EBIT 1 year lag	0.1167	0.1151	0.1135	0.1138	0.1151	0.1134
ROA 1 year lag	0.2920	0.2844	0.2848	0.2819	0.2819	0.2841
EBIT 2 years lag	0.1355	0.1282	0.1275	0.1282	0.1301	N/A
ROA 2 years lag	0.3080	0.2906	0.2931	0.2869	0.2860	N/A

4.2.1. Findings for the individual digital technologies

The “b hypothesis” connected to the annual report analysis of the digital technologies; *IoS, IoP, CPS,* and *Semantic Technologies* could not be rejected, due to not being disclosed in any announcements. Further, the digital technologies; *Robotics, Modeling, IoT, IoD, Cloud Computing, CPS,* and *Semantic Technologies,* were all found but were disclosed less than 60 times. Disclosing the technologies less than 60 times makes for a smaller data set than the *one in ten* rule of thumb suggests, thus, the exclusion of these technologies was necessary, even though they were disclosed several times. The rule describes the need to have ten events for each predictive variable, to avoid overfitting (Peduzzi et al., 1995). Neither of the null hypotheses for these technologies could be rejected, due to the sample size being too small.

The rejection of the previous hypotheses leaves the analysis with technologies, *AI, Machine Learning, Automation, Simulation,* and *Big Data,* together with the coefficient for the aggregated technologies. In general, there was no considerable significance in this analysis for any of the individual technology trends. For *Automation, Simulation*, and *AI*, there was found no pleasing significance in any of the combinations of lag and *EBIT/ROA*, thus, the null hypotheses for these digital technologies could be rejected.

Although there was found no significance in the analyses for the previous technologies, there were two technologies with significance found in the analyses. The first one, *Big Data,* is significant with -2.5203 as a decrease in *ROA*, at a 90% confidence interval, with one year lag, with an insignificant coefficient of 0.2048 for the quadratic term. The second, *Machine Learning,* gives 0.2302 in increased ROA for the quadratic term, significant at a 90% confidence interval, with two years lag, and an insignificant coefficient of -0.9765 for the linear term. Neither of these technologies shows a significant coefficient at other lags or with EBIT. Although there are some significant effects on profitability, there is not found a consistent increase in performance. Hence, the null hypothesis, also for these digital technologies, could not be rejected.

4.2.1. Findings for the aggregated technologies

Hypothesis b stated that disclosing one of *the aggregated technologies* will have no influence on the financial performance. When measured on both EBIT and ROA with different time lags, the results are divided.

First, the results of the digital technologies with no lag are found insignificant on *EBIT* due to high p-values, but significant for *ROA* with a coefficient of 0.0095 for *aggregated technologies* squared with a 99% confidence interval and an insignificant linear term with coefficient -48.326.

Second, the *aggregated technologies* are found significant with a 90% confidence interval, for the analysis with a one-year lag on *EBIT*, with the coefficient being -54.624 for *aggregated technologies* and 1.2113 for the *aggregated technologies* squared. Further, for the *ROA* analysis with one year lag, the linear term with a coefficient of -0.4132 and the quadratic term coefficient of 0.0095 are both highly significant at a 99% confidence interval level.

Finally, for the analysis with two-year lag on *EBIT*, the *aggregated technologies* are significant at a 99% confidence interval level, at a value of respectively -84.019 for the aggregated technologies and 1.7975 for the aggregated technologies squared. While for the analysis with a two-year lag measured on *ROA* the coefficients are also found significant at a 99% level with a coefficient of the linear term being -0.7753 and quadratic term being 0.0190.

In addition, all the estimated coefficients for the aggregated technologies, on *ROA* and *EBIT*, for the lag of 0, 1, and 2 years, indicate a U-shape. Therefore, with only 3 out of the 12 coefficients not being significant, the null hypothesis for the *aggregated technologies* is considered rejected.

Table 13. OLS Results Annual Report Analysis, EBIT no Lag

Variables	Aggregated Technologies	AI	ML	Automation	Simulation	Bigdata
Constant	-2882.3*** (863.39)	-2949.6*** (868.74)	-2917.6*** (862.96)	-3024.7*** (868.34)	-3048.8*** (865.51)	-2910.1*** (862.7)
Trend	-48.326 (40.227)	-90.710 (97.640)	-59.227 (245.84)	-130.68 (133.66)	-581.16 (364.56)	-260.17 (408.41)
Trend^2	1,1558 (0.79)	2.9250 (2.4049)	9.3014 (20.588)	7.0532 (9,1174)	72.804 (71.416)	22.876 (51.073)
Log (SizeSales)	1180.6*** (148.32)	1165.4*** (145.63)	1152.2*** (145.42)	1195.1*** (153,12)	1238.9*** (155.01)	1155.6*** (145.68)
Asset Turnover	7.2001** (3.037)	7.4347** (3.0609)	7.0345 ** (3.0415)	6.8714** (3.0396)	6.8016** (3.0391)	7.0677** (3.0387)
Debt ratio	18.569 *** (7.062)	19.143*** (7.0455)	18.692*** (7.0439)	18.005** (7.068)	17.711** (7.052)	18.733*** (7.0347)
Tangible asset ratio	-14.355 * (8.2844)	-13.749* (8.3437)	-13.494 (8.2734)	-13.074 (8.2576)	-13.512 (8.2462)	-13.679* (8.2791)
Foodtextileapparel	-1406.1 ** (636.22)	-1341.9** (635.38)	-1397.7** (642.5)	-1418.3** (650.79)	-1512.9** (640.74)	-1311.1 ** (644.53)
Forestpaperpublishing	-1152.2 (717.77)	-1113.2 (716.29)	-1093.8 (716.67)	-1148.6 (719.04)	-1242.2* (720.94)	-1100.7 (716.83)
Chemicalspharma	-697.03 (511,19)	-683.87 (510.86)	-674.73 (511.47)	-678.72 (510.93)	-728.76 (511.3)	-665.29 (511,13)
Refiningrubberplastic	-2084.3* (1176.8)	-2069.6* (1176.4)	-2026.2* (1177)	-2089.8* (1178.7)	-2253.4* (1182.8)	-2013.3* (1176.3)
Containersteelheavy	-929.69 (673.45)	-973.97 (673,11)	-968.04 (673.68)	-853.06 (682,14)	-966.81 (672.69)	-966.75 (673.5)
Computersautosaerospace	-990.71 ** (470.8)	-1026.2** (456.5)	-1026.9** (456.88)	-920.12* (470.41)	-913.40* (468.6)	-1015.4** (457.27)
Transportation	416.41 (416.41)	-72.949 (416.54)	-69.130 (416.92)	-40.682 (4417.66)	-107.86 (416.81)	-64.229 (416.88)
Telephoneutilities	697.93 (697.93)	-1092.4 (696.79)	-1115.0 (695.25)	-1109.6 (694.87)	-1141.1 (694.5)	-1078.1 (697,19)
Wholesaleretail	757.33*** (757.33)	-2028.2*** (759.69)	-2022.8*** (759.34)	-1985.2*** (757.62)	-2157.5*** (759.87)	-1992.8*** (758.25)
Bankfinancial	518.16 (518,16)	-443.65 (518.3)	-451.75 (518.68)	-430.70 (518.85)	-495.36 (518.67)	-436.39 (519.06)
Administrationandother	-1962.5** (841.31)	-1909.6** (838.56)	-1883.5** (839.26)	-1957.6** (843,14)	-2090.1** (846.97)	-1881.1** (838.8)
Other services	-705.78 (628.91)	-760.17 (641.79)	-747.02 (636.09)	-665.57 (613.42)	-754.17 (609.98)	-676.63 (615.32)
R^2	0.1118	0.1113	0.1099	0.1106	0.1127	0.1100

Note. Standard errors are noted in brackets behind each coefficient.
The* indicates the p-values; *= p< 0.1, **= p<0.05, ***= p<0.01

Table 14. OLS Results Annual Report Analysis, ROA no Lag

Variables	Aggregated Technologies	AI	ML	Automation	Simulation	Bigdata
Constant	-21.414*** (3.3772)	-21.411*** (3.4145)	-21.604*** (3.3855)	-21.881*** (3.4136)	-21.646*** (3.4056)	-21.752*** (3.3897)
Trend	-0.3783 (0.1574)	0.1713 (0.3838)	1.1285 (0.9645)	-0.0972 (0.5254)	-0.3045 (1.4345)	-0.8347 (1.6047)
Trend^2	0.0095*** (0.0031)	-0.0003 (0.0095)	-0.0372 (0.0808)	0.0053 (0.0358)	0.1463 (0.281)	0.1219 (0.2007)
Log (SizeSales)	6.1990*** (0.5801)	5.9453*** (0.5724)	0.5705*** (0.5705)	5.9731*** (0.6019)	5.8723*** (0.6099)	5.9648*** (0.5724)
Asset Turnover	0.0754*** (0.0119)	0.0734*** (0.012)	0.0730*** (0.0119)	0.0737*** (0.0119)	0.0743*** (0.012)	0.0739*** (0.019)
Debt ratio	0.0724*** (0.0089)	0.0747*** (0.0277)	0.0750*** (0.0276)	0.0723*** (0.0278)	0.0738*** (0.0277)	0.0728*** (0.0276)
Tangible asset ratio	0.0145 (0.0324)	0.0183 (0.0328)	0.0202 (0.0325)	0.0237 (0.0325)	0.0233 (0.0324)	0.0222 (0.0325)
Foodtextileap parel	1.0956 (2.4886)	1.4798 (2.4973)	1.0914 (2.5206)	1.5750 (2.5584)	1.6858 (2.5212)	1.5700 (2.5325)
Forestpaperp ublishing	-4.7066* (2.8076)	-4.2445 (2.8153)	-4.1823 (2.8116)	-4.2347 (2.8267)	-4.1523 (2.8367)	-4.2293 (2.8166)
Chemicalspha rma	-7.9245*** (1.9995)	-7.7050*** (2.0079)	-7.6233*** (2.0066)	-7.7412*** (1.8493)	-7.7327*** (2.0119)	-7.7147*** (2.0083)
Refiningrubbe rplastic	-7.6407* (4.6033)	-7.0839 (4.6236)	-6.9570 (4.6176)	-7.1317 (4.6336)	-6.9696 (4.6542)	-7.0779 (4.6219)
Containersteel heavy	-3.3218 (2.6342)	-3.6198 (2.6456)	-3.5221 (2.6429)	-3.4840 (2.6816)	-3.5141 (2.6469)	-3.5800 (2.6463)
Computersaut osaerospace	-10.846*** (1.8415)	-11.032*** (1.7942)	-11.003*** (1.7924)	-10.957*** (1.8493)	-11.294*** (1.8438)	-11.001*** (1.7967)
Transportatio n	-1.0051 (1.6288)	-1.0324 (1.6372)	-0.9928 (1.6356)	-1.0209 (1.6419)	-1.0443 (1.6401)	-1.0256 (1.638)
Telephoneutili ties	-0.9627 (2.73)	-1.2704 (2.7386)	-1,1857 (2.7276)	-1.0798 (2.7317)	-1.0202 (2.7327)	-0.9909 (2.7394)
Wholesalereta il	-7.0719** (2.9623)	-7.3756** (2.9859)	-7.4719** (2.979)	-7.0661** (2.9784)	-7.0641** (2.9899)	-7.0116** (2.9793)
Bankfinancial	1.6488 (2.0268)	1.5738 (2.0371)	1.5756 (2.0349)	1.5925 (2.0397)	1.6213 (2.0409)	1.6172 (2.0395)
Administratio nandother	-8.3974** (3.2908)	-7.7236* (3.2959)	-7.6026** (3.2926)	-7.7314** (3.3145)	-7.5752** (3.3326)	-7.7031** (3.2958)
Other services	0.3156 (2.46)	-0.5012 (2.5225)	-0.8804 (2.4955)	0.3579 (2.4115)	0.2779 (2.4001)	0.4559 (2.4177)
R^2	0.2837	0.2764	0.2779	0.2755	0.2759	0.2758

Note. Standard errors are noted in brackets behind each coefficient.
The* indicates the p-values; *= p< 0.1, **= p<0.05, ***= p<0.01

Table 15. OLS Results Annual Report Analysis, EBIT Lag One Year

Variables	Aggregated Technologies	AI	ML	Automation	Simulation	Bigdata
Constant	-2156.7*** (702.22)	-2220.3*** (709.49)	-2148.8*** (702.76)	-2235.3*** (706.88)	-2250.3*** (704.26)	-2156.6*** (700.98)
Trend	-54.624* (31.981)	-87.085 (78.265)	-43.605 (196.04)	-90.366 (106.98)	-380.66 (291.21)	-185.41 (325.01)
Trend^2	1.2113* (0.6293)	2.6650 (1.9258)	7.9115 (16.452)	4.7652 (7.3025)	46.860 (57.167)	14.998 (40.741)
Log (SizeSales)	875.22*** (117.26)	854.69*** (115.59)	844.37*** (115.53)	873.66*** (121.73)	899.12*** (122.86)	845.14*** (115.59)
Asset Turnover	7.3688*** (2.3686)	7.4916*** (2.3903)	7.1122*** (2.3712)	7.0082*** (2.3680)	6.9877*** (2.3688)	7.1988*** (2.3744)
Debt ratio	15.275*** (5.3520)	15.744*** (5.3513)	15.429*** (5.3495)	14.975*** (5.3618)	14.792*** (5.3542)	15.445*** (5.3454)
Tangible asset ratio	-9.4885 (6.5627)	-8.7806 (6.6540)	-9.0991 (6.5798)	-8.6696 (6.5499)	-8.9202 (6.5404)	-9.0506 (6.5538)
Foodtextileap parel	-1240.1** (511.68)	-1180.1** (511.79)	-1247.8** (517.61)	-1243.6** (524.00)	-1301.8** (515.41)	-1166.6** (519.27)
Forestpaperp ublishing	-1092.1** (540.51)	-1045.1* (539.81)	-1033.8* (540.22)	-1069.3** (542.18)	-1125.4** (543.81)	-1033.4* (540.23)
Chemicalspha rma	-1412.8*** (389.60)	-1395.0*** (389.58)	-1387.1*** (390.12)	-1390.6*** (389.80)	-1408.0*** (389.75)	-1382.8*** (389.86)
Refiningrubbe rplastic	-1686.9* (940.46)	-1659.6* (940.76)	-1625.3* (941.50)	-1666.4* (942.94)	-1764.3* (946.05)	-1613.9* (941.10)
Containersteel heavy	-908.04* (530.88)	-954.07* (530.90)	-952.67* (531.44)	-874.87 (538.00)	-949.09* (531.01)	-953.64* (531.42)
Computersaut osaerospace	-1145.9*** (378.04)	-1208.6*** (366.75)	-1209.6*** (367.08)	-1134.8*** (378.14)	-1128.4*** (377.62)	-1204.4*** (367.29)
Transportatio n	-240.30 (326.35)	-246.81 (326.71)	-241.34 (327.07)	-222.20 (327.61)	-268.07 (327.19)	-239.82 (326.96)
Telephoneutili ties	-1098.7** (556.91)	-1100.2** (557.20)	-1132.7** (555.77)	-1129.5** (555.52)	-1149.8** (555.55)	-1105.3** (557.13)
Wholesalereta il	-1823.6*** (597.44)	-1836.6*** (599.92)	-1853.8*** (599.99)	-1825.8*** (598.24)	-1937.2*** (600.29)	-1830.9*** (598.53)
Bankfinancial	-475.40 (406.09)	-478.60 (406.43)	-483.57 (406.80)	-471.92 (406.91)	-511.46 (407.01)	-472.62 (407.17)
Administratio nandother	-1620.9** (670.68)	-1553.9** (669.29)	-1537.2** (669.96)	-1585.6** (673.08)	-1662.4** (675.69)	-1532.7** (669.68)
Other services	-945.04* (483.73)	-996.13** (495.40)	-1023.3** (491.63)	-955.50** (473.41)	-1014.1** (470.99)	-967.10** (473.74)
R^2	0.1167	0.1151	0.1135	0.1138	0.1151	0.1134

Note. Standard errors are noted in brackets behind each coefficient.
The* indicates the p-values; *= p< 0.1, **= p<0.05, ***= p<0.01

Table 16. OLS Results Annual Report Analysis, ROA Lag One Year

Variables	Aggregated Technologies	AI	ML	Automation	Simulation	Bigdata
Constant	-20.743*** (3.2560)	-20.231*** (3.3043)	-20.505*** (3.2692)	-21.033*** (3.2956)	-20.851*** (3.2858)	-20.966*** (3.2623)
Trend	-0.4132*** (0.1483)	0.2328 (0.3645)	1.1898 (0.9120)	-0.0504 (0.4987)	-0.0641 (1.3587)	-2.5203* (1.5126)
Trend^2	0.0103*** (0.0029)	0.0008 (0.0090)	-0.0384 (0.0765)	-0.0032 (0.0340)	0.0624 (0.2667)	0.2048 (0.1896)
Log (SizeSales)	6.0914*** (0.5437)	5.8683*** (0.5383)	5.8296*** (0.5374)	5.8726*** (0.5675)	5.7926*** (0.5732)	5.9097*** (0.5380)
Asset Turnover	0.0798*** (0.0110)	0.0768*** (0.0111)	0.0767*** (0.0110)	0.0776*** (0.0110)	0.0779*** (0.0111)	0.0792*** (0.0111)
Debt ratio	0.0594** (0.0248)	0.0614** (0.0249)	0.0609** (0.0249)	0.0583** (0.0250)	0.0590** (0.0250)	0.0596** (0.0249)
Tangible asset ratio	0.0155 (0.0304)	0.0129 (0.0310)	0.0165 (0.0306)	0.0227 (0.0305)	0.0225 (0.0305)	0.0203 (0.0305)
Foodtextileap parel	0.5746 (2.3725)	0.8114 (2.3836)	0.4405 (2.4079)	1.1853 (2.4430)	1.1124 (2.4047)	1.4906 (2.4166)
Forestpaperp ublishing	-5.5280** (2.5062)	-5.1256** (2.5141)	-5.0518** (2.5131)	-5.0893** (2.5277)	-5.0084** (2.5372)	-5.1206** (2.5142)
Chemicalspha rma	-8.4436*** (1.8065)	-8.2180*** (1.8144)	-8.1468*** (1.8148)	-8.2732*** (1.8173)	-8.2570*** (1.8184)	-8.2219*** (1.8144)
Refiningrubbe rplastic	-7.1144 (4.3607)	-6.6386 (4.3814)	-6.4680 (4.3799)	-6.6398 (4.3961)	-6.4910 (4.4138)	-6.5787 (4.3798)
Containersteel heavy	-2.0684 (2.4616)	-2.4401 (2.4726)	-2.3245 (2.4723)	-2.3031 (2.5082)	-2.3467 (2.4774)	-2.4471 (2.4732)
Computersaut osaerospace	-10.008*** (1.7529)	-10.224*** (1.7081)	-10.221*** (1.7077)	-10.157*** (1.7629)	-10.408*** (1.7618)	-10.157*** (1.7093)
Transportatio n	-0.4913 (1.5132)	-0.4698 (1.5216)	-0.4285 (1.5215)	-0.4925 (1.5274)	-0.4960 (1.5265)	-0.4895 (1.5216)
Telephoneutili ties	-1.8671 (2.5822)	-2.2561 (2.5951)	-2.0913 (2.5855)	-1.9680 (2.5899)	-1.9177 (2.5919)	-1.6249 (2.5928)
Wholesalereta il	-7.7976*** (2.7702)	-8.3462*** (2.7940)	-8.3574*** (2.7912)	-7.8998*** (2.7891)	-7.8744*** (2.8007)	-7.6694*** (2.7855)
Bankfinancial	0.9362 (1.8829)	0.8584 (1.8929)	0.8808 (1.8924)	0.8682 (1.8971)	0.8869 (1.8989)	0.9979 (1.8949)
Administratio nandother	-8.1409*** (3.1098)	-7.5463** (3.1171)	-7.3695** (3.1167)	-7.4845** (3.1380)	-7.3441** (3.1524)	-7.5173** (3.1166)
Other services	-0.2956 (2.2429)	-1.5795 (2.3072)	-1.5837 (2.2871)	-0.2980 (2.2071)	-0.3439 (2.1974)	0.0619 (2.2047)
R^2	0.2920	0.2844	0.2848	0.2819	0.2819	0.2841

Note. Standard errors are noted in brackets behind each coefficient.
The* indicates the p-values; *= p< 0.1, **= p<0.05, ***= p<0.01

Table 17. OLS Results Annual Report Analysis, EBIT Lag Two Years

Variables	Aggregated Technologies	AI	ML	Automation	Simulation	Bigdata
Constant	-1820.1*** (617.21)	-1800.0*** (624.10)	-1753.0*** (619.38)	-1862.5*** (621.33)	-1890.3*** (620.39)	N/A
Trend	-84.019*** (30.595)	-48.757 (70.230)	-64.498 (193.48)	-109.30 (92.921)	-372.47 (251.42)	N/A
Trend^2	1.7975*** (0.6625)	1.6790 (1.6712)	13.657 (19.971)	5.3972 (6.2870)	40.005 (50.298)	N/A
Log (SizeSales)	751.50*** (101.22)	700.53*** (99.444)	695.89*** (99.427)	729.11*** (104.30)	755.42*** (105.91)	N/A
Asset Turnover	5.2577*** (2.0147)	5.1285** (2.0452)	4.8922** (2.0239)	4.7817** (2.0201)	4.6657** (2.0222)	N/A
Debt ratio	11.817*** (4.4451)	12.277*** (4.4650)	12.056*** (4.4588)	11.455** (4.4621)	11.169** (4.4625)	N/A
Tangible asset ratio	-7.5835 (5.8134)	-7.0029 (5.8701)	-7.2436 (5.8452)	-6.6095 (5.8087)	-6.7307 (5.8013)	N/A
Foodtextileapparel	-959.38** (429.57)	-926.16** (431.23)	-945.38** (433.26)	-971.90** (438.38)	-1029.1** (433.98)	N/A
Forestpaperpublishing	-898.01** (453.89)	-800.01* (454.14)	-787.16* (454.15)	-832.79* (455.76)	-875.14* (456.42)	N/A
Chemicalspharma	-1668.6*** (332.84)	-1639.8*** (334.05)	-1636.9*** (334.24)	-1641.9*** (333.99)	-1661.4*** (333.87)	N/A
Refiningrubberplastic	-1618.8* (936.96)	-1455.4 (938.59)	-1440.9 (938.94)	-1528.7 (941.88)	-1603.3* (942.44)	N/A
Containersteelheavy	-639.59 (449.85)	-695.20 (451.38)	-695.26 (451.59)	-608.11 (456.81)	-717.65 (451.27)	N/A
Computersautosaerospace	-373.32 (323.04)	-552.06* (312.20)	-548.16* (312.38)	-458.72 (322.15)	-459.09 (320.59)	N/A
Transportation	-189.59 (279.34)	-192.66 (280.51)	-191.99 (280.73)	-173.21 (280.99)	-210.19 (280.40)	N/A
Telephoneutilities	-849.07* (470.00)	-881.38* (471.69)	-891.17* (470.82)	-890.76* (470.28)	-906.82* (470.09)	N/A
Wholesaleretail	-1382.3*** (499.51)	-1434.4*** (502.32)	-1432.0*** (503.50)	-1397.6*** (501.58)	-1503.3*** (502.58)	N/A
Bankfinancial	-410.64 (341.21)	-409.05 (342.62)	-410.30 (342.77)	-399.50 (342.76)	-436.46 (342.60)	N/A
Administrationandother	-1363.3** (561.85)	-1239.6** (561.99)	-1234.8** (562.52)	-1291.5** (565.02)	-1359.2** (566.82)	N/A
Other services	-617.31 (409.45)	-768.96* (415.38)	-783.10* (418.16)	-671.25* (399.18)	-711.64* (396.90)	N/A
R^2	0.1355	0.1282	0.1275	0.1282	0.1301	N/A

Note. Standard errors are noted in brackets behind each coefficient.
The* indicates the p-values; *= p< 0.1, **= p<0.05, ***= p<0.01

Table 18. OLS Results Annual Report Analysis, ROA Lag Two Years

Variables	Aggregated Technologies	AI	ML	Automation	Simulation	Bigdata
Constant	-20.652*** (3.6255)	-20.234*** (3.6962)	-20.204*** (3.6604)	-21.066*** (3.6895)	-20.705*** (3.6900)	N/A
Trend	-0.7753*** (0.1797)	-0.0218 (0.4159)	-0.9765 (1.1434)	-0.4338 (0.5518)	-0.5803 (1.4954)	N/A
Trend^2	0.0190*** (0.0039)	0.0084 (0.0099)	0.2302* (0.1180)	0.0120 (0.0373)	0.1413 (0.2992)	N/A
Log (SizeSales)	6.3920*** (0.5946)	5.9123*** (0.5890)	5.9546*** (0.5876)	6.0221*** (0.6193)	5.8609*** (0.6299)	N/A
Asset Turnover	0.0815*** (0.0118)	0.0786*** (0.0121)	0.0783*** (0.0120)	0.0780*** (0.0120)	0.0785*** (0.0120)	N/A
Debt ratio	0.0532** (0.0261)	0.0546** (0.0264)	0.0543** (0.0264)	0.0488* (0.0265)	0.0502* (0.0265)	N/A
Tangible asset ratio	0.0117 (0.0341)	0.0159 (0.0348)	0.0149 (0.0345)	0.0249 (0.0345)	0.0245 (0.0345)	N/A
Foodtextileap parel	0.7710 (2.5233)	1.1265 (2.5540)	0.9294 (2.5604)	1.3060 (2.6031)	1.2398 (2.5813)	N/A
Forestpaperp ublishing	-6.3143** (2.6662)	-5.3502** (2.6896)	-5.3844** (2.6839)	-5.5070** (2.7063)	-5.3329** (2.7148)	N/A
Chemicalspha rma	-9.4846*** (1.9551)	-9.2181*** (1.9784)	-9.2265*** (1.9753)	-9.2888*** (1.9833)	-9.2852*** (1.9858)	N/A
Refiningrubbe rplastic	-6.6246 (5.5038)	-5.0524 (5.5588)	-5.1602 (5.5489)	-5.3958 (5.5929)	-5.0216 (5.6056)	N/A
Containersteel heavy	-1.5351 (2.6424)	-2.0966 (2.6733)	-2.0837 (2.6688)	-1.6864 (2.7126)	-2.0077 (2.6841)	N/A
Computersaut osaerospace	-8.7112*** (1.8976)	-9.9256*** (1.8490)	-9.8650*** (1.8461)	-9.5018*** (1.9129)	-10.046*** (1.9068)	N/A
Transportatio n	-1.4608 (1.6408)	-1.4892 (1.6613)	-1.4906 (1.6591)	-1.4276 (1.6686)	-1.5107 (1.6678)	N/A
Telephoneutili ties	-2.0583 (2.7608)	-2.3200 (2.7936)	-2.1823 (2.7824)	-2.1436 (2.7925)	-2.0824 (2.7960)	N/A
Wholesalereta il	-8.4393*** (2.9341)	-9.0386*** (2.9750)	-8.8833*** (2.9755)	-8.5907*** (2.9784)	-8.7444*** (2.9893)	N/A
Bankfinancial	0.5582 (2.0043)	0.5310 (2.0292)	0.5246 (2.0257)	0.5592 (2.0353)	0.5180 (2.0378)	N/A
Administratio nandother	-8.9925*** (3.3003)	-7.8389** (3.3284)	-7.9376** (3.3243)	-7.9886** (3.3551)	-7.7242** (3.3714)	N/A
Other services	-0.9483 (2.4051)	-2.3784 (2.4601)	-2.3270 (2.4712)	-0.8755 (2.3704)	-1.0979 (2.3608)	N/A
R^2	0.3080	0.2906	0.2931	0.2869	0.2860	N/A

Note. Standard errors are noted in brackets behind each coefficient.
The* indicates the p-values; *= p< 0.1, **= p<0.05, ***= p<0.01

5. Discussion

This thesis investigates whether digital technologies affect financial performance through two text analyses, namely stock market reaction, and annual report. In this section, the findings will be further investigated, contextualized, and discussed by using the defined literature to elaborate on the findings from the analysis. A larger data set was collected by using text analyses on announcements and annual reports from 2014 until the present day, providing further insight into Norwegian companies and their technology orientation. Comparing the stock market analysis and the annual report analysis gives an interesting perspective on whether the technologies are valued more by the market than their actual contribution to increased profitability.

The findings will be discussed considering the theoretical findings from the literature review. Our intention is finally to investigate whether using the identified digital technologies should be central as a strategic decision to increase firm performance. By completing this thesis, we intend to contribute to the resource-based theory and the implications of using the identified digital technologies.

5.1 General Discussion Stock Market Reaction Analysis

By investigating the results of the stock market reaction analysis, it is evident that there is a general increase in stock price based on the listing of technologies at a significant level. The increase is small but evident. Thus, the null hypothesis could be rejected. With 1 423 observations of the technologies in the announcements, there is a pattern found indicating that the market generally has a positive affiliation with the technologies. The market's positive expectations toward technology are shown as an increase in the stock prices for the firms disclosing one of the 18 technologies. The market's expectations are not necessarily reflective of the actual value. However, they reflect the perceived potential value and the likelihood of the potential value being achieved (Ofer & Siegel, 1987). In general, there were few significant results, but most of the results indicate a positive affiliation between the stock market price and the digital technologies. When measuring the results from the digital technologies against the general effect of announcements, the positive expectations for technologies far outweigh the effect of general announcements. Therefore, even though the market expectations could be unrealistically high, the positive result in this analysis could reflect an unreleased potential within these technologies that could be radical for all firms in the future.

5.2 General Discussion Annual Report Analysis

Only 5 of the 18 digital technologies investigated in this paper were disclosed enough times to be included in the annual report analysis. This could give an indication of which technologies are more trending amongst the listed Norwegian companies. On the other hand, it gives fewer results, and most of the hypotheses connected to digital technologies and financial performance could not be rejected. This could either imply that the research is not deemed fit to measure what it intends or that there is no significant effect. Both implications are interesting enough in themselves and should be researched further. Still, the analysis seems to be measuring what it intends due to the high significance level of the different control variables and R-squared values, although weak, showing that the model captures some of the intended effects.

For the technologies with a large enough sample size, there is a clear indication from the coefficients that there is a U-shape on the annual report output. This means that if the company discloses the technology to a very small degree, it will have a positive result, and the same with companies disclosing the technologies to a large extent, while the companies disclosing the technologies to some extents have a negative impact on financial performance. Although not all the U-shaped findings are significant, one could speculate that this trend implies that if the company does not disclose the technology, they do not use capital on the technology, thus, not wasting money. Further, the companies spending a bit on the technologies might not be specialized enough, thus struggling with not having sufficient capabilities to gain an advantage from the technologies. Finally, the companies disclosing the technologies to a large extent might do so, due to obtaining capabilities to exploit the digital technologies, thus implementing more digital technologies. Using the same logic, one could argue that the reason that the aggregated technologies have a positive impact on the financial performance parameters, is since the companies using a lot of the technologies often obtain the necessary capabilities to exploit the digital technologies and implement more digital technologies.

Further, it is found that the implementation of technology could lead to a competitive advantage through two parameters, either by reducing the company's cost, leading it to be a cost leader or by increasing quality and an improved product, leading to differentiation. This effect could explain the increased financial performance parameters represented by *EBIT* and *ROA* found in the annual report analysis.

5.3 Digital Technologies

5.1.1 General orientation

For the general orientation toward digital technologies, the literature expects increased financial performance but argues that the capabilities and knowledge of using them are required for the performance realization (e.g., Lichtenthaler 2019). In the findings, a moderate positive significant effect of general orientation to digital technologies is found. Further, the general orientation to digital technologies is significant for a U-shape effect on profitability with both one- and two-years lag, and partly significant for a U-shape on *ROA* with no lag. This is a clear indication that both researchers and investors are correct in assuming that companies with a greater orientation to digital technologies are expected to perform better financially. This can further lend support to the individual technologies' insignificant positive effect on stock price and insignificant delayed U-shape effect on profitability. Further, the findings indicate support for the notion that capability and knowledge are needed to capitalize on the positive effects of digital technologies. The findings on increased stock price may imply that investors expect more companies to successfully build capabilities and knowledge for the technologies. Finally, findings from both analyses may indicate support for the learning by trying method, in that trying to build capabilities in one technology may help build capabilities in others (Fleck, 1993).

5.1.2 Machine Learning, AI, Automation & Simulation

Regarding the digital technologies, *Machine Learning AI, Automation & Simulation*, the literature argues that the technologies may lead to larger market share and better customer retention with more profitable customer segments, reduce bottlenecks and increase efficiency in capturing and reacting to data. From the findings of the technologies on financial performance, one can see various degrees of moderate insignificant positive effect on the stock price. Further, when lagged two years, a partly significant U shape relationship with *ROA* is found for *Machine Learning*, and similar insignificant indications are found for *AI*, *Automation*, and *Simulation*. The effect on stock price can imply that the expected effect of the technologies in the literature is in line with the expectations of investors, while the u-shape findings are in line with the research on capabilities related to technology. With regards to the notion that the technology itself cannot be the source of increased performance, it could be expected that companies needed to have a larger focus on the technologies to create capabilities for employing the technology. If the assumption of more disclosed technologies indicates a larger technology orientation, the effect would be expected to decrease with lower levels of disclosures, and higher with many disclosures.

Further, the estimated coefficients are in line with these expectations. One reason for the U-shape effect on profitability can be due to the previously mentioned differences in the life cycle of the technologies. When looking at the number of hits on google scholar (see table 11), the technologies are mentioned to a greater extent, indicating them as more established phenomena. This can be speculated to affect investors' sentiment to be less excited about the technology because it is more established rather than novel. Further, the fact that *AI*-related technologies have been expected to change our lives, but has yet to deliver the expected performance, can have rendered investors more reluctant to their effects (Brynjolfsson et al., 2019). In line with the findings that the technology itself is not enough to realize the expected effect of machine learning, the U shape can be an indication of simpler applications of the technology solving smaller efficiency problems as insufficient to increase performance, while the greater application of technology is building capability and realizing its assumed benefits (Lichtenthaler, 2019). The significance of the findings is not consistent, and therefore the reliability of the speculated effects is limited.

5.1.3 Internet of Things & Blockchain

For *IoT*, the main expected driver of increased performance in the literature is its application with other digital tools to enable and manage data to create more efficient systems and products (Côrte-Real et al., 2020). Further, blockchain is another technology focusing on making systems more efficient with less administration needed (Dunphy and Petitcolas, 2018). From the findings on both technologies, the stock market reaction was significant with a relatively high effect, while the annual report analysis lacked sufficient observation to give robust insights. The significant effects on the stock price indicated that investors expected the technology to create increased efficiency for companies. In these cases, the investors did not seem to agree with the literature that capabilities needed to be developed to realize the performance effect. When looking at their hits on google scholar, we can see that the technologies are mentioned less than other digital technologies, but still at relatively sizable amounts (see table 2). This could imply that investors expect a larger orientation towards these technologies in the future and are investing in companies developing capabilities in these segments early. Also, one could speculate that the interest in blockchain, at least in part, has been due to the increased excitement about cryptocurrencies. Further, this would not explain the excitement about *IoT*. Another explanation could be the capabilities relating to data analysis and application being available, hence, making the efficiency gains more accessible when implementing the technologies.

5.1.2 Big Data

Investigating *Big Data*, the literature suggests that a large increase in profitability can be expected if companies can implement big data analytics. Further, literature has found that a significant number of companies struggle to realize the expected increase in financial performance from their investment in big data (Popovič et al., 2018; Wamba et al., 2017). The insignificant negative findings in the stock market reaction analysis indicate that investors are more in line with the findings that more companies struggle to capitalize on their investments. Further, the findings in the annual report analysis are partly significant for its U-shape relationship with *ROA* lagged one year. The other insignificant effects indicate the same relationship. In line with research, this can be understood as companies needing to divert sufficient attention to building capabilities for the technology to realize their expected benefits. Further, the analysis for profitability lagged by two years did not include sufficient observations and could not shed more light on the matter. As it is shown that big data investments take some time to pay off, these results would have been interesting to investigate if found significant (Wamba et al., 2017; Pappas et al., 2018). A longer lagged series could therefore be of interest. When evaluating the findings from both analyses in unison, the investors seem to expect more companies to fail than succeed, hence, not diverting enough focus to building the capabilities. From the hits on google scholar, a larger amount of research has been published on the topic in recent years. However, the market seems to be less excited about the technology. On the other hand, research indicates that the average investment increases the profitability by an expected five to six percent and should therefore be considered in terms of building capabilities (Akter et al., 2020).

5.1.10 Cybersecurity, Augmented Reality & Additive Manufacturing

For *Cybersecurity, Augmented Reality,* and *Additive Manufacturing*, the literature argues that the technologies should increase financial performance (e.g., Hasan et al., 2021, Abraham & Annunziata, 2017, Lasi et al., 2014). From the findings in this paper, no significant effect on stock price was found, and the technologies lacked sufficient observations for the profitability analysis. There was found a below-average amount of hits on these technologies on google scholar, possibly indicating less popular technologies, thus not being disclosed a sufficient number of times (see table 2). Interestingly, while *Cybersecurity* and *AR* have small effects on stock price, Additive Manufacturing has a substantial positive effect. This indicates that investors have great expectations for this technology while caring less or conflictingly about *Cybersecurity* and *AR*, but this is speculative as the findings lack significance.

5.1.13 Undisclosed Technologies

Finally, some of the technologies were not disclosed enough times, either in the annual report or the stock market reaction analysis. *Robotics, Modeling, IoS, IoP, IoD, Cloud Computing, CPS*, and *Semantic Technologies*, all belong to this category of digital technologies. Since their belonging hypotheses could not be rejected, this paper fails to draw any conclusions regarding these technologies.

Several explanatory factors could be discussed regarding these technologies. In the process of writing the literature review, fewer articles were found around these technologies than some of the other technologies, thus possibly not being disclosed in as many announcements or annual reports either (see table 2). Fewer mentions could be speculated to come from the fact that these technologies are not at the same maturity stage as the other technologies. Further, we could speculate that the technologies do not possess the same potential, or at least from the perception of the strategists within Norwegian companies. Although there is research stating its effect on productivity, this could not be proven through these analyses (Oztemel & Gursev, 2020, Akter et al., 2020).

6. Implications & Conclusion

6.1 Theoretical, Managerial & Methodological Implications

6.1.1 Theoretical Implications

Starting off, this paper elaborates on the technologies identified by Ghobakhloo (2018) and Kumar et al. (2019), and connects these technologies to the resource-based view through an extensive literature review. Further, the literature review presents how these technologies contribute to increased firm performance before the two analyses are completed to confirm whether these technologies have a positive influence on financial performance. By doing so, an overview of the orientation of the named technologies is formed.

Further, by completing the analyses this thesis indicates that the intangible part of technology as a resource is the source of competitive advantage, not the technology itself. Thus, this thesis builds on the resource-based theory by exemplifying the mechanisms of tangible and intangible assets through the application of the identified digital technologies. Moreover, this thesis builds on the technologies in the industry 4.0 literature for typical value chain industries and is further generalized for other industries (e.g., Ghobakhloo, 2018).

6.1.2 Managerial Implications

This thesis contributes to the boards across companies, indicating that some technologies obtain higher expectations within the market compared to others. Identifying and categorizing the different digital technology initiatives, so the disclosing of these technologies in the announcements and annual reports are perceived in the right manner, is a topic of interest and could have an impact on the markets stock price reaction to the companies' respective disclosures.

Further, this thesis shows the technology orientation of companies listed in Norway. It could be used as an overview to indicate what technologies competitors use and which technologies the companies should exploit. Therefore, the results of this thesis could trigger a conversation about the firm's capabilities through its internal knowledge, value offerings, and existing technologies. Then use this conversation to decide if they should take measures to keep up with the market. Also, the findings of a U-shaped relationship between the technologies and profitability implicate that managers should consider either zero or extensive focus on digital technologies to reap its benefits.

Finally, this thesis also indicates that the digital technologies are not of direct value if the capabilities to utilize the respective technologies are not in place. Thus, implementing one of these digital technologies without having clear knowledge about how to utilize it would not automatically result in increased performance but could create learning by trying effects.

6.1.3 Methodological Implications

This paper illustrates some challenges and advantages of using text analysis. First, text analysis can be a messy approach, lacking consistency and cohesion in definitions for the phenomena under consideration. Further, the findings suggest that text analysis can be used to indicate proxies when numeric data is lacking, hence overcoming the measurement problem (Waddock & Graves, 1997).

The event study methodology has multiple applications, with areas within corporate finance being proven especially effective, like mergers and acquisitions and financing decisions (MacKinlay, 1997). Researchers have also used the methodology to explore the effect digital technologies have on stock price, with previous research looking at the effect on the stock market of announcements disclosing investments in IT and IS' (Dos Santos et al., 1993, Im et al., 2001). Thus, this thesis contributes to the method by introducing an approach to digital technologies applicable for the transition into Industry 4.0 (Ghobakhloo, 2018). Further, this analysis also explores the effect of a general announcement, by adding the randomized control group to the model, and further showing its insignificant negative effect on the stock price.

The keyword frequency method for annual reports is another interesting approach, which could be used as a selection tool to identify companies of interest for technology orientation or other strategic directions, and then use this information to perform a qualitative study.

6.2 Limitations

The sample is relatively small with 209 Norway companies, where only a few companies are major international players dominating the largest industries, and only one, the state-owned Equinor, reaches the top 500 companies in size globally (Euronext, 2022b, Fortune, 2022). This sample might hinder the generalizability internationally due to different countries including a different set of company capabilities. The Norwegian working stock might have more or less technological capabilities and might be differently suited to extract the potential values contained in the digital technologies. Adding on, the firms disclosing the technologies might not obtain the capabilities needed to use the technology. A manager might want to implement the technology without totally understanding how and, therefore, not being able to utilize the technology optimally by not aligning the technologies with the rest of the organization, which is a crucial factor for the successful deployment of the technologies (Wiengarten et al., 2013).

Further, some of the technological investments might be of a size so large that the time-to-payoff would be extensive, e.g., for *Big Data Analytics* (Wamba et al., 2017; Pappas et al., 2018). This might influence how the results contribute to financial performance over time. A larger dataset with even more years of lag could therefore have been of interest. Adding on, some firms might successfully use some of the digital technologies, and although there is an assumption of transparency to shareholders and the market, there might be companies that do not want to share what technologies they are using due to strategic secrecy. If many companies operate without transparency of their digital technology orientation, the results in this study are biased.

An argued limitation of the RBV is that it assumes the best applicability of its resources, while not arguing how this is done (Melville et al., 2004).

Lichtenthaler (2019) argues that having the technology as a resource itself is not enough, but firms need to dynamically combine their human and artificial intelligence architecture. This supports Grant's (1991) view on the competitive advantage being built upon intangible assets. Thus, the technology itself as a tangible asset is insufficient to gain a competitive advantage, but the intangible part, namely the capabilities is the source of the competitive advantage (Rodriguez & Rodriguez, 2005, Hall et al., 1993).

6.3 Directions for Future Research

Lichtentaler (2019) builds on Grant’s (1996) knowledge-based view (KBV) of the firm, an offspring of a theory focusing on knowledge application, rather than creation, which again is an offspring of the RBV (Barney, 1991). Lichtentaler (2019) builds on the KBV and talks about the intelligence based-view (IBV). The IBV highlights the need for knowledge to be integrated and actionable, making it applicable to the organization. Artificial Intelligence is deemed relevant, but the interplay between human intelligence, why the firm exists, and the AI is deemed central to sustainable competitive advantage. Doing an in-depth analysis with an IBV lens to analyze the capabilities within the firms and further unravel why companies using specific digital technologies outperform their peers not using the same technology would be of high interest in this stream of research. It will also be interesting to use this framework to analyze smaller companies' capabilities like the startups in Silicon Valley, as they, according to Brynjolfsson (1994), have larger incentives to exploit technologies, to investigate how these build technological capabilities and gain a competitive advantage.

Further, the learning by trying mechanisms found in Fleck (1993) would be exciting to investigate, through analyzing companies using several of the technologies. By adopting some of the concepts in this annual report analysis, it would be interesting to build an even larger data set to catch the long-term effect, by adding even more years of lag, thus, being able to capture if there is found increased technological capabilities through the learning by trying effects.

6.4 Conclusion

This study has focused on utilizing digital technologies as a competitive advantage through the lens of the resource-based view. This thesis aimed to analyze whether some identified digital technologies could increase financial performance. By conducting two different analyses, this paper shows how the market expectations, and the actual performance are affected by the disclosure of digital technologies.

There are not found enough significant results to conclude that digital technologies increase financial performance. On the other hand, there are indications that companies who disclose the identified digital technologies get a significantly positive market reaction on the stock price and in terms of financial performance through *ROA* and *EBIT* if the technologies are disclosed many times, like for the technologies *Machine Learning* and *Big Data,* but especially *aggregated technologies U shape*. On the other hand, the lack of findings in this analysis could confirm the theory stating that technologies themself are tangible and that the true source of competitive advantage within these technologies is the intangible part, through building technological capabilities. Thus, this research gives some indications confirming previous research that finds the intangible part of the resource the source of competitive advantage. Further, even though most of the results are found not to be significant, the degree of *IoT* and *Blockchain* disclosed by the Norwegian companies listed on Oslo Børs gives increased stock prices. Thus, the market expectations are not neutral to these technologies but give indications of small, but positive expectations for these technologies.

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