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DIGITALIZATION AND FIRM PERFORMANCE
Are Digitally Mature Firms Outperforming Their Peers?

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ABSTRACT

This thesis studies the effect of digitalization on firm performance. More specifically, it investigates whether digitally mature firms outperform their less digitally mature peers. My analysis is based on literature on information technology, information and digital systems, and digitalization in general. I assess digital maturity through a suitable proxy. With data from listed Swedish firms, I deploy dynamic panel data regressions, portfolio analyses, and risk factor models in order to analyze digital maturity's effect on subsequent operating performance and stock returns. For the most part, I find inconclusive results. Consequently, the proposition of a digital advantage is not reinforced. This adds to the literature by empirically examining the effects of digitalization on firm performance.

Keywords: Digitalization, Information Technology, Portfolio Analysis, Dynamic Panel Data Regression, Operating Performance, Risk Factor Models

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List of Abbreviations

DI	Digital Intensity
DM	Digital Maturity
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
ICT	Information and Communication Technology
IoT	Internet of Things
IT	Information Technology
SWIFT	Society for Worldwide Interbank Financial Telecommunication
TMI	Transformation Management Intensity

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WE ALWAYS OVERESTIMATE THE CHANGE THAT WILL OCCUR IN THE
NEXT TWO YEARS AND UNDERESTIMATE THE CHANGE THAT WILL
OCCUR IN THE NEXT TEN.

William Henry Gates III

When my information changes, I alter my conclusions.

JOHN M. KEYNES, as cited in Samuelson's *The Keynes Centenary*

1 | Introduction

OVER THE COURSE OF THE PAST TWO DECADES, digitalization has turned from a rather abstract and futuristic concept into a transformative power that reshapes the economic landscape, and acts as a major disruptor with far-reaching consequences (Weill and Woerner, 2015; Bughin and van Zeebroeck, 2017; Schwab, 2017; Zammuto et al., 2007).

It is hard to pinpoint the arrival of digital technologies on a timeline. A few first innovations in information technology and the digital field cleared the way for countless technological innovations through a cascading effect and defined today's fifth Kondratieff wave¹: the *age of information* (Vogelsang, 2010). Originally, the notion of the so-called digital divide was coined sometime during the rise of information technology in the 1990s. It was used to explain the differences in information inequality, i.e. using computers or the Internet altogether (Yu, 2006). Over time, progress in information technology made computers, online interaction and interconnectedness commonplace (Yoo, 2010). The modern-day understanding of digitalization shifted away from simply working with a computer to a consensus that digital technologies transform how businesses interact in both business-to-business and business-to-customer settings (Loonam et al., 2018).

Digital transformation is not just limited to tech-savvy start-ups and companies operating in the high-tech sector, established companies embark on this digital transformation journey just as well (Weill and Woerner, 2018). Digitalization represents a paradigm shift that pervasively affects the most traditional of businesses and even impacts society as a whole (Gimpel and Röglinger, 2015; Sambamurthy et al., 2003).

¹Kondratieff waves are classical theoretical economic cycles that follow apparent oscillations in global activity (Korotayev et al., 2011). However, the validity of the concept is not without controversy (Focacci, 2017).

Historically, firms and organizations have always been subject to constant change. As Schumpeter (1943) so aptly put it with his concept of *creative destruction*, change should be seen as an inevitability, though, as a positive one in an economic landscape, as it fuels innovation, competition and higher standards that benefit all market actors. Nowadays, with the digital transformation in full swing (Bharadwaj et al., 2013), firms recognize their peculiar situation amongst a great many technological innovations that reshape the economic and competitive landscape (Loebbecke and Picot, 2015). Competitive dynamics have picked up in pace due to advances in information technologies and new digital solutions (McAfee and Brynjolfsson, 2008). This leads to increasing gaps between leaders and laggards and thus, sectors more closely resemble winner-take-all markets.²

Companies at the forefront of new innovative concepts, the so-called *digital frontier*, increasingly benefit from their practices as they are getting propelled onto new competitive levels from where they can increase their profits (Scott et al., 2017). The unprecedented growth of highly digital and innovative companies, regardless of size, and their ability to take market shares by storm, are a prime example of how swiftly the business world can change and how easily industry boundaries become blurred (Yoo et al., 2010). Established enterprises revamp their business strategies to stay afloat in the digital economy (Weill and Woerner, 2018). In other words, the emergence of digital technologies puts unparalleled pressure on companies to evolve.³ Ultimately, companies are confronted with a digital imperative: adapt to the new state of the art or risk competitive obsolescence (Fitzgerald et al., 2013).

It even seems that, due to the changes induced by digital technologies, established business principles no longer hold. According to the traditional technology adoption model by Rogers (1963), new innovations or products gain popularity sequentially with market segments, starting from innovators and early adopters to the late majority and laggards. In comparison, the disruption caused by digital innovations is more compressed where new products, such as smartphone apps or e-commerce, are imbibed swiftly by the vast majority (Downes and Nunes, 2013). This fast-paced change, stemming from disruptive technologies, requires companies to be prepared

²It is worth mentioning that however powerful the magnitude of information technology advances and digital innovations seem to be like, they do not affect sectors equally.

³Based on data from Standard & Poor's, Desmet et al. (2015) observe that the average corporate life span is decreasing. They find that, although the average corporate life span has been falling for the past decades, the dwindling has never been more accelerated.

for technology innovations and to react timely, if necessary. Additionally, the digital transformation process encompasses an unprecedented diffusion of digital disruptors, i.e. relatively small and young but highly innovative firms that abruptly compete with established companies (Schwab, 2017).

Digitalization and its implied changes do not only affect the way firms operate, but they also have a profound impact on consumers (Brynjolfsson and McAfee, 2014). An ever-growing number of business people and consumers act online since mobile and internet services are becoming more widespread available (World Economic Forum, 2016). Be it for online purchases, leisure activities such as consuming media, or search inquiries for information, users leave a data trail which can be analyzed and exploited by firms (Bharadwaj et al., 2013). More and more, firms see data as a form of capital and, therefore, as an asset (Westerman and Bonnet, 2015). The data companies gather can be thoroughly analyzed and used to improve understanding customer needs. Ultimately, this new information provides the basis for computer modeling and forecasting which, for instance, allows for better managerial decision making or dynamic pricing, amongst other things (Chen et al., 2016).

Gassmann et al. (2014) define digitization as “ability to turn existing products or services into digital variants, and thus offer advantages over tangible products, e.g. easier and faster distribution” (p. 6). Strictly speaking, digitization only refers to the technical aspect of the conversion from analog to digital (see OED Online, 2017; Yoo, 2010). On the other hand, the concept of digitalization goes further and describes the use of digital innovations and technologies to enhance, for instance, internal processes and business models. In short, the utilization of digital resources and IT technologies by using resources that were created by digitization. For further clarification, firms utilizing new IT innovations and digital solutions are said to be digitally mature. However, there is ambiguity when it comes to digitization and digitalization in the literature and the terms are often used interchangeably and synonymously.⁴

The goal of this thesis is to investigate whether firms which are more digitally mature have higher performance than peers which are not as digitally mature. I critically examine if digital maturity has observable effects on key performance measures and if stock prices incorporate this information. Since a plethora of papers and studies argue in favor of digitalization, the key hypothesis is that digital maturity is seen to be posi-

⁴This thesis’ intention is not to enhance the terminology, thus, I will exclusively use the term digitalization for the remainder of the thesis.

tively associated with subsequent operating performance and abnormal stock returns. Furthermore, digitalization is a widespread concept and cannot easily be described as a single item since it is more of an ongoing process. Hence, identifying the key areas of digitalization is an important part of this thesis.⁵ In order to pinpoint major digital drivers, the thesis will give a succinct, yet in-depth, overview of the following topics. First, this thesis aims to give an outline of digitalization, digital maturity, IT innovations as well as digital progress. Second, changing economic fundamentals in the wake of digitalization are elucidated. Third, general digital developments are illustrated. This serves to give a concise overview of digitalization in a broader sense and helps to define this thesis' goal in a framework.

After arriving at a definition of digitalization and its attributes, the thesis ties the theoretical aspects of digital maturity and their effects on firm performance together. For empirical testing, I deploy dynamic panel data regressions, portfolio analyses, and risk factor models. I run the dynamic panel data regression with a Generalized Method of Moments estimator suggested by Arellano and Bond (1991). For the portfolio analysis, I sort firms into two size groups and rank them according to their attached digital maturity value. Next, I calculate the monthly excess returns of the size-adjusted portfolio returns. In addition, I make use of the Fama and French (1993) three-factor and Carhart (1997) four-factor models to gain additional insights. My approach draws loosely from the analysis of innovative efficiency and contemporary firm performance by Hirshleifer et al. (2013).

The results of this thesis demonstrate that, on average, digital maturity is neither positively, nor strongly related to a firm's operating performance. There are a great many reasons why digitally mature firms should outperform their less digitally mature peers, or in other words, why digitalization should give rise to above-average performance, however, the data suggests otherwise. The results from both, the portfolio analysis and the dynamic panel data regression, show that there is no clear relation between digitalization and firm performance. More specifically, the portfolio analysis gives somewhat inconclusive results. With regard to excess returns, there is little difference between portfolios consisting of highly digitally mature firms and less digitally mature ones. At the same time, the portfolio returns of highly digitally mature firms seem less volatile compared to returns of the portfolio of less digitally mature firms.

⁵Because of the many facets that are touched upon through digital innovations, it is needless to say that not all of them will be acknowledged.

As for the dynamic panel data regression, digital maturity has a weak negative effect on subsequent firm operating performance which is in contrast to prior studies and findings. However, some argue that weak or negative results might be observed owing to implementation processes as well as the very nature of technological innovations which take some time to unfold their full potential (Scott et al., 2017). In short, my findings do not substantiate the claim that digital maturity is linked to superior performance.

The remainder of this paper is organized as follows. In section 2, I provide an in-depth overview of related research, in particular, literature related to digital innovations. In addition, the differing effects of digital innovations on organizations are illustrated. This theoretical background also presents a suggested framework for digitalization and succinctly highlights findings from previous studies. In section 3, I describe the setup of my study, the data, and the tools used in order to qualitatively explore the effects of digitalization on firm performance. Section 4 presents the empirical results from the dynamic panel data regression and the portfolio analysis in detail. Section 5 discusses the implications of the findings in the light of the reviewed literature and studies. Additionally, several limitations to my approach are outlined. Section 6 summarizes the main findings and provides a direction for further research.

2 | Theoretical Background

THIS CHAPTER OFFERS AN IN-DEPTH LITERATURE OVERVIEW which consists of the following. First, an introduction about the changes in competitive dynamics due to advancements in information technology (IT) is given. Second, this chapter sheds light on the effects of new technological and digital innovations on organizations: the digital transformation. Third, a framework to classify digital maturity is presented and discussed. Lastly, the chapter aims to answer the question why digitalization matters for firms by highlighting findings from previous studies.

2.1 THE CATALYST: ADVANCES IN INFORMATION TECHNOLOGY

Digitalization in itself is not a singular movement. It is an on-going process that does not have an ending in a traditional sense and is fueled by accelerating computing power (Evans et al., 2006; Vogelsang, 2010). The quintessence for the changes of the economic landscape is that advances in IT caused a drastic acceleration of digital innovations which is, by some, labeled as a disruption (Bughin and van Zeebroeck, 2017; Downes and Nunes, 2013). Especially technology companies seem to grow exponentially and old business principles no longer seem to hold.⁶ Digitalization does not only affect firms that are doing business in the technology sector. IT solutions also enhance all organizations' internal operations; changes that are invisible to the naked eye.

Information has always been important throughout human history. However, it has never been so easy to collect, to store, and to analyze large quantities of information as it is today. Digitalization affects every organization and industry and yet it

⁶The valuation of small start-ups, especially the ones located in Silicon Valley, cannot be explained by traditional performance measures (Damodaran, 2014).

is incredibly difficult to pin down what exactly this phenomenon comprises. Technology advances reshape the economy, businesses reinvent operations and come up with completely new products, and customer as well as supplier relationships, are deepened. Digital maturity powered by IT applications has become a defining element in corporate competition (Manyika et al., 2015).

Technological changes at many fronts simultaneously, a new competitive dynamic, and digital innovations which push the boundaries, disrupt traditional power structures. McAfee and Brynjolfsson (2008) find that the rivalry in an industry becomes more fast-paced and dynamic due to successfully implemented IT systems. While firms which fail to adapt properly and timely risk to fall behind and become irrelevant, first-movers pull away from the average company. In other words, the competitive landscape is altered by innovative enterprise IT (Yoo et al., 2010). Innovations spread rapidly amongst firms and competitors do not only try to keep up, but also try to implement IT-based innovations that are already one step ahead. With the implementation of new powerful information and communication information (ICT) systems, organizational structures are redefined (Loebbecke and Picot, 2015; Hylving et al., 2012). Especially work processes that were previously limited by either work time, office location or hierarchical work structures, are transformed into more flexible and network-like structures (Zammuto et al., 2007). Process-centered organizational designs, integrated databases, and technological systems form a relationship between organization and ICT (Hylving et al., 2012). This allows companies to visualize work processes, use real-time analyses, engage in virtual collaborations, and run advanced computer simulations (Zammuto et al., 2007). Thus, ICT improvements are positively linked to the economic success of organizations (Hernaus et al., 2012; Spanos et al., 2002).

Moreover, McAfee and Brynjolfsson (2008) argue that investments in IT are a driving force behind increasing competitive dynamics. Technology has changed traditional competition and gaps between leaders and laggards widen (Schwab, 2017). A consequence is the concentration of sectors to an extent where they resemble winner-take-all markets. This constellation benefits firms that move quickly and before their competition. Lieberman and Montgomery (1988) find that technological leadership is one of the main contributors to first-mover advantages and such advantages often translate to enhanced future profitability. In more detail, the first-mover advantage describes the ability to earn abnormal economic profits - typically exceeding the cost of

capital (Kerin et al., 1992). This technological leadership is linked to digital maturity since digitalization is a part of technological dominance. Missing a new technological innovation such as a new digital application could have far-reaching implications for a firm's future competitive environment (Fitzgerald et al., 2013). Furthermore, McAfee and Brynjolfsson (2008) identify patterns in their data which support their argument that, due to frequent competitive moves, through which only the best companies can keep up, competition becomes more concentrated and accelerated. IT can be both, a catalyst for new ideas and the means to implement them successfully. A major US retailer, for instance, records and stores data gathered from customers indefinitely. The aforementioned customer data, or shopper history, is obtained throughout the entire shopping experience, item for item. The company then maps and updates the data by store and region. Computer models fed with customer data are increasingly used to supplement managerial decision-making. Such knowledge is considered to be powerful since the superior decision-making is reflected in profits (Hays, 2004).

In a study of the insurance market, Barrett and Walsham (1999) investigate the implications and effects of the introduction of interorganizational systems and electronic data interchange for transactions in the London insurance market network. In order to increase the market efficiency, an electronic placing support system was introduced. Barrett and Walsham (1999) find that these changes allowed brokers and underwriters to work in an electronically supported trading environment which helped to increase both profitability and efficiency. Even the classic role of a bank as a financial intermediary is challenged since start-ups are now able to perform tasks that were solely in the domain of huge corporations before the age of digitalization (Bank for International Settlements, 2002). Scott et al. (2017) take the same line and state that technological advances and new digital innovations, such as improved and more powerful applications and systems, override current market conditions. According to Schumpeter (1943), innovations then fuel the motor of *creative destruction*, where companies, which are the most innovative, increase their market share to the detriment of less innovative competitors. In short, companies at the digital frontier increasingly benefit from their innovations as they are getting propelled into new competitive positions from where they can increase their profits. Subsequently, the magnitude of the contribution of digital maturity is dependent on economies and sectors (Scott et al., 2017).

Evidence from the financial sector suggests that the incorporation of improved ICT

has major implications for the financial system. These implications are far-reaching and have altered the global financial system. This leads to the creation of newly invented financial products (Barrett and Walsham, 1999), better service, and a more interconnected global financial market. The following example might illustrate this change more coherently. In a study of the impacts of global information processing services (SWIFT) on the banking sector, Scott et al. (2017) find robust evidence that technology investments have a positive and significant impact on profitability and performance in the long run. Despite the long-term benefits, they find that in the short run a weak or even negative result might be observed. This can, on the one hand, be explained by in-depth organizational changes due to the implementation processes of information services. On the other hand, weak early results can be explained by the very nature of technological innovations, which usually take some time to unfold their full potential. Additionally, Scott et al. (2017) find that banks were pressured to implement the new technology due to competitors upgrading their systems.⁷ Inaction or waiting too long might put a smaller bank out of business because it gradually worsens its competitive position. Yet, if they adapt in time, their range of potential clients significantly increases and thus, the change is ultimately beneficial. This example depicts the inevitable need for organizations to keep up with technological innovations (see also Manyika et al., 2015).

It is, however, difficult to pin down the exact impact of new technologies and subsequently findings are hard to generalize due to the overall complexity of this topic. Yet, several studies come to the conclusion that ICT boost returns, increase firm value and have a positive impact on performance (Jun, 2008; Anderson et al., 2006).

2.2 TECHNOLOGY TRENDS AND DATA CAPITAL

Nowadays, mobile and internet services are widespread and increasingly available. According to the World Economic Forum (2016), there are more mobile devices than humans, and consumers' online purchases are ever increasing. In the first quarter of 2014, for instance, almost 80 percent of US consumers purchased something online. Moreover, consuming media digitally is on the rise. In the US, around 50 percent of media viewed or listened to was digital (World Economic Forum, 2016). Using

⁷One of the original SWIFT engineers said that any bank which is not on SWIFT loses business because banks that have already upgraded will not do business without SWIFT anymore (see Scott et al., 2017, p. 996).

online services generates data trails that consumers leave behind. Consumer data encompasses a variety of information that can be analyzed and subsequently exploited by companies. This new insight thus provides a valuable source for adding value and receiving feedback. For example, Netflix, a US-based streaming service, gains a lot of view time and therefore higher retention due to its well-optimized recommendation algorithm (Vanderbilt, 2013). As a result, people use the streaming service longer and are more willing to keep their current subscription.⁸ The World Economic Forum (2016) defines four key improvements for organizations that use data as an asset. First, in-depth insight into customer behavior and preferences allow firms to make marketing more personalized. Second, digital platforms are a means to connect with customers and potential customers to increase brand strength.⁹ Third, product design processes can be improved (see also Hylving et al., 2012). Lastly, consumer data can be monetized by companies by sharing with other stakeholders. All in all, these key areas are estimated to influence both revenue and cost savings positively.

In this day and age, firms are in the midst of the change from computing architecture, such as hardware as a capital asset, to data as a new form of capital. Data is considered an asset that companies become more aware of since the technological developments have implications on firms' strategies, characteristics, and business opportunities (MIT Technology Review Custom, 2016; Weill and Woerner, 2018). In addition, Bharadwaj et al. (2013) argue that the data excavated by digitalization is effectively transforming the availability of information. Firms therefore no longer operate under information scarcity but, with all the data readily available, enter a time of information abundance. Westerman and Bonnet (2015) add, in comparison to financial and human capital, data may be considered an asset class. Generally speaking, the term capital is subject to change throughout economic history. Typically, in classical economics, capital is any good that helps create another good or a service (Hodgson, 2014). Data capital, however, is more complex, harder to access and sometimes not obvious. Companies gather data from customers, but fail to analyze it properly. Without adequate applications and an up-to-date computing infrastructure, some information that is potentially valuable for the company, cannot be extracted

⁸Other prominent examples, where customized advertising that is specifically targeted at individuals is common practice, would be Facebook or Google. Also, for Amazon, the related article suggestions, created by consumer data analyses, are at the core of their business model (World Economic Forum, 2016). See also chapter 2.3.

⁹This effect, however, also works against companies' efforts to increase sales since consumers have access to more information and a greater variety of products to choose from (Dehning et al., 2003).

from the data.¹⁰ In the MIT Technology Review Custom (2016) data capital is defined as follows (see also Vogelsang, 2010; Quah, 2003).

First, data is non-rivalrous which means that a single piece of data can be used by different applications or algorithms simultaneously. This is in contrast to financial capital. For instance, an unspecified amount of money can only be invested in as much as one opportunity. Second, data is non-fungible which means that certain data cannot be substituted for another one due to the uniqueness of each data piece. Third, data is considered to be an experience good. The usefulness of information contained in data is not immediately obvious. Only after analyzing data its true value becomes visible. This includes a certain degree of uncertainty due to the following reasons. On the one hand, the information might be useless for the recipient, and working or analyzing the data, therefore, is a waste of money and time. On the other hand, the information might be valuable, but the applications and algorithms used to extract and structure the information might not be able to do so. Information as a resource is both used and produced on a daily basis for companies. Therefore, *datafication*¹¹ and digitalization of more internal activities have effects on a firm's competitive strategy.

The MIT Technology Review Custom (2016) abstracts data capital with the following three principles. First, data derives from activities. Almost all activities by companies can produce digital data if the companies decide to use some kind of device or application in order to capture it. It is needless to say that not all activities provide equally important data for the company. Therefore, it is of importance to focus on activities that are linked to a company's competitive advantage, revenue, and cost drivers as well as interactions with customers or partners. Second, data tends to increase the amount of data by implication (Yoo et al., 2010). Data analyses, data interpretations, and data-driven algorithms tend to increase the total amount of data over time.¹² Dynamic pricing algorithms, for instance, that change pricing automatically and dynamically when demand changes, profit from previously gathered data. The more data about demand changes is available for the computation – favorably with different conditions – the better the fine-tuning of the algorithm and

¹⁰Especially demographic data is becoming more important for numerous companies. It helps companies to understand clients and allows, for instance, advertisement campaigns to be targeted at the main buyer group directly (Westerman and Bonnet, 2015; MIT Technology Review Custom, 2016).

¹¹A term first introduced by Cukier and Mayer-Schönberger (2014) in 'Big Data: A Revolution That Will Transform How We Live, Work, and Think'.

¹²In a recent study about data valuation, Short and Todd (2017) find that companies' data increase, on average, by 40 percent per year.

thus an improvement in future performance. This is helpful for firms, for instance, to adjust prices continuously or to increase the accurateness of credit approvals for credit companies. Third and last, digital platforms tend to win. This is closely linked to the winner-takes-all characteristics of new digital innovations. In other words, network effects are pivotal for digital services (Evans et al., 2006). According to Shapiro and Varian (1999), the network's value is a function of its size. This means that the more firms are actively adopting the new standards, the more valuable the network becomes for other firms. Since firms profit from the network, they create affirmatory feedback effects and thus, make the network more attractive to others which in turn increases the network's size and benefits (Shapiro and Varian, 1999).

However, the inaccessibility of data assets leads to increasingly difficult firm valuations. In 2016, when Microsoft Corp. acquired LinkedIn, a social network service for professionals, many wondered why the software giant was willing to pay USD 26 billion (Short and Todd, 2017). It can be assumed that Microsoft Corp.'s main interest in the acquisition of this online professional network was LinkedIn's user data. Valuation of data as it turns out, is highly complex and context-dependent. For instance, the value of data for an outside party might be drastically different from an insider's point of view. Monetary value from data can be derived in two ways for firms. On the one hand, data can generate value indirectly. By using data internally, customer behavior can be explained and thus processes can be redefined. This leads to an increase in profits. On the other hand, a company can generate monetary value directly by selling or trading customer data.¹³

In summary, an in-depth analysis of the data available to a company may give the company unique insight into various business activities that have not yet been touched upon. For the majority of firms, the data available from analytics is the single biggest asset that they possess. However, some firms do not take advantage of that or are not aware of the usefulness of the information that data provides them with.

2.3 DIGITALIZATION'S IMPACT ON ORGANIZATIONS

As companies of any sector invest in digital solutions and start digital initiatives, competitors are forced to act (Fitzgerald et al., 2013). Manyika et al. (2015) argue that

¹³The consulting company PricewaterhouseCoopers estimates the revenue generated from commercializing data in the financial sector to be USD 300 billion by 2018 (see Short and Todd, 2017, p. 18).

digitalization is inevitable for organizations and in order to become digitally mature, going digital by implementing new systems and purchasing IT systems is not enough. Considering that early movers typically realize a major payoff, a timely reaction is pivotal (Lieberman and Montgomery, 1988). As more and more companies choose to go digital and a critical mass is reached, a ripple effect takes place which leads to a new competitive dynamic and alters the commercial ecosystem. Digitalization can be seen as a collecting basin where new innovations are captured. Predominantly, this includes digital applications which heavily rely on data, that affect how firms are operating as well as how they structure and design internal processes. Although these changes do not affect all sectors evenly, none is unaffected by it (Schwab, 2017). Firms mainly acting as intermediaries, for instance, are replaced by digital platforms and slowly put out of business. Manyika et al. (2015) and Yoo et al. (2010) find that digitalization is a disruptor, but at the same time opens up rigid barriers which leads to new opportunities. They state that digitalization allows companies to increase operation efficiency, to broaden their innovation efforts, and to better allocate their resources. Fitzgerald et al. (2013) emphasize that today's organizations have to reinvent the way they do business constantly, otherwise, they risk falling behind.

Fuentelsaz et al. (2009) argue that the implementation of new technology directly affects firm productivity through changes in the production process. This increase in productivity, or productivity effect, can be decomposed into two areas. On the one hand, technological change enhances productivity directly on a technical level. On the other hand, the operating efficiency altogether increases, however, this effect is harder to determine because of the variety of factors affecting it.

For the increase in operational efficiency, Manyika et al. (2015) state that companies profit from e-commerce, cost savings, and streamlining of operations. The digital retail giant Amazon, for instance, uses advanced algorithms that show customers related products based on predictive computations and alters prices dynamically in order to increase sales and profit (Chen et al., 2016). Moreover, retail banks use automated digital systems, such as mobile channels and online presence, in order to increase paperless work flows and to cut costs (Gordon et al., 2013). Furthermore, Manyika et al. (2015) argue that digitalization does not stop at the implementation of new technologies that automate processes and lead to substantial cost savings. Additional insight, such as analytics, helps firms to understand their customers better. A recent example from the automotive industry illustrates how customer service

may go beyond physical limitations. Tesla Inc., a US-based based car manufacturer, can update the software of its electric cars without the assistance of the car's owner (Kessler, 2015). These updates are downloaded automatically and improve current features or add new ones.¹⁴ As mentioned earlier, new technological innovations, solutions, and processes speed up the competition and may overwhelm individuals. Digitalization disrupts traditional companies' daily business and operations. However, a new hyper-competitive world fueled by digital transformation offers smaller businesses new opportunities since the barriers of entry are lower than ever. Small businesses have fewer constraints, are typically more innovative, and are unburdened by outdated legacy systems (Manyika et al., 2015).

According to a study conducted by Dobbs et al. (2015), firm profits for idea-intensive sectors are rising, especially leading firms in sectors with a higher average digital maturity are gaining market shares. This new competitive landscape influences the modus operandi for established companies' M&A activities, especially in high-tech or highly digitalized sectors. Smaller merger and acquisition endeavors that would not have been undertaken with regard to traditional valuation practices are suddenly on the rise (Picker, 2017). More specifically, smaller firms with a lot of intellectual property and cutting-edge technologies are sought after by larger companies which try to either take over the high-value intellectual property from the small firm, or to thwart off competitors before they turn into a real threat (Hildebrandt et al., 2015; Luckerson, 2015). The Achilles' heel, however, for a M&A transaction in high-tech sectors to be beneficial, is the proper integration of the acquired firm's knowledge into the acquiring firm (Cloudt et al., 2006). Moreover, for the acquisition to generate long term benefits in innovative performance, the firms involved in the M&A transaction should be somewhat related but not too similar with regard to their individual knowledge base (Cloudt et al., 2006).

Van Bommel et al. (2014) find that virtual environments, the ubiquity of big data, and digital channels change the consumer decision journey. Today, consumers know more about products and are aware of their enhanced choice. Lucas et al. (2013) label this increased knowledge of products as consumer informedness. Hence, it is important for companies to stay in touch with customers that use mobile phones to search for new products and ultimately purchase them. Van Bommel et al. (2014) remark that

¹⁴In late 2015, with an overnight update, Tesla Inc. updated their car software by adding advanced self-driving capabilities (Kessler, 2015).

companies not only need to capture data but should also use sophisticated analytics in order to interpret the data. In marketing, for instance, algorithms model costs, determine the efficiency of a new campaign, and identify new customer segments.

Furthermore, Manyika et al. (2015) investigate potential future economic growth due to changes induced by the ongoing process of digitalization. More specifically, they analyze two topics in-depth which they consider to have an impact on future growth, namely, capital efficiency and multifactor productivity. On the one hand, the Internet of Things (IoT) offers great potential to use assets more efficiently and effectively, thus business processes increasingly revolve around data-driven services (Pflaum and Gölzer, 2018). Automated systems in manufacturing companies, for instance, help to reduce outages and downtimes, and to increase throughput through the analysis of performance data (Haverkort and Zimmermann, 2017). With the help of sophisticated IT and IoT applications and systems, there are no limitations for improving work flows, streamlining operations and cost reductions (Manyika et al., 2015). On the other hand, gathering information in digital form and subsequently analyzing data, improves management decisions and operational efficiency. For instance, real-time data on inventory and forecasts of demand, computed by predictive algorithms, help companies to decrease mismatches between the two and therefore mitigate both stock-outs and excess ordering. Advanced software allows for more realistic simulations and therefore helps designers or engineers to use less raw materials and to eventually arrive at a leaner production approach. All in all, the impacts of digitalization on these main areas are estimated to boost the annual gross domestic product (GDP) in the US by approximately USD 1.6 trillion to USD 2.2 trillion by 2025.¹⁵

2.4 THE DIGITAL DISRUPTION

The rapid digitalization of the business world causes turmoil. Traditional industry barriers are broken down, which results in lower barriers of entry for smaller businesses, such as start-ups, which are generally highly innovative and more flexible due to fewer legacy systems. Digitalization as a disruption has both the potential to create new business opportunities and the power to destroy long-successful business models (Weill and Woerner, 2015). In this new digital ecosystem, traditional firms, regardless of how well-established they are, may struggle to keep up. New forms

¹⁵McKinsey Global Institute analysis (see Manyika et al., 2015, p. 61).

of customer relationships and engagement allow innovative businesses to overtake markets (Downes and Nunes, 2013) and engage in unique and unexplored business opportunities (Loebbecke and Picot, 2015).

However, the digital era and its disruption is a double-edged sword. This means that companies that exploit the opportunities provided by digitalization thrive. Others that do not utilize new technologies fall behind. In a recent study, Bughin and van Zeebroeck (2017) investigate the magnitude of the digital disruption's impact on (1) companies, both traditional, that is typically less digitally mature ones, and new digital entrants as well as (2) industries. They find that incumbents¹⁶ experience a negative impact on profits due to the fierce competition caused by new entrants (see also McAfee and Brynjolfsson, 2008). In other words, digital entrants change the dynamic of markets. Bughin and van Zeebroeck (2017) estimate that new digital entrants take up to 20 percent of market shares. Moreover, new entrants do not only seize shares of revenue but also change customer behavior which puts additional pressure on traditional firms.¹⁷ Moreover, the threat of new entrants for incumbents is not only the loss of market share, it is also the head start new entrants have if their strategy appears to be successful. Incumbents then have to react timely and adequately. Additionally, Bughin and van Zeebroeck (2017) find evidence that companies that try to tap their full digital potential gain the most and their returns are higher compared to the average firm. While 90 percent of firms engage in digitalization efforts¹⁸, only a third of all companies try to conquer new markets which is one of the big opportunities digitalization has to offer. The two key areas firms have to focus on, are new customer segments and new markets. New customer segments arise from the use of a digital platform, or social media, in order to reach a new audience. New markets can be developed by selling differently. It is estimated that, on average, one third of firms' revenues are digitized globally. As their main finding, Bughin and van Zeebroeck (2017) note that, on a global scale, incumbents' revenue and EBIT growth is reduced by up to 30 and 25 percent, respectively, due to the effect of digital disruption. This revenue reduction for traditional firms mainly stems from two major effects. The first effect manifests itself in the very existence of new entrants.

¹⁶Companies that have been around for a longer period of time, in other words, established companies.

¹⁷For instance, the navigation service provided by Google Maps took over the market for stand-alone GPS makers in less than two years (Downes and Nunes, 2014).

¹⁸However, less than ten percent of respondents in the study state that their business processes and operations are digitized on a high level.

As mentioned above, digital entrants claim market shares. New entrants, however, do not only take over market shares aggressively, they also increase the size of the industry by an estimated 0.5 percent yearly. The change in market dynamics results in a new level of competitiveness and causes yet another change. Legacy companies engage in the competition against both new entrants and other legacy companies. Bughin and van Zeebroeck (2017) label this as some sort of *Red Queen*¹⁹ competition (see also Dutta et al., 2014). When a company launches a new digital innovation, others must respond in a similar manner which might result in an unintentional race for revenue-reducing moves.

The package-delivery market offers an illustration of this predicament. Over years the two major US parcel services, FedEx and UPS, were in close competition for the package-delivery market. As one of them introduced online parcel tracking, for instance, the other reacted quickly and did not only add a similar feature shortly afterward but also pushed other digital features in order to surpass the competitor. This led to higher spendings on IT than on transportation assets over time (Dutta et al., 2014). Normally, new value added by major investments are not realized instantaneously. Also, countermoves by competitors require some time during which the first-mover benefits. However, IT investments and new innovations increase the speed with which companies react to each others' moves. Therefore, it does not come as a surprise that organizations invest heavily in IT to reduce the delays in competitive responses (Dutta et al., 2014). This is what strategy literature labels *Red Queen* theory or competition. Similarly, in financial services, as mobile payments and mobile banking became more widespread, traditional banks had to react, by either reducing or eliminating fees.²⁰ Ultimately, both effects put pressure on incumbent firms' revenue and subsequently reduce margins (Bughin and van Zeebroeck, 2017). Analogously, there is a relation between the digital maturity of an industry and these effects mentioned above (McAfee and Brynjolfsson, 2008). They tend to be more severe for firms in highly digitalized sectors, particularly for companies that have not yet utilized their digital potential. In the high tech sector, for instance, the impact on revenue growth is four times the average compared to other sectors. However, in

¹⁹This is a reference to the famous sentence "it takes all the running you can do, to keep in the same place" in Lewis Carroll's (1871) *Through the Looking Glass*; closely related to the proverbial shark that needs to keep swimming in order to survive.

²⁰The reduction or elimination of fees of one bank forces other banks to react, otherwise, consumers might shift services. Needless to say, such actions are typically considered revenue-reducing moves.

manufacturing which is a less digital mature sector, the effect is attenuated to a mere 60 percent of the average (Bughin and van Zeebroeck, 2017).

Digitalization is a central catalyst when it comes to the unprecedented levels of competition next to other major factors that include higher M&A activities, more R&D investments and local markets that open up to global ones.²¹ More specifically, IT investments and, correspondingly, more powerful IT systems are major drivers for the new competitive dynamic (Yoo et al., 2012). This new dynamic results in a fiercer competition amongst organizations and an increasing gap between individual competitors, the leaders and laggards, in an industry. Ultimately, this ends in higher concentrated industries where leaders try to revamp business in order to stay on the top, whereas laggards are left behind. New technological innovations are at the core of new competitive dynamics (Haverkort and Zimmermann, 2017). In particular, digital products and especially digital internal processes are accelerating competition. For instance, a company that reinvents its business processes and comes up with something more unique and more efficient can easily implement this change in the entire organization with high accurateness. Enterprise software and cutting-edge networking technologies help to implement the new processes easily and independently of any physical restriction, such as a different geographical location. Thus, a valuable innovation which allows a company to perform better has the potential to dominate a sector. Direct competitors, in turn, try to roll out innovations also to pull ahead and gain market shares and thus the frequency of competitive moves and their responses is increased (McAfee and Brynjolfsson, 2008).

Dutta et al. (2014) deploy a sophisticated model in order to investigate the mechanics of competition with regard to digital systems and competitive responsiveness. In simple terms, they analyze the dynamic behavior with varying levels of investments in digital systems between companies. Their results indicate that digital innovations help to capture market share for both the innovative firms, the first-mover, and its competitors. Moreover, the first-mover may stay ahead of its competitors if the investments in digital systems are substantial and do not fall below a certain threshold.²² However, if the first-mover fails to stay above the threshold, it runs the risk of getting

²¹It is an ongoing dispute amongst researchers which of these shifts essentially drives the changes in competitive dynamics. For instance, researchers find contradictory results when it comes to the impact of R&D spending or M&A activities on competition changes (see Comin and Philippon, 2005; White, 2002; Cloudt et al., 2006). However, this assessment is beyond the scope of this thesis.

²²The results also depend on the level of customer sensitivity.

surpassed by a competitor if the competitor chooses to invest more in digital systems. The threshold to dethrone a competitor varies with the intensity of customer sensitivity in a certain sector. As a result, returns from new investments in digital systems are diminishing for firms (Dutta et al., 2014).

McAfee and Brynjolfsson (2008) identify a stronger link between technology advancements and an increased competition today, compared to the levels in the 1990s. Additionally, McAfee and Brynjolfsson (2008) find evidence that the increase in the quality and quantity of IT investments has a direct impact on industry concentration, turbulence in markets and performance spread.²³ As expected, their findings are the most pronounced in IT-intensive industries. Moreover, they contend that these alterations in competitive dynamics are not yet completed as they are an on-going process of organizations fostering and propagating process innovations.

2.5 DIGITAL TRANSFORMATION - A NEW DIGITAL FUTURE

Digital technologies encompass data analytics, big data, social media, cloud computing and smart devices amongst other things. Traditional firms are slowly starting to transform their business due to several reasons. Generally speaking, a transformation alters conventional ways of doing business fundamentally Dehning et al. (2003). For the digital transformation, two main concepts act as a watershed. On the one hand, firms acknowledge the potential of new technologies which have the power to redefine operational processes and business models (Yoo et al., 2010; Schwab, 2017). However, it is not as simple as implementing a new technology that drives technological progression, it is the attentive and smart selection of advanced systems that help to redefine functions and push the boundaries of the firm (Westerman et al., 2011). On the other hand, firms feel the pressure from customers and competitors alike (Fitzgerald et al., 2013). For customers, social media and online services are increasing in importance ever since. If a company fails to satisfy customers' needs, it might face severe limitations for a successful future. Also, a new digital comparative forces firms to either keep up with new techniques and processes or to face competitive obsolescence (Fitzgerald et al., 2013). In addition, organizations are starting to understand the power of data which is the fuel for data analytics.

²³They find some correlations between M&A activity, R&D, globalization and the change of competitive dynamics, however, they argue that none of them were superior to their measures.

2.5.1 DATA ANALYTICS

Analytics is changing the way companies can transform insight into action. New technologies allow companies to think ahead, i.e. use information gathered to improve forecasting. Knowing what happened and for what reasons is no longer sufficient. Organizations need to be kept informed about what is happening at the moment and what is likely to happen in the near future. These insights are superior to traditional measures and metrics since they allow organizations to react timely and adequately whenever necessary (LaValle et al., 2011). Traditional decision support tools and business intelligence are superseded by technical innovations and advancements in big data analytics. Typically, big data analytics refers to the “focus on very large, unstructured and fast-moving data” (Davenport, 2014, p. 10). Sophisticated algorithms, artificial intelligence and cognitive computing capabilities which improve digital services and products, are dependent on big data analytics.

More precisely, digital transformation manifests itself in two key areas. The first is the increase in computational power and big data which provide the basis for computer modeling, forecasting and artificial intelligence, amongst others (Zammuto et al., 2007). In short, the implementation of innovative digital solutions that allow companies to operate in a digital ecosystem. The second is the more in-depth insight into human reasoning and judgment. Organizations have the desire to know more about customers and customer behavior in general. Digitalization efforts typically revolve around the integration of these two streams (Weill and Woerner, 2015; Schoemaker and Tetlock, 2017).

In order to assess the impact of advanced analytics, LaValle et al. (2011) conducted a global survey in collaboration with the IBM Institute for Business Value. According to their findings, the extensive use of information and its interpretation with analytics, increases firm performance. Top-performing companies use, on average, five times more analytics than lower performers. Organizations want more insight, at a faster pace and try to enhance their analytics approaches. Data management with strong abilities to capture, store, aggregate and analyze data separates organizations and acts as a differentiator. Managerial decision-making is not anymore only supplemented by but based on data-driven decisions. Optimal solutions to a variety of scenarios are calculated by computers through simulations, mathematical optimization and choice modeling. LaValle et al. (2011) find that top performers rely more heavily and more often on business information and analytics. In other words, there is a clear trend to

rely on analytics rather than intuition. A common struggle companies face, however, is to find an adequate way to analyze the sheer amount of data. According to the study, the main issue is the lack of understanding how to make use of analytics. This supports findings that adoption barriers are mostly managerial (LaValle et al., 2011; Kane et al., 2015; Schoemaker and Tetlock, 2017).

Another aspect is the amount of data available today which is ever increasing. Companies actively collect and mine data from a multitude of internal and external sources.²⁴ Similarly, the cost of processing and storing data, even on a massive scale, is negligibly low. These effects allow companies to deploy machine-based readouts and with the help of appropriate software, the interpretation of data in order to enhance decision-making (Loebbecke and Picot, 2015). With a sheer abundance of data and more sophisticated technical advancements in data analytics, organizations rely more heavily on data-driven managerial decision-making. Furthermore, Loebbecke and Picot (2015) argue that digitalization is still reducing marginal costs and leads to positive economies of scale²⁵ which favors a more centralized production approach.

Ultimately, the goal is to optimize business processes, to increase efficiency and to enhance product quality as well as service quality powered by cutting-edge ICT systems (Loebbecke and Picot, 2015; Majchrzak and Malhotra, 2013; Spanos et al., 2002). Big data analytics and data abundance allow firms to predict the present and to improve their forecast for the future based on information stored in the data. Firms that sell to a broad variety of customers, such as retailers, use big data analytics in order to analyze buyer behavior. On the one hand, this allows firms to target certain customers directly through customized advertisements. On the other hand, discovering what customers usually buy together, or if a special event comes up, allows firms to adjust their stock accordingly. For instance, Walmart, a US retailer, uses data from both weather and inventory stock in order to predict future sales. By analyzing shopper history inside Walmart's computer network, the company starts predicting sales before they are going to happen (Hays, 2004). Both uses of customer behavior analyses eventually increase sales and reduce mishaps caused by miscalculations.

²⁴For instance, Google Trends, a publicly available report service provided by Google, shows the volume of any search phrase listed ranked according to general search interest and based on regional importance. Most search queries are an indication of a person's interest which can be exploited by data analytics.

²⁵Independent of the digital good, whether it be for entertainment (music or film) or business solutions (software or application), in short, intangible goods, can after completion be distributed globally with minimal marginal costs.

Moreover, big data analytics does not have to stop at the customer side. Processes spanning over the entire supply chain can be stored and analyzed by computer models. The ultimate goal for firms is twofold: to increase efficiency at all levels through optimization and leaner operations and to use data in order to forecast and drive the business (Hays, 2004).

2.5.2 COMPUTER SIMULATIONS

Advanced computer models have the capability to run simulations and to conduct what-if scenarios. Companies use dashboards that show data from business operations in real time. In this way, users can act early and resolve problems when performance indicators suggest that there may be a problem. For manufacturing companies with multiple steps, this helps to avoid situations where later steps in the production line may be affected. The full potential of using data unravels when it is being used for simulations and forecasts. Algorithms and the use of artificial intelligence make it possible to identify patterns in data. Findings are then projected in order to predict buying behavior, supplier relationships, and competitor as well as industry-level behavior. What-if analyses allow firms to detach real figures and replace them with alternative actions to observe changes (Zammuto et al., 2007). This allows firms to discover new possibilities such as alternative actions, to reduce uncertainty and to push into new directions. For instance, a manufacturer can run a simulation of what happens to supplier availability if it decides to change certain parts or materials in an assembly process. In short, simulations augment organizational and managerial decision-making (Zammuto et al., 2007).

2.5.3 CLOUD COMPUTING

Another topic which is part of the digital transformation is cloud computing. Callewaert et al. (2009) state that using external computing power introduces unprecedented opportunities for organizations that heavily rely on the aforementioned computing power. The characteristics of cloud computing are as follows. First, since the cloud primarily is an internet-based service provider that organizations can subscribe to, it is immediately scalable for an individual company. If a company wants to store a significantly larger amount of data, it can simply increase the storage provided by the cloud with minimal time delay. Additional capacities are at the ready if the company wants more storage. Second, due to their high degree of abstraction, cloud services

are pay-as-you-go. This improves cost-effectiveness for organizations since they only pay for services used. If an organization wants to run less analytics, it can offload unused capacity quickly. Third, in case that an organization wants to use additional analytics, its own infrastructure which is physical hardware is no longer limiting the computational power that an organization has access to. This means that companies are more flexible with regard to cloud services. More specifically, unexpected events no longer push organizations to their limits since they can easily scale up or down their cloud usage (Callewaert et al., 2009).

2.5.4 DIGITAL PLATFORMS

Digital platforms²⁶ are a sublime example for making new markets accessible for firms and targeting selective customers with the help from insights through data analytics (Tiwana et al., 2010). For instance, Danske Bank, a Danish bank, revamped its online presence with an e-banking platform a couple of years ago which led to beneficial relationships with customers. As a result, nearly two out of three customers use the online service for bank transactions (Weill and Woerner, 2018). For retailers, algorithm controlled recommendations of related products bring new products to customers' attention. Technically speaking, the recommendation list is put together based on previously gathered data generated by the digital trails of customers and ultimately plotted as customer choice patterns. The more the company knows about the customer (based on the customer's search history and past purchases), the more accurate and relevant the recommended product list will be (Oestreicher-Singer et al., 2017). However, Oestreicher-Singer et al. (2017) also argue that a company's promotion of its products might as well benefit their competitors due to the digital network's demand spillovers. It is difficult to anticipate the network structure effects for an individual company.

Yet another interesting insight is the recommendation network's guidance when it comes to products purchased together by customers. Companies might realize that there is a product offered by a competitor that is often bought together with their own product, and thus recommendations reveal demand characteristics. This could help companies upgrade their products or plan entirely new ones (Oestreicher-Singer et al., 2017). Numerically speaking, research conducted by the McKinsey Global In-

²⁶This can be either a firm's own web presence, other online services or the listing on retail websites etc.

stitute (MGI, 2015) estimates that online platforms might add nearly USD 500 billion to the GDP by 2025 in the US.

Moreover, new developments such as crowdsourcing²⁷ are surfacing. For instance, General Electric, a US energy giant, launched a sustainability challenge where outsiders were asked to suggest a solution to the issue at hand. In the wake of this project General Electric acquired a small firm and thus unconventionally added new business intelligence. Essentially, crowdsourcing is a means for companies to ask customers what they should add to or improve in existing products. Firms benefit from an outpour of ideas and creativity, however, often suggestions are not feasible or implementable in the end (Majchrzak and Malhotra, 2013).

2.5.5 DIGITAL TRANSFORMATION DRAWBACKS

The above-mentioned features and advantages paint a very optimistic picture of the digital future. Yet, there are obstacles to circumvent for organizations and pitfalls to take into consideration. Using digital technologies is only one part of going digital. If a company does not know how to interpret data or what it is looking for in specific, data and analytics will not have a significant impact. Especially physical industries require a sophisticated digital business strategy in order to adapt (Bharadwaj et al., 2013). Kane et al. (2015) argue that the greatest difference between digitally mature and less mature companies comes from strategy, culture and the company's vision of a more digital future. Essentially, companies which are willing to use digital transformation and adjust the business accordingly are amongst the leaders in their industry. The systematical integration of computational power and the understanding of human judgment, or the human mind, lead to substantial competitive advantages (Schoemaker and Tetlock, 2017). Most companies want to use digital technologies, but only some of them know how to use them to their advantage.

Kane et al. (2015) state that a firm's organizational culture is crucial for the implementation of digital technologies. This is also one factor why smaller businesses potentially profit more from digital innovations because they are less restricted with a leaner organizational structure. Additionally, smaller and fast growing enterprises can build their infrastructure with advanced ICT in mind, whereas established companies

²⁷Crowdsourcing is defined as an online activity in which individuals or institutions can participate in order to arrive at a solution for a task presented by generally another organization. In other words, it is the process of an open announcement that invites outsiders to participate in a task (Estellés-Arolas and de Guevara, 2012; Gassmann et al., 2014).

have to deal with legacy systems and overlapping IT infrastructure. Centralized and standardized systems increase agility in processes across the firm. The core platform used throughout the organization, processes integrated data and increases efficiency. Local variations of the standard platform can then be created for single divisions. If a firm fails to standardize digital processes, one result might be messy data and entails higher long-term costs (Westerman and Bonnet, 2015).

According to Westerman (2017), the true value of technological innovations does not come from data analytics and more advanced algorithms, but from doing business differently. At its core, digitalization allows companies to understand internal processes and customers better. Although there is a necessity to engage in digitalization (Schwab, 2017) or digital transformation, not all companies have embraced becoming digital as part of a new corporate strategy. In a global survey of executives and managers, conducted in 2015 by the MIT Sloan Management Review, the vast majority (almost nine out of ten) of respondents agreed to the statement that digital innovations and digital transformations will shape their industries to a moderate or great extent. However, 56 percent of the respondents stated that their company is not properly prepared for a possible digital disruption (Kane et al., 2016).

2.6 DIGITAL MATURITY AND FIRM PERFORMANCE

In general, new digital technologies gain ground quickly and change the economic landscape. Innovations put forth by small and fast moving innovative companies take over industries and reshape how business is conducted. Traditional companies which are typically more inflexible are faced with rapidly moving digital technologies that permeate industry standards. Digital innovations offer new opportunities, however, only a few companies capture the real benefits. The digital innovation level and affinity of companies can be captured in a metric: digital maturity.

Kane et al. (2016) argue that digital maturity in different organizations stems from common features. Specifically, they identify the following features which drive digital maturity. First, digitally advanced organizations have a higher risk tolerance. They accept a certain level of risk which, logically, is attached to the implementation of new technologies. Second, more digital mature organizations are willing to experiment which is closely linked to the higher risk tolerance. Rolling out new technology is cumbersome and might disrupt day to day business at first. Third, digitally maturing

organizations invest heavily in the recruitment of talents and leaders with transformative visions. Those key employees help to shape a digital culture in the organization. It is important that digital innovations, organizational culture, and employees of an organization are in sync.

Bughin et al. (2017) argue that a company's future success in a more digital environment can be partially derived early on in its transformation journey by analyzing its digital intelligence. Digital intelligence²⁸ is one of the key drivers to a successful digital transformation, besides, clear digital vision and adequate technology improvements, as previously mentioned (Kane et al., 2015). Furthermore, Bughin et al. (2017) find that digital intelligence is positively correlated with financial performance. In detail, a higher score of digital intelligence has a positive impact on revenue, EBIT, and company growth after controlling for industry, company size, and location. Their results are statistically significant and the correlation holds in various industries, i.a. business services, manufacturing, and high-tech. Moreover, they find that (1) digital intelligence scores are the highest for digitally savvy firms and (2) the effect of the four dimensions (and their sub-dimensions) on digital intelligence is approximately the same, meaning the individual dimensions carry roughly the equal weight. Interestingly, the individual scores of the four dimensions are very consistent with the group ranking. In other words, digital leaders have higher scores across all dimensions compared to the average group and the same holds for the average group and laggards.

2.6.1 DIGITAL MATURITY: A FRAMEWORK

The following is a framework put forth by the Massachusetts Institute of Technology Center for Digital Business (Westerman et al., 2011). According to this report, digital maturity can be seen as a combination of two dimensions. On the one hand, digital innovations which incorporate technology initiatives, new internal processes, and business models. This is captured by *digital intensity* (DI): processes and new technologies that change how the company operates. On the other hand, company-wide transformations which incorporate leadership changes, new visions, and the mission to drive digital transformation. This is captured by *trans-*

²⁸In their study, Bughin et al. (2017) use the following four dimensions to assess digital intelligence: strategy, culture, organization and capabilities. The capability dimension encompasses the IT architecture, whereas the first three describe the digital strategy and management practices. They obtain the scores by interviewing 250 firms around the globe.

formation management intensity (TMI): IT-business relationships and governance that change the vision of the firm’s future. Figure 1 shows the proposed categorization of digital maturity. DI and TMI are divided into two sections that reflect a company’s progression level (Westerman et al., 2011). Companies with little digital capabilities, that is, low DI and TMI levels are labeled as Beginners.

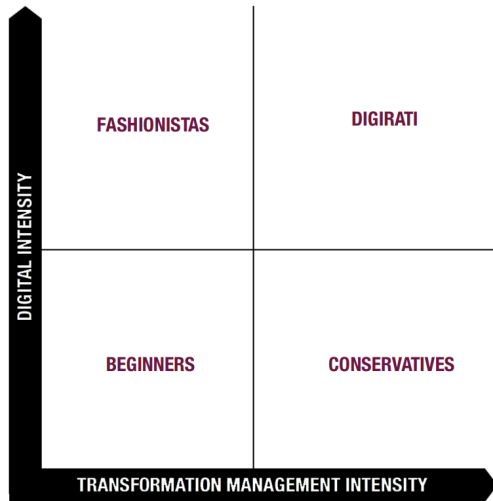


Figure 1: The DI and TMI framework and the corresponding categories (Westerman et al., 2012, p. 4.).

Beginners are either firms that are getting started or firms that are unaware of digital change and its advantages. Firms that implement new digital solutions, have a willingness to experiment, and strive for a digitally powered change, that is, high DI and low TMI are categorized as Fashionistas. These firms use a brute force approach to become digital leaders. However, they often miss the crucial step of implementing proper governance internally, which dampens the outcome of digital innovations because digital efforts cannot be utilized optimally. Digital Conservatives are companies that value slow but steady progress over a fast digital overhaul, that is, low DI and high TMI. These firms emphasize corporate culture and good management, and they have a more skeptical outlook when it comes to digital innovations. Firms with high DI and high TMI are classified as Digirati. Companies of this type are believed to fully understand how to utilize digital innovations and the implementation of such innovations. They excel at driving value through digital transformation. They balance vision and engagement optimally, invest in upcoming technologies, and develop an adequate digital culture. In general, companies at the digital frontier encompass characteristics such as a high speed of innovation, automation of tasks, openness to experimentation, and the creation of digital assets (Manyika et al., 2015). The balanced coordination of both, technologies that increase digital intensity and a digital road map that outlines firms’ digital future, further strengthens their digital competitive advantage (Westerman and McAfee, 2012).

2.6.2 DIGITAL MATURITY EFFECTS ON FIRM PERFORMANCE

The study conducted by Westerman et al. (2012) sheds light on the relationship between digital maturity (inside the DI and TMI framework) and financial performance. 184 publicly traded companies were analyzed in order to establish a connection between digital maturity and financial performance.

In short, they find that firms, which are either high DI or high TMI, are outperforming firms which are neither high DI nor high TMI. Subsequently, firms categorized as Digirati have the highest performance, leaving not only Beginners behind but also firms that have only either high DI or high TMI. The authors compare financial figures such as revenue generation, profitability, and market valuation.

They find that firms with either high DI, high TMI or both, derive more revenue from physical assets measured by fixed asset turnover and revenue/ employee multiple. Figure 2 illustrates the individual digital maturity levels for firms in the study within the DI and TMI framework. Digirati have, on average, a nine percent higher revenue

Figure 2: Scatter plot of 184 publicly traded firms and their corresponding digital maturity levels. The comparison value is the revenue generating abilities of these firms. High digital intensity is an indicator that firms generate revenue more efficiently (Westerman et al., 2012, p. 7.).

Companies with stronger digital intensity derive more revenue from their physical assets

Basket of indicators:

- Revenue / Employee
- Fixed Assets Turnover (Revenue / Property, Plant & Equipment)



generation compared to the average firm. The researchers argue that these firms have the ability to manage more volume with the same physical capacity. It appears that more advanced technologies, such as tracking demand in real time, help to utilize physical assets more optimally. The allocation of human and physical assets is also

improved. When it comes to profitability, firms with low TMI, regardless of DI levels are worse off compared to firms that have high TMI levels. Therefore, firms with higher TMI are more profitable. Digirati and Digital Conservatives are, on average, 26 and 9 percent, respectively, more profitable compared to the average firm. The researchers argue that a clear vision of the new digital future aligns investments. Moreover, firms with high TMI levels have a higher market valuation (measured as PtB ratio) compared to firms that do not. In general, firms that are more mature on either the DI or TMI dimension are outperforming (Westerman et al., 2011). In short, there is a pronounced gap between digital leaders and organizations that lack digital maturity, which leads to a growing opportunity cost for the latter. The results of the study are clear, however, they must be treated with some reservation since not every industry is affected equally.

In a study conducted by Bughin et al. (2017), firms' digital intelligence is mapped on a 100-point scale. Subsequently, they categorize firms into three groups with regard to their digital intelligence scores, namely, digital leaders (score of 41 and above), average firms (score between 25 and 40) and laggards (score below 25). In their study, the average firm achieves a score of 34. Their findings are as follows. First, firms in the top group, the digital leaders, are capable of repelling the digital pressure and using digitalization to their advantage. Their scores are highly correlated with margin growth and revenue. Second, firms labeled as average do neither profit nor experience negative growth. This group also represents the majority of companies with around 60 percent. Bughin et al. (2017) state that these companies neither benefit from digitalization, nor are they affected by the digital disruption. Third, laggards underperform and are faced with shrinking revenue and negative growth profiles (see also Fitzgerald et al., 2013). Moreover, Weill and Woerner (2015), in a recent study for the MIT Center for Information Systems Research, find that firms with a profound engagement in digital ecosystems outperform their industry peers. Numerically, companies with at least 50 percent of their revenue from a digital ecosystem, outperform competitors by 32 percent in revenue growth and by a 27 percent increase in profit margins.²⁹

Digital transformation is not affecting all industries at the same pace. On the one hand, some industries were hit early due to the arising digital competition. The music industry, for instance, adopted early to new digital concepts which emerged as new

²⁹Similarly, in a study of the announcements of IT investments, Dehning et al. (2003) find positive, abnormal returns related to said announcements. They continue and argue that new IT investments are more likely than not able to produce out of the ordinary returns.

threats to traditional business strategies. On the other hand, some industries have yet to be affected by severe digital transformation. An example would be manufacturing which is an industry that traditionally reacts slowly to new changes. Other industries such as the insurance or retail sectors are somewhat in the middle. Generally speaking, industries that have a tight regulatory environment, risk-averse culture and complex organizational structures, suffer limitations with regard to advanced technological innovations (Westerman et al., 2011).

In conclusion, the general understanding of digitalization's effect on firm performance is threefold. First, higher levels of digitalization normally benefit companies when it comes to profitability and imposes a competitive edge across the board. Second, the speed of digitalization is uneven and thus, companies that are ahead of their peers, reap disproportionate benefits. Third, for certain sectors, there is a development towards a winner-take-all dynamic which is a severe threat to companies that fall behind (Fitzgerald et al., 2013; Bughin et al., 2017).

3 | Methodology and Data

THIS CHAPTER AIMS TO PRESENT THE TOOLS used in order to qualitatively explore the effects of digitalization on firm performance. To begin with, this chapter gives a distinct overview of the composition of the digital maturity proxy. Next, it presents the summary statistics for the firm data used. Additionally, it illustrates the empirical models that are deployed for the empirical testing process. The model description section itself is split into two stages. The first part introduces the portfolio analysis which looks into the effects of digitalization on stock performance. The second part presents the regression analysis approach which aims to answer the question, whether digital maturity has a profound impact on subsequent operating performance.

3.1 THE DIGITAL MATURITY MEASURE

In my attempt to investigate the effect of different levels of digitalization, that is digital maturity, on firm performance, a proxy needs to be found to adequately model digital maturity. Since digital maturity is not a single metric that simply can be looked up, such as the unemployment rate or the number of patents granted for a company, it must be constructed manually. However, there is no real consensus as to what digitalization and digital maturity encompass. Moreover, information about a company can be gathered either by an outside view or through a survey, e.g. a questionnaire.

For my analysis, I use a measure created by von Blixen-Finecke et al. (2017) for the digital maturity levels. In their study, von Blixen-Finecke et al. (2017) measure degrees of digital maturity in six dimensions, namely, digital marketing, digital product experience, electronic commerce (E-commerce), electronic customer relationship management (E-CRM), mobile and social media.

In more detail, digital marketing assesses a firm's ability to utilize search engine marketing and advertising in order to reach customers. Digital product experience evaluates a firm's online presence which includes functionality and content. E-commerce captures a firm's capability to sell products via digital channels and additionally looks into the purchasing processes. E-CRM encompasses a firm's skill to enhance customer relationships within digital channels, such as unique personalization for customers and customer engagement. The mobile category assesses a firm's ability to utilize mobile channels, which are mobile sites and mobile applications. Social media, finally, evaluates a firm's engagement on social media platforms, such as Facebook or Twitter (von Blixen-Finecke et al., 2017).

According to MIT Center for Digital Business, the key areas transformed as result of digital innovations in organizations are the following: business model, operational process and customer experience (Westerman et al., 2011). The first building block, the business model, includes product augmentation, transitioning from physical to digital, and new digital business such as digital products. These digital modifications elevate the organizational boundaries and pave the way for digital globalization with shared digital services. Digital products are often supplementing the previously offered products by a company. Going digital also means offering mobile apps as a substitute for a company's internet website (Tiwana et al., 2010; Westerman et al., 2011).

The second building block encompasses operational processes which include process digitalization such as new analytics that improve performance, knowledge sharing and faster communication, and an increase in operational transparency. In short, the performance management is streamlined. With new digital innovations, such as self-service systems, automation does not stop at production but can be extended to tasks and processes where human interaction was previously involved but is no longer required. The digital transformation also affects performance management at its core. By measuring and storing an increased amount for data, performance transparency and the level of detail shown by analytics are increasing. Managers can rely on real figures often close to real-time and can compare key figures across sites. Powerful analysis tools, which turn information stored in data into insights, can help organizations to gain a strategic advantage (Westerman et al., 2011; Weill and Woerner, 2018).

The last building block is customer experience. Digital transformation is capable of enhancing and deepening the experience for customers. Whereas transformed operational processes are mostly internal processes that are invisible for third parties,

changing the customer experience is more visible. For organizations, it is important to better understand their customers. Customer demographics can be analyzed in-depth in order to improve customer processes, marketing, and digital sales. Organizations can launch social media campaigns to promote a new product and to target a very specific audience. Moreover, touch points with customers, such as customer services, need to be updated. This might include building an online community where customers stay connected with each other and share their experience with the product.³⁰ Creating touch points with customers strengthens and extends the brand. Moreover, organizations invest heavily in analytics in order to gain additional knowledge about their customers. Through customer analytics, companies can offer customized products and personalize customer service (Westerman et al., 2011).

All in all, the measure for digital maturity is constructed as follows (von Blixen-Finecke et al., 2017).

$$DM_i = 0,2DIM_i + 0,2DPE_i + 0,2EC_i + 0,15CRM_i + 0,15MO_i + 0,1SM_i, \quad (1)$$

where DM_i is the final value for digital maturity for firm i and where DIM_i is the value for digital marketing, DPE_i is the value for digital product experience, EC_i is the value for e-commerce, CRM_i is the value for e-customer relationship management, MO_i is the value for mobile and SM_i is the value for social media for firm i , respectively.

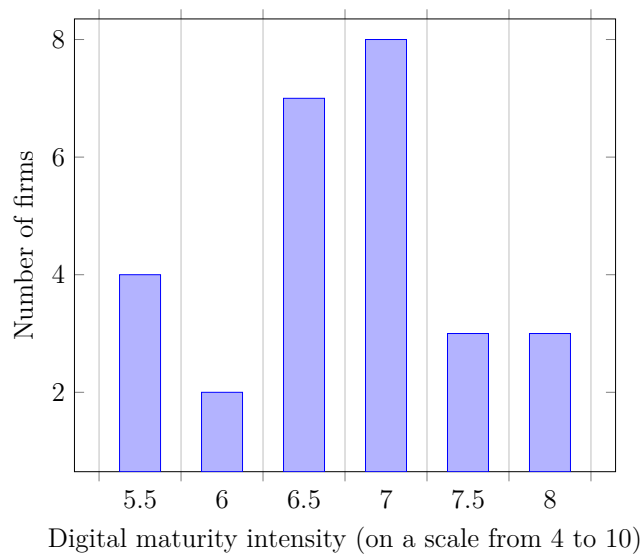
I can be fairly confident that with the key areas outlined by the MIT Center for Digital Business and the measures put forth by von Blixen-Finecke et al. (2017), I am able to classify companies according to their digital maturity adequately. The weighting is to some extent discretionary, but overall it should reflect digital maturity adequately as it touches upon at least two of the three major building blocks suggested by the MIT Center for Digital Business for digitalization. Admittedly, the proxy rather heavily reflects companies relationships with customers and, arguably, neglects internal processes, such as big data analytics. However, I believe, given the complexity of digitalization and its impact on virtually all different business practices, it is suitable to use in my analysis.³¹ The digital maturity (DM) measure is evaluated

³⁰Major car manufacturing companies, such as Mercedes Benz or BMW, have a very active presence on Facebook where they engage with customers, potential customers and fans alike. The car manufacturers regularly display pictures of their cars taken and shared by owners.

³¹To my knowledge, there are no metrics available that capture all facets of the digital transformation. Especially the transformation of internal processes of a company still remains a black box

and adjusted annually for each firm in the sample period (von Blixen-Finecke et al., 2017). Therefore, changes in the levels of digitalization over time are incorporated. Figure 3 shows the distribution of the individual firms' average digital maturity values in the sample. There are substantial differences in the digital maturity levels, which is convenient for the ranking and exploitation for the analysis.

Figure 3: Overview of the average individual digital maturity values for each firm in the sample.



The values for DM go as low as 5.5 for the least digital mature firms and as high as 8.0 for the digital leaders. The DM values for most firms are between 6.5 and 7.0. The median is 6.5 and firms categorized as laggards have an average DM value of 5.6. On the other hand, the digital leaders are firms with an average DM of 7.3.³² Overall and with regard to the scaling from four to ten, it is obvious that the sample distribution of firm digitalization levels are slightly skewed to the left.

for most outsiders.

³²An in-depth categorization of firms according to their DM rank follows in the Model Description section (see chapter 3.3).

3.2 SUMMARY STATISTICS

I gather publicly available yearly firm data and monthly stock returns for Swedish companies from Thomson Reuters Datastream. The measure for DM is taken from von Blixen-Finecke et al. (2017) and Statista. Table 1 reports the summary statistics for the firms in the sample. The sample consists of 24 Swedish firms which are listed on the NASDAQ OMX Nordic (both large and mid cap). The time period is from

Table 1: Sample data description.

<i>Variable</i>	<i>Median</i>	<i>SD</i>
Return on Assets	5.04	5.57
Cash flow to Sales	11.2	14.77
Digital maturity score	6.50	0.72
Total assets	7 566	180 242
Capital Expenditure	258	441
Market value	7 026	12 966
Operating Profit Margin	11.37	9.91

The sample period is 2010-2016.

Data source: Datastream. Return on assets, cash flow to sales, and operating profit margin are reported in percent. Total assets, CapEx and market value are reported in MUSD.

the beginning of 2010 until the end of 2016, totaling 168 observations.³³ The firms are predominantly from the following sectors: communication, consumer, financial services, industrial, retail, technology, and autos.

Table 2 shows the Spearman and Pearson correlation coefficients between digital maturity and various firm characteristics of interest in the analysis, such as ROA or $\ln(TA)$. Strikingly, the association between the DM measure and ROA is slightly negative. In detail, the correlation's magnitude is negative 0.172 and negative 0.119, for the Spearman correlation and the Pearson correlation, respectively. The correlation, however, is only significant for the Spearman correlation coefficient and the

³³The data for stock returns is differing (time period from January 2013 to December 2016).

Table 2: Pearson and Spearman correlation coefficients of DM and firm characteristics.

Spearman (below-diagonal) and Pearson (above-diagonal) correlation coefficients						
	<i>DM</i>	<i>ROA</i>	ΔROA	<i>CFS</i>	$\ln(TA)$	$\ln(MV)$
<i>DM</i>		-0.119	-0.115	-0.188 [∅]	-0.142 [∅]	-0.050
<i>ROA</i>	-0.172 [∅]		0.396 [∅]	0.034	0.091	0.221 [∅]
ΔROA	0.017	0.114		0.071	0.011	-0.070
<i>CFS</i>	-0.276 [∅]	0.124	0.169 [∅]		0.231 [∅]	0.118
$\ln(TA)$	-0.238 [∅]	0.183 [∅]	-0.092	0.270 [∅]		0.262 [∅]
$\ln(MV)$	-0.229 [∅]	0.101	-0.078	0.283 [∅]	0.882 [∅]	

This table reports the correlation coefficients for following variables. *DM* denotes the firm’s digital maturity value, *ROA* the return of assets at time t , ΔROA the change in return of assets from $t - 1$ to t , *CFS* denotes cash flow to sales, $\ln(TA)$ is the logarithm of the firm’s total assets and $\ln(MV)$ is the logarithm of the firm’s market value. [∅] denotes correlation coefficients that are significant at the 0.1 level.

magnitude is far from being clear without ambiguity. Furthermore, the correlation coefficients between operating performance, or *ROA*, and firm size measured in total assets $\ln(TA)$ and market value $\ln(MV)$ are positive for both the Spearman and Pearson correlation. As expected, the association between total assets and market value is positive and of a high magnitude, especially for the Spearman correlation coefficient with 0.882.

3.3 MODEL DESCRIPTION

3.3.1 PORTFOLIO ANALYSIS

I construct six portfolios in order to analyze whether or not digitally mature companies are outperforming peers in the stock market.

I construct the portfolios as follows.

$$\mu_{PF} = \sum_{i=1}^n x_i \mu_i \quad (2)$$

where μ_{PF} is the return for the portfolio *PF*, μ_i is the return of security i , x_i is the portfolio weight of security i in portfolio *PF*. The portfolio return is, thus, the

weighted average security return. The weighting is based on the market capitalization in year t , which yields two size groups³⁴, the small (S) and big (B) portfolios. In the next step, I sort the companies according to their DM rank and categorize each into one of three groups, based on the 30th and 70th percentiles of the corresponding DM rank. Based on their DM rank, these portfolios subsequently are labeled low (L), middle (M) and high (H). Therefore, six size- DM portfolios are formed through the intersections: BH , BM , BL , SH , SM and SL . Following Hirshleifer et al. (2013), I hold these portfolios over a period of twelve consecutive months and compute the monthly size-adjusted returns of the *low*, *middle* and *high* DM portfolios using the following formulas.

$$\frac{(S/L + B/L)}{2} \quad (3)$$

$$\frac{(S/M + B/M)}{2} \quad (4)$$

$$\frac{(S/H + B/H)}{2} \quad (5)$$

where S , B stand for small and big portfolios, respectively, and L , M and H indicate low, middle and high levels of digital maturity, respectively. In order to calculate the monthly excess returns³⁵ of the size-adjusted portfolio returns, I use the Swedish one-month treasury bill rate for the corresponding months.³⁶

Additionally, I use the Sharpe (1966) ratio in order to analyze whether there are significant differences in risk-adjusted portfolio performance between different levels of digital maturity. This ratio measures the average excess returns of a portfolio relative to its volatility. This is naturally interesting since the ratio answers the question whether the risk-return relationship is adequate (Cochrane, 2000).

The Sharpe (1966) ratio is defined as follows.

$$SR_{PF} = \frac{E[R_{PF}] - R_f}{\sigma_{PF}} \quad (6)$$

³⁴Contrarily to Hirshleifer et al. (2013) who sort firms into size groups based on the NYSE median breakpoint, I have to adjust the size breakpoint to the sample differently otherwise, and due to the limited sample size, there would have been a disbalance in favor for large firms.

³⁵Excess does not connote that the returns are bound to be positive.

³⁶I retrieve the Swedish one-month treasury bill rates directly from the official website of the Swedish central bank (Riksbank, 2018).

where SR_{PF} is the Sharpe ratio for portfolio PF , $E[R_{PF}]$ is the average return of portfolio PF , R_f is the risk free rate and σ_{PF} is the standard deviation of portfolio PF . In order to ascertain that the Sharpe ratio results are robust and meaningful for a comparison, I determine the significance of the ratios. Hence, I deploy a significance test suggested by Jobson and Korkie (1981) and amended by Memmel (2003). The hypothesis for testing for equality is as follows.

$$H_0 = SR_i - SR_j = 0 \quad (7)$$

where the null hypothesis H_0 states that the Sharpe ratios SR_i and SR_j are equal and thus, do not differ from each other, statistically speaking.

For the hypothesis test, I compute the following z test statistic.³⁷

$$z = \frac{\widehat{SR}_{ij}}{\sqrt{\hat{v}}} \sim N(0, 1) \quad (8)$$

3.3.2 RISK FACTOR MODELS

Moreover, I use the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model to analyze whether the size-adjusted returns of the DM portfolios are captured by risk factor models.

The Fama and French (1993) three-factor model looks as follows.

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t + \eta_{i,t} \quad (9)$$

where $R_{i,t}$ is the return of portfolio i at time t , $R_{f,t}$ is the risk free rate at time t , $R_{m,t}$ is the return of the market portfolio at time t ³⁸, SMB_t is the *small minus big* factor (small minus large firms) at time t and HML_t is the *high minus low* factor (high book-to-market minus low book-to-market stocks) at time t .

As for the second risk model, Carhart (1997) proposes the following four-factor model which is an extension of the Fama and French (1993) three-factor model.³⁹

³⁷See Appendix A for more details about the significance test.

³⁸This factor, $(R_{m,t} - R_{f,t})$, is oftentimes labeled as MKT .

³⁹Findings by Jegadeesh and Titman (1993) suggest that past year ‘winners’ outperform compared to past year ‘losers’ and this momentum factor should also be included in the risk model.

The Carhart (1997) four-factor model is specified as follows.

$$\begin{aligned}
R_{i,t} - R_{f,t} = & \alpha_{i,t} + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb}SMB_t \\
& + \beta_{i,hml}HML_t + \underbrace{\beta_{i,mom}MOM_t}_{\text{Added momentum factor}} + \eta_{i,t}
\end{aligned} \tag{10}$$

where $R_{i,t}$ is the return of portfolio i at time t , $R_{f,t}$ is the risk free rate at time t , $R_{m,t}$ is the return of the market portfolio at time t , SMB_t is the *small minus big* factor (small minus large firms) at time t , HML_t is the *high minus low* factor (high book-to-market minus low book-to-market stocks) at time t and MOM_t is the *momentum* factor (high minus low momentum return on portfolios) at time t . In this four-factor model, the α is an estimate of net returns earned by the portfolio after adjusting for risk.

3.3.3 PANEL DATA REGRESSION

To examine the relation of digital maturity with operating performance more thoroughly, I use cross-sectional time-series data and deploy dynamic panel data regressions.⁴⁰ In general, a panel data regression can be distinguished from both, time-series or cross-section regressions, by a double subscript on its variables. Furthermore, dynamic panel data models differ from standard panel data models by the presence of a lagged dependent variable which indicates the dynamic relationship.

The general form of dynamic panel data models looks as follows (see Baltagi, 2005), in equation form:

$$\begin{aligned}
Y_{i,t} = \gamma Y_{i,t-1} + X_{1i,t}\beta_1 + \cdots + X_{Ki,t}\beta_K + \eta_{i,t} \quad \text{with } i = 1, \dots, N; \\
t = 1, \dots, T
\end{aligned} \tag{11}$$

where $Y_{i,t}$ is the dependent variable with entity i at time t , $Y_{i,t-1}$ is the lagged dependent variable, $X_{i,t}$ are the independent variables and $\eta_{i,t}$ is the error term.

⁴⁰According to Hsiao (2003), benefits from using panel data include, but are not limited to, the ability to give more informative data, less collinearity and more efficiency and thus, more reliable estimates for parameters can be produced with more informative data. Naturally, the requirements and assumptions for panel data regressions have to hold.

My approach to investigate the relationship between operating performance and digitalization draws from Hirshleifer et al. (2013), where the relationship between innovative efficiency and operating performance is investigated. In more detail, for my analysis I run the following specification, in equation form:

$$OP_{i,t+1} = \beta_0 + \overbrace{\beta_1 DM_{i,t}}^{\text{Digital Maturity}} + \beta_2 \ln \left(1 + \frac{CapEx_{i,t}}{TA_{i,t}} \right) + \beta_3 \ln(MV_{i,t}) + \beta_4 OP_{i,t} \quad (12)$$

$$+ \beta_5 \Delta OP_{i,t} + \beta_6 Technology_t + \eta_{i,t}$$

where $OP_{i,t+1}$ is firm i 's operating performance in year $t+1$ measured in return on assets (ROA), DM is the digital maturity measure (see section 3.1), $\ln \left(1 + \frac{CapEx}{TA} \right)$ is the natural log of one plus capital expenditure to TA , $\Delta OP_{i,t}$ is the yearly change in operating performance (year t and year $t-1$), $\ln(MV_{i,t})$ is the natural log of market value of equity and $Technology$ is a dummy variable that equals 1 for firms that operate in the technology, financial or communication sector and 0 otherwise.

Following Hirshleifer et al. (2013), I measure operating performance by ROA . Additionally, several controls are put in place. Similarly to Lev and Sougiannis (1996), I include capital expenditure ($CapEx$) deflated by average total assets since a $CapEx$ ratio is found to explain operating performance to some extent⁴¹ (see also Pandit et al., 2011). In addition, I use MV to proxy firm size account for competitive advantages (Kousenidis et al., 2000; Charitou et al., 2001). Moreover, the regression includes two more controls that are current operating performance (OP) and the change in operating performance (ΔOP), which is the difference between current and previous OP . The theoretical motivation is as follows. Gu (2005) argues that operating performance has an inherit persistence, thus it should be used in the regression to capture this effect (see also Pandit et al., 2011; Hirshleifer et al., 2013). Following Hirshleifer et al. (2013), I also add ΔOP to control for the change in operating performance to capture the mean reversion in profitability (see also Fama and French, 2000).⁴² Lastly, the dummy variable is to control for sector effects.

Because of some missing observations in my sample, I deal with a so-called unbal-

⁴¹Moreover, Lev and Sougiannis (1996) also use advertising expenditure ratios to explain firm operating performance, however, I refrain from including it.

⁴²Additionally, Bond (2002) states that, from an econometrical point of view, allowing for dynamics in the regression process may be essential to receive consistent estimates of parameters, even though, the coefficients for the lagged dependent variable are not the main interest.

anced panel.⁴³ Randomly missing observations in panels, however, should not affect the outcome of a regression⁴⁴ (Baltagi, 2005). Due to the lagged independent variable, I use the Generalized Method of Moments (GMM) estimation technique. Generally speaking, when it comes to dynamic panel data, GMM is considered to be superior to other estimation techniques (Judson and Owen, 1999). More specifically, I use a GMM estimator proposed by Arellano and Bond (1991).⁴⁵ This estimator handles modeling concerns well and prevents dynamic panel bias (Roodman, 2009).

⁴³According to Baltagi (2005), missing observations in panel data models, unbalanced panels in general, are quite common in economic empirical settings. He argues that unbalanced panels are, indeed, the norm in economic settings (Baltagi, 2005, p. 165).

⁴⁴Ahrens and Pincus (1981) recommend an index to measure the *unbalancedness*, but this index rarely ever surfaces and if, mostly in purely econometrical discussions.

⁴⁵The Generalized Method of Moments was originally developed by Hansen (1982). For this GMM estimator, see also Arellano (2003).

4 | Empirical Research

THIS CHAPTER PRESENTS THE FINDINGS AND RESULTS of the empirical testing. The first part illuminates the findings from a capital market point of view and is subdivided into two parts: portfolio testing and risk factor models. The second part presents the results from the dynamic panel data regression and thus gives insight from an operating performance point of view.

4.1 PORTFOLIO ANALYSIS RESULTS

4.1.1 DIGITAL MATURITY AND PORTFOLIO RETURNS

Table 3 presents the results of the portfolio analysis. In general, the portfolio analysis yields mixed results. Interestingly and contrarily to the proposed research question, more digitally mature firms' returns are not visibly outperforming compared to their peers. In more detail, the monthly size-adjusted excess returns on DM_{low} portfolios are 127 basis points. On DM_{middle} portfolios the monthly size-adjusted excess returns are 128 basis points. The monthly size-adjusted returns on DM_{high} portfolios are 64 basis points. The average digital maturity measures for DM_{low} , DM_{middle} and DM_{high} portfolios are 5.59, 6.59 and 7.30, respectively. The entirety of the monthly average size-adjusted excess returns of the constructed portfolios are presented in table B1 (see appendix B). Subsequently, DM_{high} portfolios only outperformed low and middle DM firms in one year (2014) during the sample period. During the entire sample period, firms with high DM values outperform firms with medium DM values and firms with low DM values, 23 and 18 out of 48 months in total, respectively. Therefore, over the four year sample period, high DM firms did not outperform either medium or low DM firms. However, the difference between excess returns of high DM firms compared to medium DM firms is not statistically significant ($p=0.43$). The same

holds for the comparison of excess returns between high DM firms and low DM firms where there is no statistically significant difference between the two ($p=0.44$).

Table 3: Digital maturity and monthly average portfolio returns.

$DM_{portfolio}$	ER_{2013}	ER_{2014}	ER_{2015}	ER_{2016}	$ER_{overall}$
Excess returns in percent					
Low	1.43	0.80	1.62	1.25	1.27
$\emptyset DM$	5.54	5.67	5.70	5.70	5.59
Middle	1.57	0.93	0.90	1.70	1.28
$\emptyset DM$	6.57	6.72	6.70	6.38	6.59
High	-0.13	1.30	0.16	1.23	0.64
$\emptyset DM$	7.24	7.40	7.41	7.13	7.30

This table presents the monthly average size-adjusted excess returns of the constructed portfolios for the years 2013 to 2016. The portfolio construction is outlined in chapter 3.3.1. The excess return is calculated as the difference between the Swedish Treasury bill rate and the size-adjusted portfolio returns. Additionally, the average digital maturity ($\emptyset DM$) values are reported for each portfolio and year.

In table 4 additional insight in form of the monthly average size-adjusted returns (excess returns), the standard deviation and the Sharpe ratio is displayed. The standard deviation for DM_{high} portfolios is close to being strictly smaller compared to DM_{middle} portfolios and only falls short in one year compared to the DM_{low} portfolios. Firms with higher digital maturity seem to have less fluctuating returns. In detail, the average standard deviation for the DM_{high} portfolio revolves around 3.48, whereas it is 4.45 for the DM_{low} portfolio. As for the Sharpe (1966) ratio comparison⁴⁶, there is no distinct difference between the portfolios. According to this performance measure, the DM_{high} portfolio does not outperform either the DM_{middle} or DM_{low} portfolios. This means, although the volatility of the DM_{high} portfolio is somewhat smaller compared to the DM_{low} portfolio, the smaller excess returns offset it.⁴⁷ In short, the Sharpe ratio results are ambiguous and the differences are most of the time not sta-

⁴⁶Additionally, I use a closely related performance measure, the Modigliani and Modigliani (1997)'s risk-adjusted performance (RAP) criteria. The results can be found in table C1 in appendix C.

⁴⁷The Sharpe ratio, as a risk-adjusted measure, will score higher, all else equal, under less volatility (see Opdyke, 2008).

Table 4: Results of portfolio analysis with returns, excess returns, standard deviation and Sharpe (1966) ratios.

Year	PF DM_{high}	PF DM_{middle}	PF DM_{low}
Average return			
2013	0.85	2.55	2.41
2014	1.76	1.39	1.26
2015	-0.14	0.61	1.32
2016	0.59	1.06	0.61
Average excess return			
2013	-0.13	1.57	1.43
2014	1.30	0.93	0.80
2015	0.16	0.90	1.62
2016	1.23	1.70	1.25
Standard deviation			
2013	3.52	3.90	3.87
2014	2.87	3.19	2.85
2015	3.70	5.66	6.06
2016	3.82	4.73	5.00
Results above are reported in percent			
Sharpe ratio			
2013	-0.13	1.39	1.28
2014	1.56	1.01	0.97
2015	0.15	0.55	0.92
2016	1.12	1.24	0.86

This table shows the monthly average size-adjusted returns, monthly average size-adjusted excess returns, the standard deviation and the Sharpe ratios of the constructed portfolios.

tistically significant. Only the difference of the Sharpe ratios in the years 2013 (for both $DM_{high}-DM_{low}$ and $DM_{high}-DM_{middle}$) and 2015 (only $DM_{high}-DM_{low}$) are statistically different from zero. In 2013, the difference is significant at the 0.01 level both times. For 2015, the difference is significant at the 0.1 level. For all other years, inference about performance cannot be made with statistical significance. The same holds when the entire period is investigated.⁴⁸ Overall, it seems, although without sufficient statistical significance, that digital maturity is not influencing stock performance.

⁴⁸See tables A1 and A2 in Appendix A for all Sharpe ratio significance tests.

4.1.2 DIGITAL MATURITY AND RISK FACTOR MODELS

The results from the Fama and French (1993) three-factor and the Carhart (1997) four-factor risk models with the *DM* portfolios are depicted in tables 5 and 6, respectively. The insights from the risk models are the following.

Table 5: Result of the *DM* portfolios and the Fama and French (1993) three-factor model.

<i>DM</i>	Excess Return	Fama French three-factor model			
		α	MKT	SMB	HML
Low	1.27	0.99	0.71	-0.13	-0.69
<i>t</i>		(1.75)	(4.43)	(-0.37)	(-2.70)
Middle	1.28	0.89	0.67	0.23	-0.03
<i>t</i>		(1.63)	(4.38)	(0.71)	(-0.11)
High	0.64	0.55	0.54	-0.38	-0.03
<i>t</i>		(1.35)	(4.72)	(-1.54)	(-0.14)

This table reports the monthly average size-adjusted excess returns to the constructed portfolios and the risk factor loadings from regressing portfolio excess returns on factor returns. MKT, SMB and HML are the market, size and book-to-market factors of Fama and French (1993). Excess return and α are displayed in percent. Factor returns are obtained from Kenneth French's website.

The intercepts, or α are the active return of the portfolios given the portfolios' exposure to the risk factors. For the Fama and French (1997) three-factor model, the α is 0.99, 0.89 and 0.64 for the low, middle and high *DM* portfolios, respectively. This means all *DM* portfolios posted positive active returns, i.e. they outperform against the benchmark. As for the Carhart (1997) four-factor model, the α ⁴⁹ is 1.02, 1.27 and 0.68 for the low, middle and high *DM* portfolios, respectively. Again, all *DM* portfolios perform above their corresponding risk levels and earn positive active returns.⁵⁰ In more detail, the *DM_{middle}* portfolio's α is slightly higher than the *DM_{low}* and noticeably higher than the *DM_{high}* and is significant at conventional levels. This

⁴⁹The α is commonly referred to as Carhart (1997)'s four-factor alpha (Farah, 2002).

⁵⁰For the sake of brevity and to avoid tedious repetition of the factor models' results, I will lay the focus on the outcome of the Carhart (1997) four-factor model in the following paragraph. The factor loadings are very similar in both models in any case.

finding contradicts the statement that high digital maturity firms outperform firms with lower digital maturity. However, the α values for DM_{low} and DM_{high} portfolio are not statistically significant, therefore, this interpretation stands on shaky ground. The

Table 6: Result of the DM portfolios and the Carhart (1997) four-factor model.

DM	Excess Return	Carhart four-factor model				
		α	MKT	SMB	HML	MOM
Low t	1.27	1.02 (1.62)	0.71 (4.32)	-0.13 (-0.37)	-0.70 (-2.46)	-0.03 (-0.10)
Middle t	1.28	1.27 (2.16)	0.64 (4.18)	0.23 (0.72)	-0.21 (-0.78)	-0.40 (-1.59)
High t	0.64	0.68 (1.53)	0.53 (4.55)	-0.38 (-1.53)	-0.09 (-0.44)	-0.14 (-0.74)

This table reports the monthly average size-adjusted excess returns to the constructed portfolios and the risk factor loadings from regressing portfolio excess returns on factor returns. MKT, SMB and HML are the market, size and book-to-market factors of Fama and French (1993). MOM is the momentum factor of Carhart (1997). Excess return and α are displayed in percent. Factor returns are obtained from Kenneth French's website.

risk factor loadings are as follows. First, the market risk factor, MKT (or $R_{M,t} - R_{f,t}$) which shows the sensitivity of the DM portfolios to the market, is positive and smaller than 1 for all DM portfolios. In detail, the MKT is 0.71, 0.64 and 0.53 for the low, middle and high DM portfolios, respectively. This means all portfolios move with the market, but are, in general, less sensitive to movements ($MKT < 1$).⁵¹ Additionally, the positive market factor strictly decreases from low to high, which means PF_{high} are less sensitive to the overall market compared to the other DM portfolios. In other words, the more digital a firm, the smaller the MKT effect. Admittedly, this difference in MKT factors is relatively small. Nonetheless, the relation is highly statistically significant. Second, the size factor, SMB which shows the sensitivity of the DM portfolios to firm size effect, is small but varies between a negative relation for DM_{low} and DM_{high} portfolios and a positive relation for the DM_{middle} portfolio. More specifically, the SMB is -0.13, 0.23 and -0.38 for the low, middle and high DM

⁵¹Generally speaking, equity-only funds tend to have MKT values around 1.

portfolios, respectively. Third, the value factor, *HML* which shows the sensitivity of the *DM* portfolios to the value effect, is negative for all *DM* portfolios. In detail, *HML* is -0.70, -0.21 and -0.09 for the low, middle and high *DM* portfolios, respectively. The value factor strictly increases from the *DM_{low}* portfolio to the *DM_{high}* portfolio where it is very close to zero. This could be interpreted that low *DM* firms are more likely to be growth stocks whereas high *DM* firms are less likely to grow and converge more closely to value stocks, while technically still being in the between growth and stock categorization. In other words, with higher digital maturity, firms leave the realm of growth stocks and approach value stocks. However, only the *HML* factor for the *DM_{low}* portfolio is statistically significant at conventional levels, thus, this interpretation is to be treated very cautiously. Fourth and lastly, the momentum factor, *MOM* which shows the relation between past returns and the *DM* portfolios, is negative for all *DM* portfolios. There is little difference between the returns for the *DM_{low}* and *DM_{high}* portfolios according to the data. Moreover, the *MOM* factors are not statistically significant.⁵²

In conclusion, the data from portfolio testing and risk models does not support the hypothesis that digitally mature firms have superior stock performance compared to less digitally mature ones. The results are inconclusive at best.

4.2 PANEL DATA REGRESSION RESULTS

This section presents the results from the dynamic panel data regression. A visual representation of the panel data regression results with the average slopes, intercept and corresponding *t*-values is given in table 7 (see also table D1 in appendix D). Interestingly and inconsistent with most of the theoretical findings, the results indicate a significantly negative relation between the *DM* measure and future *ROA*. This effect is significant at the 0.05 level.⁵³ This suggests that higher levels of digital maturity

⁵²Additionally, I tried to implement the Carhart (1997) four-factor model augmented with the *UMO* factor (undervalued minus overvalued) introduced by Hirshleifer and Jiang (2010). The authors argue *UMO* factor loadings help identify stock misvaluation. This augmentation is suggested by Hirshleifer et al. (2013) in order to analyze whether or not portfolios are under- or overvalued. Unfortunately, the data for the *UMO* factor is only provided until the year 2015 which reduces my already small sample period by another year. Also, after running the regressions, the *UMO* factors for all three *DM* portfolios were indistinguishable from zero and of little significance.

⁵³This finding affirms the negative correlation for both the Spearman and Pearson correlation coefficient between digital maturity and operating performance. To recall, the coefficients are -0.172 for the Spearman correlation and -0.119 for the Pearson correlation.

reduce subsequent operating performance slightly which is contrary to the findings put forth by Westerman et al. (2012) and Bughin et al. (2017). The negative coefficient for DM , however, ties into findings by Scott et al. (2017), where a temporary negative relationship between DM and firm performance is hypothesized.

Consistent with literature, the highly significantly positive slope on ROA and the highly significantly negative slope on ΔROA confirm, in each case, persistence as well as mean reversion in firm operating performance (Hirshleifer et al., 2013; Pandit et al., 2011; Gu, 2005). These effects are significant at the 0.01 level. Capital

Table 7: Digital maturity and subsequent operating performance panel regression results.

	Operating Performance
	ROA
Intercept	9.22 (3.51) ^{***}
DM	-0.88 (-2.01) ^{**}
$\ln(CapEx/TA)$	-1.75 (-0.18)
Current ROA	0.65 (7.65) ^{***}
ΔROA	-0.39 (-12.54) ^{***}
$\ln(MV)$	-0.13 (-2.23) ^{**}
Technology	-1.16 (-2.79) ^{***}
Adjusted R^2	0.48

The panel data regression results are reported in this table. Heteroscedasticity robust t-statistics are reported in parentheses. ^{***}, ^{**} and ^{*} indicate the statistical significance levels at $p < 0.01$, $p < 0.05$ and $p < 0.10$, respectively.

expenditure correlates negatively with subsequent operating performance, however, the relation is not statistically significant at conventional levels. Typically, capital expenditure is expected to benefit future profitability (Lev and Sougiannis, 1996). As for the controls for market value and firms, I find that the slope for natural log of

MV is very close to zero, yet significant at the 0.05 level. It appears that firm size does not affect operating performance for the firms in the sample. In literature, there is plenty of evidence for both negative and positive effects of firm size (Hansen and Wernerfelt, 1989; Amato and Wilder, 1985).⁵⁴ In addition, the slope for the dummy variable is negative and significant at the 0.01 level. A slight underperformance is attributable to technology-heavy industry sectors.

In summary, the results of the dynamic panel data regression show that digitalization is not positively related to subsequent firm operating performance. In fact, it is weakly negatively associated with the following year operating performance. Again, this in contrast to the suggested positive effect of digitalization on firm performance, i.e. the general concept of a *digital advantage* is not confirmed. I will further elaborate on the peculiarities and implications of the findings in the following chapter.

⁵⁴The differences depend on the model set-up as well as the theories used to interpret the results.

5 | Discussion

THIS CHAPTER FURTHER ILLUSTRATES AND ANALYZES THE RESULTS from the empirical testing for both, the portfolio analysis and the regression model. First, an interpretation of the results is presented. Second, findings from the theoretical background are tied into the empirical testing results in order to corroborate the discussion. Ultimately, the goal of this chapter is to arrive at a comprehensible understanding of the findings. In addition, the limitations of the thesis are addressed.

5.1 INTERPRETATION OF THE RESULTS

To begin with, existing literature has emphasized the beneficial role of digitalization on overall firm performance. However, the ambiguous results from the empirical research in this thesis impede a clear insight into the expected effects of digitalization on firms' stock returns and operating performance. The data from the portfolio analysis suggests that there is no clear relationship between digitalization and stock returns. In addition, empirical factor pricing models, such as the Fama and French (1997) three-factor model and the Carhart (1997) four-factor model, do not entirely explain the DM-return relation. The result from the dynamic panel data regression suggests that digital maturity is weakly negatively associated with firm operating performance. These results, however, give rise to the question as to why there was no coherent outcome.

More in-depth, my results do not substantiate the findings of various studies⁵⁵ (Westerman et al., 2012; Bughin et al., 2017; Weill and Woerner, 2015). Because of a different setup and focus of the studies, the findings are not directly comparable to each other, yet, coherent inferences can still be made. Westerman et al. (2011) in their

⁵⁵For the terminology see chapter 2.6.1.

study find that profitability and revenue generation are higher for firms with above average DI values. Numerically, digital leader's profitability is about ten percent higher compared to the average firm. Weill and Woerner (2015) report an increase of around 30 percent in revenue growth and a 27 percent increase in profit margins for companies that are embracing digital technology and operate within the digital ecosystem, compared to direct competitors. In contrast to these findings, I cannot observe a pattern or relationship between digital maturity and profitability. Somewhat similar to my study set-up, Bughin et al. (2017) split firms into three groups according to their digitalization ranking. They find that digital leaders gain positive revenue growth, whereas average firms neither profit nor experience negative growth and laggards face shrinking revenue. In short, they find a significant correlation between digital leaders and revenue growth. Contrarily, in my results digitally mature firms do not outperform their peers, when, in fact, DM is linked to a weaker subsequent operating performance.

A possible explanation is as follows. Some changes due to digital innovations and technology transformations will not be visible in the short run. Their effects seamlessly merge into present business practices and thus make it increasingly difficult to pinpoint their actual contribution to firm performance (Weill and Woerner, 2018). Moreover, information about digital maturity is difficult to process. In general, ICT advances affect changes in firm structure positively (Spanos et al., 2002) and contribute to productivity and economic success of organizations (Hernaus et al., 2012). Realistically speaking, not all firms will benefit from digital innovations.

In their study about innovative efficiency and stock returns, Hirshleifer et al. (2013) find robust evidence that more innovative firms outperform peers. Needless to say, digital maturity levels do not necessarily correspond to innovative efficiency levels, however, my methods are related to their approach. Therefore, I believe some inference can be made. Whereas innovative efficiency (measured in patents or citations and corresponding R&D levels) is generated internally, digital maturity can be raised by implementing and using available external systems. It is one thing for a company to use, for instance, customer demographics in order to enhance marketing and digital sales. But to actually reap the benefits from doing so is another thing. This may even be an intractable process for some firms. Weill and Woerner (2018) bluntly describe this predicament as firms trying to pursue digital transformation "without any sense where they are going" (p. 21). Thus, the positive outcome of digital maturity

is not only dependent on the implementation of new digital solutions but also on the subsequent use internally. However, an in-depth study that quantifies firm stock performance of digitalization effects has yet to be published.

The above-mentioned shortcoming of digital maturity and its effect on firm performance is one of the reasons why Westerman et al. (2012) use DI and TMI in their framework. Firms with high DI and low TMI values would still be considered to be digitally mature, however, they often miss the consequential step of implementing adequate governance internally. This dampens the outcome due to the suboptimal utilization of digital efforts. Nevertheless, in their study Westerman et al. (2012) find that firms with high DI, regardless of their TMI, still perform at higher levels compared to firms with low DI, again regardless of their corresponding TMI. Another possible explanation follows the findings of Scott et al. (2017). In their study, the authors, indeed, find robust evidence that technology innovations have a positive impact on profitability, however, they also argue that these changes take time to unfold their full potential. Scott et al. (2017) find robust evidence that an adoption of a new digital innovation reduces long-term returns (measured in return on sales) for up to four years, before the positive effects prevail. In conclusion, the long run effect of digital innovations on profit margins is positive after the initial drawbacks are overcome. Changing internal processes is no easy task and especially the fine-tuning as well as synchronizing are time-consuming. Additionally, replacing processes at the core of a business can be a multiyear undertaking (Weill and Woerner, 2018). In any case, some changes are inevitable and firms that do not transform accordingly will presumably be put out of business, or suffer from reduced growth perspectives (Fitzgerald et al., 2013).

5.2 LIMITATIONS, PROXY AND SAMPLE IMPLICATIONS

My findings are subject to several limitations that need to be taken into consideration for the interpretation of the results.

My digital maturity factors condensed into the digital maturity proxy might not capture all the details accurately enough and therefore digital maturity might not be adequately captured. This has implications for firm sorting for the portfolio construction as well as individual firm performance. However, the paucity of digital maturity measures owing to the cumbersome collection process of meaningful variables makes

it difficult to obtain an impeccable measure. In addition, the digitalization of firms is not a uniform transformation which makes it difficult to access different levels of digital maturity with great accuracy. Thus, finding an adequate proxy is virtually a herculean task.⁵⁶ Even though I tried to triangulate the digital maturity proxy with various papers and it seems to be adequately well defined for the analysis, it is unclear how big the impact of additional factors, such as big data analytics or managerial aspects, would have been.⁵⁷ Including different proxies, or with altered emphasis, may seem innocuous at first, but the results could differ and the conclusions drawn would not be the same. Strictly speaking, dissimilar results with a different proxy cannot be ruled out. However, this data can only be retrieved via surveys and extensive questionnaires which would have been beyond the scope of this thesis. As for the measure for firm performance itself, although return on assets is widely regarded as a key performance metric, no single metric is flawless. Thus, another performance measure such as cash flows would not be amiss.

Furthermore, the sample I used in this thesis is relatively small (due to the limited accessibility of digital maturity measures) and this could have implications for the results. A limited sample size is by definition prone to extreme values and individual firms that are for some unspecific reason under- or overperforming might distort the data. Despite my efforts to find a suitable sample for testing, it is a possibility that the results are to some extent driven by individual firm performance independent of digital maturity. Generally speaking, the testing would positively benefit from a higher number of observations.

Additionally, it is worth mentioning that the geographical scope and the focus on Swedish firms are acknowledged as another limitation. Traditionally, Swedish companies are on the forefront of technological change and new trends. Thus, it is very likely that Swedish firms might be more digitally mature compared to the average European or US firm and the nuances between firms might be marginal.

⁵⁶It is worth mentioning that there are reliable sources and accurate data collections of digitalization levels. However, and especially because this information is of interest for a great many of players, this information, more often than not, is not accessible for outsiders.

⁵⁷As a short marginalia, since non-financial indicators are not subject to well-defined standards of measurement, the relation between operating performance and non-financial indicators is not always straightforward (Gu, 2005).

Everything changes and nothing stands still.

HERACLITUS, as cited in Plato's *Cratylus*

6 | Conclusion

THE PRIMARY GOAL OF THIS THESIS was to critically examine the effects of digitalization on firm performance, thus, to advance the understanding of this topic. Its main purpose was to find a concise, yet thoroughly data-driven, answer to the crucial question whether or not a *digital advantage* exists.

By collecting data from various Swedish firms in different sectors, my research sought to shed light on the effect of digital maturity on subsequent operating performance as well as stock returns. In an effort to analyze this relationship, I deployed two empirical methods. Namely, a portfolio analysis where firms of different sizes and digital maturity levels were sorted into different portfolios and examined with regard to their stock performance, and a regression model which incorporated accounting measures and digital maturity levels. Furthermore, I examined various articles and papers during an extensive and systematic investigation of research articles in order to create a solid theoretical foundation for my empirical analysis. Generally speaking, there is very little academic work on digitalization's effect on performance on firm level. The majority of studies revolve around a simple comparison of accounting measures. Hence, the inherent objective of this research was to investigate the relation between digital maturity and firm performance empirically. My findings, however, do not support the hypothesis that digitally mature firms outperform their less digitally mature peers, i.e. I cannot corroborate the argument of a digital advantage.

Undoubtedly, the effects of digitalization are transforming firms and doing business will be subject to change in digital technologies. The *digital revolution* is in progress, yet it is not foreseeable how far it will go. New innovative concepts, such as machine learning, digital tokens⁵⁸ or artificial intelligence are not limited to certain

⁵⁸Digital tokens which are closely related to cryptocurrencies, can store information which subsequently can be used for communication or payment; a step closer to, for instance, smart factories.

firms or sectors. They could potentially benefit all business entities to some extent. Unlike previous technological improvements, digital innovations are not bound to a firm's total assets, access to raw materials or resources. Recent developments seem to further justify the beneficial aspects of digitalization (Loonam et al., 2018). An important consideration to keep in mind when looking at the findings in retrospect, is the complexity aspect of digitalization. The inherent expansive nature of digital innovations with their endless possibilities makes it difficult to arrive at a common consensus as to how digitalization should be quantified. Therefore, reaching a consensus on how to define and measure digitalization could be a wellspring for continuous debate. This would also be advantageous for future research by making results more comparable.

This thesis has shown that digitally mature firms' stock returns do not differ significantly compared to returns of less digitally mature firms. Also, the results from the dynamic panel data regression indicate that digital maturity is linked to a lower subsequent operating performance, therefore, digitalization's conjecturable positive effects on firms are not reinforced. Further research in the area of digitalization should be more exhaustive, in-depth and over an extended period of time, in order to substantiate the claims put forward by literature.

In concluding, my intent with this thesis was also to venture into uncharted territory and to add a small contribution to the research landscape. Even though this thesis cannot provide a definite answer to the effects of digitalization on firm performance, it paves the way to arriving at a better understanding of one, if not the most interesting transformations for businesses and organizations in the years to come.

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Appendix A

TEST FOR SIGNIFICANCE (SHARPE RATIO)

This section presents the equations and background for the significance testing of the portfolio Sharpe ratios. The following hypothesis is used to test for the equality of two Sharpe ratios:

$$H_0 = SR_i - SR_j = 0 \quad (13)$$

The test statistic is as follows:

$$z = \frac{\widehat{SR}_{ij}}{\sqrt{\hat{\nu}}} \sim N(0, 1) \quad (14)$$

Jobson and Korkie (1981)'s variance of the statistic with Memmel (2003)'s correction is given by (see also Opdyke, 2008):

$$\nu = 2 - 2\rho_{i,j} + \frac{1}{2} [SR_i^2 + SR_j^2 - 2SR_iSR_j\rho_{i,j}^2] \quad (15)$$

where $\rho = \frac{\sigma_{i,j}}{\sigma_i\sigma_j}$ is the correlation coefficient of the excess returns of portfolio i and j .

To test the hypothesis, estimators for the Sharpe ratio have to be used.

$$\widehat{SR}_i = \frac{m_i}{s_i} \quad (16)$$

with

$$m_i = \frac{1}{T} \sum_{t=1}^T d_{it}$$

$$s_i = \sqrt{\frac{1}{T} \sum_{t=1}^T (d_{it} - m_i)^2}$$

(Continued on next page)

$$d_{it} = (R_{it} - R_{bt})$$

where R_i and R_b are the returns on portfolio i and benchmark b , respectively.

Calculating equation 15 with the estimators yields $\hat{\nu}$ and as such the hypothesis can be tested.

The results depicted in table A1 as well as table A2 paint a clear picture.

Table A1: Sharpe ratio significance test results as suggested by Jobson and Korkie (1981) and Memmel (2003).

Year	PF DM_{high}	PF DM_{low}	z scores	p-values
Sharpe ratio				
2013	-0.13	1.28	-3.478	0.000
2014	1.56	0.97	1.320	0.187
2015	0.15	0.92	-1.775	0.075
2016	1.12	0.86	1.285	0.199
All periods (2013-2016)	0.61	0.99	-0.622	0.534

This table shows the yearly Sharpe ratios of the DM_{high} and DM_{low} portfolios as well as the corresponding z -scores and probability values.

Table A2: Sharpe ratio significance test results as suggested by Jobson and Korkie (1981) and Memmel (2003).

Year	PF DM_{high}	PF DM_{middle}	z scores	p-values
Sharpe ratio				
2013	-0.13	1.39	-3.499	0.000
2014	1.56	1.01	1.270	0.204
2015	0.15	0.55	-1.095	0.274
2016	1.12	1.24	0.237	0.813
All periods (2013-2016)	0.61	0.24	-0.921	0.357

This table shows the yearly Sharpe ratios of the DM_{high} and DM_{middle} portfolios as well as the corresponding z -scores and probability values.

Appendix B

Table B1: Excess returns of monthly size-adjusted portfolios within the portfolio analysis with high (DM_H), middle (DM_M) and low (DM_L) digital maturity portfolios. Excess returns calculated with the Swedish one month Treasury bill rate.

Date	PF DM_H	PF DM_M	PF DM_L	DM_H vs DM_L
Monthly excess returns in percent				
01/2013	2.98	6.78	3.15	-0.17
02/2013	-1.98	9.52	5.80	-7.78
03/2013	1.39	-3.61	1.41	-0.02
04/2013	-1.10	-1.01	1.87	-2.97
05/2013	2.06	3.40	3.46	-1.40
06/2013	-8.18	-4.20	-4.60	-3.58
07/2013	6.10	2.38	6.02	0.08
08/2013	-2.70	1.80	-1.80	-0.90
09/2013	-0.63	2.07	5.80	-6.43
10/2013	1.08	1.42	-4.80	5.88
11/2013	0.97	0.54	2.59	-1.62
12/2013	-1.59	-0.31	-1.79	0.20
01/2014	-2.26	0.59	-1.63	-0.63
02/2014	6.92	5.10	2.04	4.88
03/2014	-1.57	0.96	0.83	-2.40
04/2014	2.10	6.09	-0.42	2.52
05/2014	0.50	-0.24	3.75	-3.25
06/2014	-2.45	-2.13	-2.80	0.35
07/2014	1.68	-0.11	1.22	0.46
08/2014	0.47	-3.75	-0.13	0.60
09/2014	1.30	-3.23	-2.48	3.78
10/2014	6.39	2.59	-1.82	8.21
11/2014	1.74	1.32	5.73	-3.99

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Table B1 – continued from previous page

Date	DM_H	DM_M	DM_L	DM_H vs DM_L
12/2014	0.78	3.99	5.28	-4.50
01/2015	4.53	3.81	5.64	-1.11
02/2015	3.38	10.67	8.26	-4.88
03/2015	-1.45	1.69	2.51	-3.96
04/2015	3.10	0.66	-5.96	9.06
05/2015	-1.04	3.07	3.03	-4.07
06/2015	-3.08	-6.55	-7.41	4.33
07/2015	1.12	2.99	5.04	-3.92
08/2015	-2.84	-7.36	-5.47	2.63
09/2015	-6.88	-4.42	-0.47	-6.41
10/2015	4.51	5.90	7.22	-2.71
11/2015	2.70	5.12	10.19	-7.49
12/2015	-2.16	-4.74	-3.17	1.01
01/2016	-7.61	-5.24	-6.48	-1.13
02/2016	1.69	3.04	0.57	1.12
03/2016	5.38	5.04	7.12	-1.74
04/2016	1.28	0.21	-3.93	5.21
05/2016	2.24	0.73	3.68	-1.44
06/2016	-4.27	-7.21	-3.47	-0.80
07/2016	3.17	9.53	5.48	-2.31
08/2016	1.69	6.63	2.75	-1.06
09/2016	4.25	2.05	2.48	1.77
10/2016	2.87	2.65	-6.09	8.96
11/2016	-1.27	-1.71	5.66	-6.93
12/2016	5.35	4.68	7.18	-1.83

Appendix C

MODIGLIANI-MODIGLIANI RISK-ADJUSTED PERFORMANCE

Another way to measure and evaluate portfolio performance is suggested by Modigliani and Modigliani (1997). This is an alternative measure of risk-adjusted performance.

$$RAP_i = \left(\frac{\sigma_M}{\sigma_i} \right) (r_i - r_f) + r_f \quad (17)$$

where RAP_i is the risk-adjusted performance of portfolio i , σ_M is the standard deviation of market returns, σ_i is the standard deviation of returns for portfolio i , r_f the average return for portfolio i and r_f the risk-free return.

Reformulating the risk-adjusted performance measure to solely base it on excess returns ($RAPA$) yields (Farah, 2002):

$$RAP_i - r_f = \left(\frac{\sigma_M}{\sigma_i} \right) (r_i - r_f) \quad (18)$$

and hence

$$RAPA_i = \sigma_M \left(\frac{r_i - r_f}{\sigma_i} \right) \quad (19)$$

Table C1 shows the results of the RAPA criteria for the DM portfolios.

Table C1: Result of the Modigliani and Modigliani (1997) risk-adjusted performance measure (RAPA).

Year	PF DM_{high}	PF DM_{middle}	PF DM_{low}
RAPA criteria			
2013	-0.14 %	1.48 %	1.36 %
2014	1.43 %	0.92 %	0.89 %
2015	0.16 %	0.62 %	1.03 %
2016	1.25 %	1.39 %	0.96 %

Appendix D

Table D1: Digital maturity and subsequent operating performance panel regression overview.

Dependent Variable: ROA_{t+1}
Panel Generalized Method of Moments
Sample Period: 2010-2015 (adjusted)
Periods included: 6
Cross-sections included: 24
Effects Specification: Period fixed
White period standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
<i>ROA</i>	0.652	0.085	7.646	0.000
Intercept	9.223	2.628	3.509	0.001
$\ln(CapEx/TA)$	-1.758	9.569	-0.183	0.855
<i>DM</i>	-0.880	0.438	-2.008	0.047
ΔROA	-0.388	0.031	-12.543	0.000
$\ln(MV)$	-0.132	0.059	-2.230	0.028
Industry Dummy	-1.161	0.417	-2.788	0.006

R-squared	0.525	Mean dependent var	5.880
Adjusted R-squared	0.476	S.D. dependent var	5.330
S.E. of regression	3.857	Sum squared resid	1577.2
J-statistic	0.001	Instrument rank	12
Durbin-Watson stat	2.156		

This table reports the detailed results of the dynamic panel data regression estimated with Generalized Method of Moments and the Arellano and Bond (1991) estimator.