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The effect of digital disruption on the pecking order theory and firm performance

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Abstract

This research evaluates the effect of digitalization on the consistency of the pecking order theory and examines the relationship between digitalization and firm performance. The dataset consists of all companies included in the AEX, AMX, or AScX from 2015 to 2019. The level of digitalization is measured by text-mining, meaning that the words related to digitalization in annual reports are automatically counted. The results do not provide any significant relationship between digitalization and the consistency of the first assumption of the pecking order theory, which states that internal financing is preferred over external financing. However, the findings significantly suggest that a higher level of digitalization leads to firms acting less consistently with the second assumption of the pecking order theory, which states that debt is preferred over equity when there is a financial deficit. Further, there is evidence that a higher level of digitalization has a positive effect on the ROA. In addition, there is an insignificant positive relationship between digitalization and Tobin's Q. This research serves as an important contribution to existing research regarding digitalization and could serve as a foundation for further research on the impact of digital disruption on financial economics.

Keywords: Digital disruption, Digitalization, Capital structure, Pecking order theory, Firm performance

JEL Classification: G32, 033

Table of contents

List of tables

1. Introduction

Of all U.S. companies, 91% engage in digital initiatives, and 87% of senior management suggests digitalization is a priority (Gartner, 2020). For example, the famous furniture company IKEA has optimized its processes and costs with several new technologies. Microsoft is another leading company that has switched to mainly digital processes, opening the doors to new markets and products (Knoll and Pluszczewska, 2020). Further, literature and empirical research about digital disruption has grown by more than 150 percent from 2017 to 2020. These statistics and examples show that digital disruption is a growing field of interest. Digital disruption describes the restructuring process of economies, institutions, and society due to new digital innovations and digital technologies. For companies, digitalization resulting from digital disruption can lead to more efficient processes, higher customer satisfaction, and reduced costs (Butt and Butt, 2020). In the end, this could lead to higher firm performance. However, digital changes may also lead to employee resistance and tension between old and new processes, leading to a less optimal result.

Further, these new digital technologies can work disruptive and make companies act inconsistently with traditional corporate finance theories (Skog et al., 2018). One of such traditional corporate finance theories is the pecking order theory. The pecking order theory suggests that companies facing investment opportunities have to rely on internal financing. If internal financing is not sufficient, companies must prefer debt over equity (Donaldson, 1961). Recent research still finds evidence for the consistency of the pecking order theory in different environments (Indahwati, 2021; Mueller and Sensini, 2021). However, there is also empirical evidence for the opposite, which indicates that companies are acting inconsistently with the pecking order theory (Aghion et al., 2004; Coleman and Robb, 2012; Kedzior et al., 2020). Therefore, the research question of this thesis is as follows:

"Are digitalized firms making financial decisions that are in line with the pecking order theory, and what is the effect of digital disruption on the firm performance?"

This research question is highly relevant due to the growing trend of digital disruption, which is also reinforced by the Covid-19 crisis (EY Global, 2020). Furthermore, no research directly measures the impact of digitalization on the pecking order theory. This research will therefore fill this gap in the literature. Additionally, as digital technologies and innovations are partly taking over the traditional economy, it is essential to investigate the effect on firm performance. Lastly, existing literature regarding digitalization and the pecking order theory has mainly focused on U.S. companies, whereas this research investigates Dutch companies, which adds relevance.

To answer the research question, the existing literature is examined, and three hypotheses are formed. These hypotheses are tested with data from annual reports and the databases Bloomberg and DataStream. This thesis will focus on Dutch companies within the AEX, AMX, and AScX indexes. There is no measure for digitalization that can be researched in current databases. Therefore, Kriebel and Debener's (2020) method for measuring the level of digitalization is applied. With this method, the number of relevant keywords related to digitalization in annual reports will be counted. The pecking order theory is tested using Shyam-Sunders and Myers's (1999) method and ordinary least square regressions. Finally, the effect of digital disruption on firm performance is also tested with an ordinary least square regression.

The results of this research are as follows. In the regression of digital score on the level of internal financing relative to the total financing, while controlling for firm characteristics and fixed effects, the results do not provide statistically significant results. Therefore, it cannot be concluded whether digital firms are holding onto the first assumption of the pecking order theory, which states that internal financing is preferred over external financing. However, in the regression of financial deficit and digital score on the change in long-term debt, while controlling for firm characteristics and fixed effects, the pecking order coefficient is equal to 0.35, significant at a 10% level. This indicates that only 35% of the financial deficit is covered with debt, which is inconsistent with the second assumption of the pecking order theory, as the second assumption states that debt is preferred over equity. Furthermore, the interaction effect between the pecking order coefficient and the digital score is negative. Therefore, the results suggest that a more digitally experienced firm acts less consistently with the second assumption of the pecking order theory than a less digitally experienced firm. Further, in the regression of digital score on ROA, while controlling for firm characteristics and fixed effects, the regression coefficient is equal to 0.16, significant at a 1% level. This indicates that digitalization has a positive impact on the financial performance of a firm. Finally, there is an insignificant positive relationship between digitalization and Tobin's Q.

In the following section, the existing literature on digital disruption, pecking order theory, and firm performance is discussed. Further, the theoretical findings from interviews will also be highlighted. The dataset, transformations on the data, and the descriptive statistics are explained in section 3. In section 4, the methodology of the used OLS regressions and the OLS assumptions are highlighted. In section 5, the results are presented. This thesis will end with a discussion and conclusion of the results in section 6.

2. Theoretical framework

The theoretical framework explains the theory behind the research question, which will lead to several hypotheses. First, the concept of digital disruption and its economic impact on companies is discussed. Subsequently, digitalization is linked to the capital structure of a firm. The focus here is primarily on the pecking order theory and whether digitalized firms act consistently with the pecking order theory. Lastly, the effect of digital disruption on firm performance is highlighted and the theoretical findings from interviews are discussed.

2.1 Digital disruption

Digital disruption has gained the interest of much literature and empirical research, which has led to different definitions to describe digital disruption (Sarı et al., 2020). The core of digital disruption is the combination of digital changes and speed. A common term in digital disruption is Industry revolution 4.0, indicating the change of the production and consumption of goods and services within the economy due to the availability of new technologies (IED, 2019). For example, this revolution enables a firm to switch manual processes to efficient, automated processes (Vagadia, 2020). Leischnig et al. (2016) describe digital disruption as a new lifecycle of business where organizations are changing their processes and business models. Hereby, the goal is to gain strategic advantages in order to increase the firm's value. Digital disruption can also be described as the increased use of information technologies enabling new products and services (Martinez-Caro, 2020). Salo (2006) and Legner et al. (2017) define digital disruption as adopting technologies that convert physical information into a digital form. Further, digital disruption can also create new opportunities and break down the structure of industries as incumbents are challenged by digital entrants (Weill and Woerner, 2015). Valenduc and Vendramin (2015) describe digitalization as the synergy of digital innovations in the economy and society. After considering all definitions from existing literature, the definition of digital disruption in this thesis will be as follows:

'Digital disruption is the growing use of technologies, bringing changes in business models and the emergence of new products and services, which then lead to strategic advantages.'

Novak et al. (2019) argue that in Central and Eastern Europe this disruption can result in a growth of €200 billion of additional GDP by 2025. However, they also highlight the rising challenges for companies and the impact digital disruption has. Skog et al. (2018) additionally highlight these challenges and argue that companies need to immediately react when faced with digital disruption in their industry due to the rapidity of this change. The way companies react to digital disruption can be seen as digitalization, which is changing to a digital company in line with the digital technologies and innovations (Gartner, 2020). In this thesis, the assumption is made that firms with higher digitalization have more capacity to react to digital disruption. With this, reference is made to the digital maturity of companies, measured with their digital score.

To further clarify the disruptive way of these technologies, a comparison to technological substitutes and complements should be made. Technological substitutes can be described as the replacement of old technologies by new technologies (Miranda and Lima, 2013). When a company is adding some new technologies to the old process to improve the quality of the process, it can be seen as a technological complement (Makri et al., 2010). These technological substitutes and complements can be seen as digitalization. Digital disruption can also be seen as digitalization but with the added requirement that the digital change affects the strategic- and competitive position. Another distinction comes from the fact that with technological substitutes and complements, the company always decides by itself to change a specific part of the business model. With digital disruption, the change either comes from the firm itself, but companies are often forced to change in line with their competitors to both maintain a competitive position and retain market value (Adner and Lieberman, 2021). Hereby, the disruptive innovations come from outsiders or not influenceable events instead of the market-leading companies themselves (Bughin, 2017).

2.1.1 Impact of digital disruption

The impact of digital disruption should not be underestimated. Weill and Woerner (2015) state that digital disruption breaks down industry barriers and creates new valuable opportunities. However, it may also lead to the destruction of successful business models. Companies with the capacity to benefit from digital disruption can gain firm value. In contradiction to this, companies that do not have this capacity will lose part of their market position due to competitive disadvantages (Weill and Woerner, 2015). Further, there is a difference in the way companies are dealing with the impacts of digital disruption. For small and young companies, it is often easier to react with high speed on digital disruption because of their agile and flexible characteristics. In contrast, mature companies often face difficulties responding to this digital disruption (Stonehouse and Konina, 2020).

Digital disruption mainly causes two effects. First, the internal business processes will change. For example, processes will be automated, and algorithms or robotizing will be used. The change of internal processes leads to several side-effects, such as new requirements regarding the skills and competencies of employees. On the one hand, digital disruption could increase business productivity and create new jobs. On the other hand, new technologies often require another degree of qualification and will make some jobs within a company less critical or even unnecessary (Chinoracky and Corejova, 2019). Paul et al. (2020) highlight the importance of training the new skills required with new technologies. Therefore, digital disruption impacts the employment part within a company. Further, there will be more transparency within the business processes as the new technologies are often data-driven. This transparency will lead to more objectivity and trust. However, these data-driven technologies increase the importance of corporate governance. Cyber risk, for example, is the exposure to potential harm or loss of personal or organizational information (Sheth, 2020). The leakage of such private information can have significant and value-destroying consequences. A company needs to invest in a control framework to avoid these risks. The third side-effect is the change from a competitive perspective. The growth curves of digital companies are almost exponential due to many advantages. Not being physically limited anymore and mitigating the finance cash constraints due to online sales are examples of these advantages (Barrett et al., 2016). Further, new digital products could dominate the old standard products and could lower the entry barriers, making the market structure more fragile. Therefore, companies must react with high urgency to digital disruption (Skog et al., 2018). The question here is, what is the best response companies can give? The literature mentions several aspects that make digitalization within a company successful. For example, Cameron and Green (2019) argue that enough time and budget are needed to digitalize business processes successfully. Further, if a manager is more committed and supportive towards digitalization, the success of digital change will be higher (Wang and Dass, 2017). Lastly, to lower the resistance from employees towards the change, it is critical to demonstrate digital advantages and the need for urgent implementation.

The second main effect of digital disruption is the change of consumers' or clients' expectations as they realize a digital economy is emerging (Shrivastava, 2017). These expectations could force companies to respond to digital disruption and create power asymmetries (Véliz, 2021). If companies are not comfortable using digital applications due to risks or concerns, they can opt-out. However, due to the dominance of these technologies, opting out can lead to competitive disadvantages. Thus, as a company, it is almost impossible to avoid the digital economy as the outside world expects companies to move with the digital economy (Zadravec, 2020). Further, as more information is available online to compare products and prices, consumers' behavior will change (Krämer and Kalka, 2017). Lastly, investment behavior needs to be considered. On the one hand, the current interest rates are low, indicating that investing, in general, is a valuable option. On the other hand, there is high volatility in some markets due to digital disruption (Prem et al., 2018). Furthermore, the current leading digital companies do not gain value from tangible assets but do gain value from intangible assets and human capital (Beutel et al., 2019). Therefore, it is difficult for an investor to value such a company, leading to potential over- and undervaluations in the investment market (Gillpatrick, 2019).

2.2 Capital structure

The above has shown that digital disruption has a broad impact. In this research, the impact of digital disruption on a capital structure theory will be discussed in more detail as this is an essential part of the financial economy. Capital structure theory studies the mix of securities and financial sources that companies use to finance investments and operations (Myers, 2001). Companies have, in general, three different ways to finance their business. First, they can reinvest their profits into the company. Second, they can borrow money by issuing bonds or by taking out a loan. Issuing equity is the third way for firms to finance investments and operations. The first capital structure theory was introduced by Modigliani and Miller (1958). They argue that the financial investment decisions in a perfect market should be independent of its capital structure. They further state that the company value is determined by the profits a firm makes and not by the way this profit was financed in the first place. This theory is therefore called the irrelevance theory. However, the irrelevance principle only holds in the absence of taxes, bankruptcy costs, agency costs, and asymmetric information. Further, the market must be efficient, indicating that all public information is incorporated into the prices (Fama, 1970). These unattainable assumptions have led to much criticism. As a result, several economists react to the irrelevance theory by developing other capital structure theories. The main capital structure theories are the trade-off theory, the pecking order theory, the signaling theory, and the agency theory. The pecking order theory can be seen as a highly influential theory in corporate finance (Chen and Chen, 2011). This is confirmed by recent research that finds evidence for the consistency of the pecking order theory in different environments (Indahwati, 2021; Mueller and Sensini, 2021). Therefore, the pecking order theory is chosen from the four different capital structures to investigate the effect of digital disruption on a traditional capital structure theory.

2.3 Pecking order theory

Donaldson (1961) introduced the pecking order theory, stating that management prefers internal cash flows over external financing. Later on, a similar assumption was made by Myers and Majluf (1984), who introduced the name pecking order theory. Myers (1984) formulated the pecking order theory based on the following assumptions. First, companies prefer internal financing over external financing. Second, when internal financing is insufficient to finance all investment opportunities and operations, the safest securities are preferred indicating that debt is preferred over equity.

The cost of asymmetric information causes this hierarchy. With asymmetric information, internal managers have more inside information than outside investors (Ripamonti, 2020). As a result, outside investors will under-price the securities. If the company then needs finance sources, issuing securities would be expensive and undesirable for the existing shareholders as the company receives less money for the security than the actual value of this particular security (Bharath et al., 2009). Firms intend to mitigate the cost of asymmetric information. As a result, firms prefer internal financing over external financing. The other assumption, where debt is preferred over equity in the case of financial deficit, can also be explained with asymmetric information costs. Firms prefer to issue equity when their securities are overvalued (Hovakimian, 2016). Therefore, issuing equity is often seen as an overvaluation signal. This overvaluation signal can lead to a sharp decrease in a firm's market value as investors assume securities' overvaluation (Dissanaike et al., 2014). In order to avoid this loss in market value, managers will prefer to issue debt instead of equity.

2.3.1 Determinants of pecking order theory

Many researchers have studied the factors that determine the capital structure. According to the existing literature, profitability, tangibility, growth, and firm size are the leading firm factors that influence the proportion of internal and external financing and the proportion of debt and equity within a firm (Frank and Goyal, 2003; Kayo and Kimura, 2011; Panda and Nanda, 2020). Profitability refers to the ability of a firm to generate profits. According to the pecking order theory, there will be a negative relationship between external financing and profitability as highly profitable firms rely less on external financing than less profitable firms, assuming that profits will lead to higher internal funds (Wijaya, 2020). Further, Ooi (1999) argues that profitable firms have easier access to debt than less profitable firms indicating that profitable firms tend to prefer debt over equity. This is in line with the pecking order theory. The level of tangibility in a firm indicates the level of assets that can easily be transferred into real money. For outside investors, it is not easy to estimate the actual value of a firm when there are only a few tangible assets compared to the total assets. Therefore, it can be expected that firms with low tangibility levels will have higher asymmetric information costs (Bharath et al., 2009), which will strengthen the assumptions of the pecking order theory. The third determinant of the capital structure, growth, refers to the potential of a firm to increase, for example, in size, sales, or profits due to valuable investment opportunities (Coad, 2018). To benefit from these investment opportunities, firms need additional financing compared to low-growth potential firms. Therefore, it can be expected that firms with high growth potential are forced to rely on external financing as the internal funds are not enough (Michaelas et al., 1999), indicating a negative relationship between growth and the consistency of the pecking order theory. Furthermore, the value of a firm with high growth potential is often determined by their future opportunities making them less attractive for lending institutions (Chen, 2002). Therefore, growth firms are often limited in their debt level implying that they will rely on equity issuance which is not in line with the pecking order theory. Another aspect that plays an important role in the capital structure choice is the firm size. Smaller firms often wish to minimize the intrusion of outsiders (Chen and Chen, 2011). Further, smaller firms are less required to disclose information compared to large firms. These low information requirements would lead to higher asymmetric information problems, leading to the expectation that small firms will act more consistently with the pecking order theory than large firms (González and González, 2011).

2.3.2 Digitalization and pecking order theory

Capital structures are influenced by changing business circumstances and the arising of innovations and technologies (Yan-xi et al., 2006). Previous literature has mainly focused on the relationship between innovative- and technology-based firms and the pecking order theory. Aghion et al. (2004), Coleman and Robb (2012) and Kedzior et al. (2020) find that these firms make other financial capital structure decisions compared to non-innovative or non-technology-based firms. Digitalization often leads to implementing innovations and new technologies within a firm. Therefore, innovative- and technology-based firms are to a certain extent comparable with digitalized firms. This makes it possible to base expectations regarding the effect of digitalization on the consistency of the pecking order theory on previous findings regarding the consistency of the pecking order theory within innovative- and technology-based firms. The existing literature provides mixed results about the effect of innovations and new technologies on the consistency of the pecking order theory.

Hogan and Hutson (2005) did investigate the capital structure of Irish software companies and find that these companies preferred equity over debt. Therefore, they concluded that the pecking order theory is not appropriate to explain the capital structure of technology-based firms. Further, Salvi et al. (2021) argue that investors are increasingly taking into account digitalization in their investment decisions. Digitalized firms attract external investors who realize the high growth potential and specialized expertise of such digitalized firms, which lowers the equity cost of capital. Therefore, Audretsch and Lehmann (2004) argue that technology-based firms rely more on equity sources. Coleman and Robb (2012) confirm these ideas and find hard evidence that innovative firms are not acting consistently with the pecking order theory. To be more precise, their results suggest that of 4000 companies in the USA, 51% rely on external equity, 28% on external debt, and only 21% are internal financing sources.

However, many researchers conclude that innovative firms' capital structure can be explained using pecking order theory (Cohn and Coleman, 2000; Giudici and Paleari, 2000; Robb and Robinson, 2014). Coleman and Robb (2012) argue that innovative firms face higher asymmetric information problems due to the unknown value and growth potential of new products and technologies. These asymmetric information problems possibly lead to a higher cost of external capital as outside investors will demand higher compensation for the unknown risk of their investment (Kedzior et al., 2020). Furthermore, Colombo and Grilli (2007) argue that innovative firms have less tangible assets and, therefore, few collaterals for issuing debt. This intangibility could lead to financial constraints, forcing firms to rely more on internal financing than external financing. Westhead and Storey (1997) already confirmed these financial constraints within technological-based firms as their survey shows that 25% of British high-tech firms are facing external financing problems. Further, Calcagnini et al. (2011) find evidence that innovative firms follow the pecking order theory. Only 20% of their investigated companies have issued external equity, and these innovative companies were less dependent on debt than non-innovative companies. There is yet no research that directly investigates the effect of digitalization on the allocation of financial sources. Considering the different views from existing literature, the following hypotheses are formed:

Hypothesis 1: Assuming that digital firms will follow the pecking order theory, internal financing is preferred over external financing.

Hypothesis 2: Assuming that digital firms will follow the pecking order theory, debt is preferred over equity when there is a financial deficit.

2.3 Digitalization and firm performance

The existing empirical research about the effect of digitalization on firm performance is quite contradictory. Currently, many companies are digitizing their business processes and models as a reaction to digital disruption (Leischnig et al., 2016). However, pitfalls arise with this. First, digitalization can lead to some tension between old processes and new processes. This tension could then form an obstacle for successful digitalization, therefore not leading to increased firm performance (Del Giudice, 2019). For example, these tensions could result from a change between the relation of the company and their customers or the new working environment that employees face (Preston and Allmand, 2001). Second, many companies fail to gain the benefits of digitalization because the organization's culture is clashing with the digitalized change (Wokurka et al., 2017). This gap between the new technology and the existing organizational culture needs to be filled to improve the firm performance (Kaushal, 2011; Büschgens et al., 2013). This is confirmed by Kane et al. (2015), who suggest that the success of implementing digital technologies within a firm is highly dependent on the organizational culture. For example, flexible companies are more likely to benefit from new technologies (McDermott and Stock, 1999). Brynjolfsson (1993) provides evidence that digitalization is negatively related to firm performance when high costs are involved, but firms have low growth potential. Further, research from the World Development Report argues that the profits of digitalized firms and economic growth are disappointing (Couzy, 2016).

However, there is also much empirical research that provides evidence for digital disruption leading to higher firm performance. In general, it is found that digitalization brings lower costs, higher efficiency, more flexibility, and new valuable products and services (Martinez-Caro et al., 2020). For example, Tambe and Hitt (2014) find that higher IT spending relative to the average IT spending across U.S. companies brings higher output elasticity, indicating that the production is reaching higher returns. Further, it is argued that digital disruption adds new capabilities which can lead to higher profits. For example, digitalization makes it easier for firms to react to valuable opportunities or abandon value-destroying aspects in their business processes (Drnevich and Croson, 2013). Furthermore, firms with many digital resources such as technical knowledge and intangible assets can make their business processes more efficient than firms with lower digital resources. This higher efficiency can lead to a difference in firm performance between those two kinds of firms (Chitsaz et al., 2017). Yunis et al. (2017) highlight the chances of digitalized firms to gain higher market share, create new products and services, and reach higher efficiency. Furthermore, investors are increasingly taking digitalization into account within their investment decisions. Salvi et al. (2021) find a positive relationship between disclosing the level of digitalization within a firm and their firm value. This finding indicates that a higher digitalized firm can gain extra value through investors. Bellakhal et al. (2020) also provide evidence for a positive relation between digitalization and firm performance due to the possibility to develop new business activities, higher sales, and the ability to participate in international markets. It is expected that these benefits will outweigh the pitfalls related to digitalization. Therefore, the following hypothesis is formed:

Hypothesis 3: Higher digitalization within firms will lead to higher firm performance.

2.4 Digitalization and practical experiences

For this thesis, there was the valuable opportunity to interview five companies within the AEX/AMX/AScX to combine the theory about digital disruption with the practical experiences of these companies. Several interesting points emerge from these interviews, which are discussed below. All findings below are retrieved from the interviews, and permission has been given from the interviewed companies to use this information.

The interviews confirm the statement made in this research that digital disruption is a growing field of interest. Digitalization has become a priority and is reflected in the strategic pillars. For example, companies have created separate departments dealing with digitalization to make internal operations more efficient by using new techniques. Furthermore, companies recognize the importance of digital tooling for their employees. With this, among other things, they want to higher their internal capacity to provide digital solutions for their consumers. In addition, due to the new techniques, companies are increasingly focusing on cyber risk. New departments have been created to ensure data safety, and companies are continuously making employees aware of these cyber risks.

The interviewed companies are large, long-existing companies, and all indicate that it is not easy to implement digital changes. Due to their long history, these companies are dealing with their data leverage. In addition to this, employees often wish to stick to old processes. Further, the large size of these companies makes it complex to implement digital changes in all departments of the companies. Lastly, the international aspect also brings difficulties. The head offices are attached to different, local organizations. These local companies all have their own culture and way of working, making it hard to standardize processes.

Although implementing digital changes is a challenge for the interviewed companies, they are aware of the urgency to keep up with the digital trend to satisfy their consumers and to hold their market value. Consumers are much more mobile-driven and expect the companies' products and services to be digital-driven. The digital trend also influences the competition within industries. Companies that have started with their digitalization in the early years of the digital trend face a competitive advantage over their peers. However, this advantage is diminished by fast-growing, small companies. These start-ups are not tied to old processes and ways of working. As a result, they can implement the latest techniques in a concise time horizon. One of the companies has even entered a partnership with various digitally-driven start-ups to keep up with the latest techniques. Therefore, it is clear that fast-growing start-ups are challenging large companies within the AEX/AMX/AScX.

The last point discussed with the interviews is the added value to the company due to digitalization. The companies that were relatively early with their digital strategy, benefit from low costs and high efficiency. This is, for example, because of few physical offices and high digital interactions with customers. Further, companies also highlight the importance of a digital appearance to the outside world to have a higher investor valuation. However, the cost and time required for digital changes are often higher than expected. The companies also notice that expectations associated with digitalization are not easily realized in the first few years.

3. Data

In this section, the dataset and the input variables are described. Further, all transformations on the data and the descriptive statistics are discussed.

3.1 The data sample

All companies included in the AEX, AMX, or AScX from 2015 to 2019 are incorporated in the dataset. In addition, companies that were only partly included in the AEX, AMX, or AScX from 2015 to 2019 are also included. In this way, the initial data sample consists of 400 observations of 80 companies. The data can be considered panel data as it consists of different observations for each company over different time windows.

First, annual reports are used to retrieve the digital score of the companies by counting words related to digital disruption in the annual report. Unfortunately, some annual reports were not publicly available. Therefore, the observations for which the variable digital score had a missing value are deleted. As a result, there were 11 missing observations. From there on, the dataset consisted of 389 observations of 80 companies. Second, the ISIN codes of these 80 companies are used as an input for the database DataStream to retrieve most of the data related to capital structure and firm performance. The data for the dependent variable change in outstanding long-term debt is retrieved from Bloomberg. These two datasets were taken together. The missing values were manually retrieved from annual reports. Therefore, there were no new missing values. Eventually, the panel data consists of 5057 observations of 80 different companies.

3.2 Dependent variables

Hypothesis 1 will test whether companies are holding onto the first assumption of the pecking order theory, which assumes that internal financing is preferred above external financing. Hereby, the dependent variable is *the ratio of internal financing relative to the total financing.* Internal financing is the difference between the change in capital expenditures and external financing, which is the newly issued debt and equity. A relatively high internal financing ratio refers to a firm acting consistent with the pecking order theory, and contradictory, a relatively low internal financing ratio refers to a firm acting inconsistently with the pecking order theory (Myers, 1984).

Hypothesis 2 will show whether companies hold onto the second assumption of the pecking order theory, which is the assumption that debt is preferred over equity when internal financing is insufficient. The dependent variable is the *change in the outstanding long-term debt*. This variable shows the amount of long-term debt that is issued in a specific year. If the change in debt equals the lack of internal financing, it can be assumed that, on average, companies are acting strictly consistent with the pecking order theory (Myers, 1984). In that case, only debt is used to cover the insufficient internal financing. In addition, if more than 50% of the financial deficit is covered with debt, companies also act consistently with the second assumption of the pecking order theory as debt is then still preferred over equity.

Hypothesis 3 investigates the effect of digitalization on firm performance. To test hypothesis 3, two different performance measures will be analysed. First, *return on assets (ROA)*, which is an accounting measure and is expressed as a firm's net income divided by its average total assets. ROA is a widely used measure to analyse the impact of digitalization on firm performance (Vitolla et al., 2020; Salvi et al., 2021). How higher the ROA, how higher the firm performance. Secondly, *Tobin's Q* will be used as a measure of firm performance. Previous literature has provided evidence that Tobin's Q and firm performance are related. Thus, a higher Tobin's Q will lead to higher performance (Figueiredo and Junior, 2002). Tobin's Q is expressed as the firm's market value divided by the replacement cost of assets (Chung and Pruitt, 1996). A Tobin's Q higher than 1 indicates that the market value of a firm is worth more than its asset value, indicating that the firm value is determined by future opportunities rather than assets in place (Chen, 2002). Therefore, firms with a high Tobin's Q have relatively high growth opportunities. Furthermore, Tobin's Q higher than 1 indicates that the firm's stock is overvalued as buying a stock of such a firm is more expensive than the replacement cost of its assets. A Tobin's Q between 0 and 1 indicates undervaluation of the firm's stock. How higher Tobin's Q, how higher the firm performance.

3.3 Independent variables

The main variable of interest is the *digital score* used to determine a company's digital maturity. The higher this score is, the more digital mature the company is, indicating a higher capacity to react to digital disruption. The digital score is based on the method of Kriebel and Debener (2020). With this method, the number of words related to digitalization is counted within annual reports. These keywords can be found in Appendix Table A1. The higher the number of words related to digitalization, the higher a company's digital score. If it turns out that the digital score has a positive coefficient for a particular dependent variable, it means that digitalization has a positive impact on that dependent variable. Conversely, a negative coefficient of the digital score for a particular dependent variable indicates that digitalization negatively influences that dependent variable. The digital score will be used as the independent variable for all three hypotheses.

For hypothesis 2, another independent variable is included, which is the *financial deficit*. The strict pecking order theory assumes that the financial deficit equals the change in the outstanding long-term debt. In that case, the pecking order coefficient, which is the regression coefficient of financial deficit, will be equal to 1. However, a pecking order coefficient higher than 0.50 still indicates that debt is preferred over equity as more than 50% of the financial deficit is covered with debt. Concluding, a pecking order coefficient higher than 0.50 indicates that firms, on average, are acting consistently with the second assumption of the pecking order theory. A pecking order coefficient lower than 0.50 indicates that firms, on average, are not acting consistently with the second assumption of the pecking order theory, as equity is then preferred over debt. The input variables to calculate the financial deficit are dividend payments, capital expenditures, the net increase in working capital, the current position of long-term debt, and operating cash flows (Shyam-Sunder and Myers, 1999). The formula to calculate the financial deficit looks as follows:

$$Financial\ deficit_t = Dividend_t + Capital\ expenditures_t + \ \Delta Working\ capital_t + Current\ position\ long\ term\ debt_t \ - \ Operating\ cash\ flows_t$$

3.4 Control variables

The dataset consists of several control variables. The control variables can be divided into capital structure control variables and firm performance control variables. The determinants of the capital structure, which are explained in section 2.3.1, are added as control variables to test the two pecking order hypotheses. *Profitability* is the first control variable and is used to control for differences in profitability. For this, operating revenue will be used as an input variable. This variable is also used by Titman and Wessels (1998), who argue that a firm's profitability strongly influences the capital structure. Based on Campello and Giambona (2010), a measure for *tangibility* as a control variable is added. The level of tangibility within a company is calculated by the number of tangible assets divided by the total amount of assets. Michaeles et al. (1999) argue that a firm needs capital to realize growth. Therefore, *growth* is added as a third control variable to control for differences in growth between firms. This will be measured by the growth in operating revenue and is calculated as follows:

$$Growth = \frac{Operating\ revenue_t - Operating\ revenue_{t-1}}{Operating\ revenue_{t-1}}$$

Lastly, the book value of total assets is used to control for differences in *firm size*, which is also done by Kurshev and Strebulaev (2015), who researched the relation between firm size and capital structure.

The first control variable for firm performance is *firm size*. As with the capital structure, the book value of total assets will be used to measure firm size. It can be expected that larger firms will have higher firm performance due to their capabilities and resources to gain from investment opportunities (Lee, 2009; Hejazi et al., 2016). Second, *ROA* will be included as a control variable. According to Lee and Yeo (2016), ROA is positively related to firm performance as it measures the capacity to generate returns by effectively using productive assets. Further, the number of years between the firm's foundation and the observation year will be used to control *firm age* (Martin-Pena, 2019). In addition, there is empirical evidence that *growth* positively influences firm performance (Brush et al., 2000). The control variable growth is measured in the same way as for capital structure. There is much empirical evidence that a firm's capital structure also influences the firm performance (Saeedi and Mahmoodi, 2011; Dao and Ta, 2020). To control for differences in the capital structure, the amount of *leverage* is added. Seventh, *risk* is added as a control variable measured with the company's stock return volatility level.

Furthermore, a fixed year effect is added in every main regression. This enables to control for factors changing each year that are common to all firms in the sample. Further, the year fixed effects are added to eliminate annual trends. Such an annual trend could be for example a result of the Covid-19 crisis, where many firms were forced to work from home resulting in investments regarding digital working. In addition, a fixed industry effect is also added in every main regression to eliminate time-invariant industry characteristics that play a role in determining the capital structure and the financial performance. For example, some industries are more well-doing than other industries. If a company falls within a well-earned industry, the chance to have a high financial performance is higher compared to a firm that is in a less-earned industry. The primary codes of the Standard Industry Classification (SIC) are used to include industry as a fixed effect. The data sample is divided into different categories based on their SIC Codes, shown in Appendix Table A2. By adding these year fixed effects and industry fixed effects, more of the variation in the dependent variable is explained by firm-specific characteristics.

3.5 Descriptive statistics

Histograms were made to see whether the data were normally distributed. The histograms show that the data was not normally distributed. As the dataset consists of several zero- and negative values, the most appropriate way to normalize data is taking the Cube Root of all the variables (Vadali, 2017). After these adjustments for all variables, the different histograms showed normally distributed data. Further, boxplots were made to determine if the dataset contains huge outliers. Some observations had significantly lower or higher values than the average value of observations for that specific variable. However, these observations were clustered together and therefore not seen as an individual outlier. In addition, the descriptive statistics (Table 1) show that for all variables, the difference between the mean and median is relatively small. This indicates that the data does not contain extreme outliers. Therefore, it is not necessary to winsorize the data.

In Table 1, the descriptive statistics of the variables are shown. The mean of change in long-term debt is 0.67, which is approximately €673.000. ROA has an average of 1.21%, a minimum of -3.92%, and the maximum ROA in this dataset is 5.82%. The mean of Tobin's Q is 0.93, indicating that, on average, investors have negative growth expectations regarding the firms in this dataset. The average digital score is approximately 3.62. The minimum digital score equals 1, and the maximum digital score in the dataset is 7.09.

Table 1: Descriptive statistics of the numerical variables

Variable	Observations	Mean	Median	Std. Dev.	Min	Max
Internal financing/Total financing	389	-2.457	-1.899	13.359	-52.643	91 .430
Change in long-term debt	389	0.673	0.112	7.548	-30.517	31.090
ROA	389	1.207	1.737	1.491	-3.915	5.816
Tobin's Q	389	0.934	0.944	0.328	0.215	2.231
Digital score	389	3.624	3.517	1.106	1.000	7.087
Financial deficit	389	3.608	3.443	9.346	-24.319	44.240
Profitability	389	5.711	4.812	5.476	-6.672	29.939
Tangibility	389	0.512	0.538	0.285	-0.677	1.418
Growth	389	0.023	0.322	1.143	-15.097	3.935
Firm size	389	18.353	12.658	17.535	0.852	96.227
Firm age	389	3.633	3.362	1.211	0	7.629
Leverage	389	3.662	3.922	2.977	-23.334	12.250
Risk	389	0.652	0.636	0.101	0	1.204

In Table 2, the descriptive statistics for the categorical variable Industry code are shown. The Industry code most represented in this dataset is code 4, which is the manufacturing industry. There are also many companies with code 9, 20.62%, from the Services industry. No companies appear in the dataset from the Agriculture, Mining, and Public Administration industry which are respectively coded 1,2, and 10.

Table 2: Descriptive statistics of the categorical variable Industry code

		Frequency	Percentage
Industry code	1	0	0
	2	0	0
	3	5	1.29
	4	140	36.08
	5	33	8.51
	6	45	11.60
	7	25	6.44
	8	60	15.46
	9	80	20.62
	10	0	0

4. Methodology

This section starts with the Hausman test to determine the use of random effects or fixed effects. Second, the method to measure digitalization within a firm is elaborated on. After that, the regressions used to test the hypotheses are separately discussed per hypothesis. Hereby, the input variables of the regression formulas are explained. Lastly, the ordinary least square assumptions are highlighted.

First of all, a Hausman test is performed for all regressions to test whether random effects or fixed effects should be included. The results are shown in Appendix Table A3. The null hypothesis is in favour of a random model and the alternative hypothesis is in favour of a fixed model. All tests give significant p-values, which indicates to reject the null hypothesis. Therefore, year fixed and industry fixed effects are added to the regressions. With the use of fixed regression models, endogeneity problems resulting from omitted variable bias will decrease. Furthermore, year fixed effects are able to eliminate annual trends and industry fixed effects are able to eliminate time-invariant industry characteristics.

Kriebel and Debener's (2020) method is used to determine the digital score for all companies over the different years. With this method, the annual reports of the companies in the dataset are analysed. The analysis of annual reports consists of text mining whereby the words related to digitalization are counted. A self-written code automatically does text mining in Python. First of all, the words related to digitalization are linked to the code. After that, some restrictions are added. For example, Python should not count the word if it is part of another word and not when only a part of the keyword is described. After this, all annual reports were downloaded and used as input in Python. The code has analysed these annual reports and the output consisted of the digital score for every company within the AEX/AMX/AScX from 2015 to 2019.

4.1 OLS regressions

Hypothesis 1, which states that digital firms follow the pecking order theory and thus prefer internal financing over external financing, will be tested first. For this, a multivariate OLS regression will be used, which looks as follows:

$$\frac{Internal\ financing_t}{Total\ financing_t} = \alpha + \beta_1 * Digital\ score_t + \beta_2 * Profitability_t + \beta_3 * Digital\ score_t\ x\ Profitability_t + \beta_4 * Tangibility_t + \beta_5 * Digital\ score_t\ x\ Tangibility_t + \beta_6 * Growth_t + \beta_7 * Digital\ score_t\ x\ Growth_t + \beta_8 * Firm\ size_t + \beta_9 * Digital\ score_t\ x\ Firm\ size_t + F_{Year} + F_{Industry} + \varepsilon_t$$

In this equation, α is the intercept with the y-axis and β_x is the slope coefficient for each independent variable. This slope indicates the direction and size of the relationship between the independent and dependent variable. Internal financing/Total financing stands for the amount of internal financing used to finance investment and operations relative to total financing. Internal financing is here defined as the difference between the change in capital expenditures and the external financing, which is the newly issued debt and equity. Total financing consists of the total amount of internal financing and external financing. The ratio Internal financing_t/Total financing_t is the dependent variable in this regression. The digital score represents the company's digital maturity and is determined by counting the words related to digitalization within annual reports. The digital score_t is the independent variable of interest. A positive coefficient for the digital score indicates that digitalization increases the ratio of Internal financing/Total financing, implying that higher digital mature firms act more consistently with the pecking order theory than lower digital mature firms. In that case, hypothesis 1 can be accepted. A negative coefficient indicates the opposite. From theory, there are mixed expectations regarding the sign of this digital score coefficient. In general, digitalized firms gain their value from intangible assets making it more difficult for investors to value these companies (Beutel et al., 2019). The unknown value of these intangible assets will increase the asymmetric information costs, leading to the expectation that digitalized firms will prefer internal financing over external financing. However, much empirical evidence shows that technology- and innovation-based firms do not act consistently with the first assumption of the pecking order theory (Audretsch and Lehmann, 2004; Coleman and Robb, 2012). This indicates that no expectation of the coefficient can be made. Therefore, the hypothesis will be tested with a two-sided t-test. Profitability stands for the operating revenue of a company. It is expected the coefficient for profitability to be positive as profits will lead to higher internal funds (Wijaya, 2020). The interaction effect between digital score and profitability captures the effect that profitability has on the digital score. From literature and practical interviews, it has become clear that digitalization requires high investments (Mottaeva et al., 2020). It may therefore be that companies with higher profits are more able to finance these digital investments. Therefore, the coefficient of this interaction effect is expected to be positive. Tangibility stands for the number of tangible assets divided by the total amount of assets. For outside investors, it is easier to estimate the actual value of a firm with a high level of tangibility compared to a firm with a low level of tangibility. A low tangibility level will thus higher the asymmetric information costs, which strengthens the pecking order theory (Bharath et al., 2009). Therefore, the coefficient for tangibility is expected to be negative. The interaction effect between digital score and tangibility captures the fact from the literature that firms with a low level of tangible assets are often data-driven, leading to a higher digital score than firms with high tangibility (Beutel et al., 2019). This leads to the expectation of a negative interaction effect between digital score and tangibility.

Growth is defined as the growth in operating revenues between $year_{t-1}$ and $year_t$. In order to grow, firms need additional financing. Therefore, it can be expected that firms with high growth potential are forced to rely on external financing (Michaelas et al., 1999), leading to the expectation of a negative sign for the coefficient growth. For this variable, also an interaction effect is added. Firms with high growth potential are often start-ups that are not already stuck to old processes and systems. Therefore, these companies can quickly adapt to the digital world, possibly leading to a higher digital score (Stonehouse and Konina, 2020). The coefficient for the interaction effect between digital score and growth is thus expected to be positive. The variable firm size stands for the book value of total assets of a firm. Smaller firms are often dealing with high asymmetric information problems, due to the low information requirements towards the outside world. This leads to smaller firms acting more consistently with the pecking order theory (González and González, 2011). Therefore, the expected coefficient for firm size is expected to be negative. According to Weil and Woerner (2015), large firms have a higher capacity to react to the digital trend. However, it can be concluded from interviews that it is difficult for large firms to immediately adapt to the newest technologies due to the complexity of their firm. The interaction effect between digital score and firm size captures these two-sided effects. Further, year fixed effects and industry fixed effects are added to the regression. As already explained in section 3.4, these fixed effects are added to control for factors that are changing each year commonly to all firms in the sample, to eliminate annual trends, and to eliminate time-invariant industry characteristics. By adding these fixed effects, more of the variation in the internal financing relative to the total financing is explained by firm specific characteristics. The epsilon represents the error term of the regression model which accounts for the variation in the ratio Internal financing/Total financing that is not explained by the independent variables. The error term is expected to be zero as then only a random error is left in the error term. This is forced by adding a constant in the regression.

Second, hypothesis 2 will be tested which states that digital firms follow the pecking order theory and thus prefer debt over equity when there is a financial deficit. This hypothesis will be tested according to the model of Shyam-Sunders and Myers (1999), with the following multivariate OLS regression:

$$Change\ in\ long-term\ debt_t = \alpha + \beta_1 * Financial\ deficit_t + \beta_2 * Digital\ score_t + \beta_3 * Financial\ deficit_t\ x\ Digital\ score_t + \beta_4 * Profitability_t + \beta_5 * Financial\ deficit_t\ x\ Profitability_t + \beta_6 * Tangibility_t + \beta_7 * Financial\ deficit_t\ x\ Tangibility_t + \beta_8 * Growth_t + \beta_9 * Financial\ deficit_t\ x\ Growth_t + \beta_{10} * Firm\ size_t + \beta_{11} * Financial\ deficit_t\ x\ Firm\ size_t + F_{Year} + F_{Industry} + \varepsilon_t$$

In this equation, α is the intercept with the y-axis and β_x is the slope coefficient for each independent variable. The dependent variable is the change in long-term $debt_t$ and stands for the amount of long-term debt issued in a specific year and consists of debt that matures in more than one year. Financial deficit shows the number of investments and operations that need to be covered by external financing due to insufficient internal financing. The financial $deficit_t$ is the first independent variable in this model, represented by the pecking order coefficient. According to the pecking order theory, the pecking order coefficient for financial deficit must be higher than 0.50. In this case, firms prefer debt over equity as more than 50% of the financial deficit is covered by debt (Myers and Majluf, 1984). In the method of Shyam-Sunders and Myers (1999), the main interest is to look at the consistency of the pecking order theory. This can be seen through the pecking order coefficient, as that coefficient shows by which amount the financial deficit in a certain year is covered with newly issued long-term debt. Therefore, the interaction effects between financial deficit and the other explanatory variables are of main interest. It can be concluded from the sign of these interactions terms whether a certain variable heightens or lowers the pecking order coefficient, which then indicates whether that certain variable strengthens or weakens the second assumption of the pecking order theory. The independent variables are also added as single effects in order to capture part of the single effect of a variable on the change in long-term debt. Otherwise, the interaction terms would capture both the single effect and the interaction effect, leading to biased estimates.

The digital $score_t$ is the second variable of interest. Firms with higher digital scores could gain higher efficiency and lower costs (Martinez-Caro et al., 2020). As a result of these positive effects of digitalization, higher internal capital can be reached. When companies have a lower degree of digitalization than their competitors, their income may be reduced due to competitive disadvantages, leading to lower internal financing (Weil and Woerner, 2015). According to several empirical research, it is argued that high internal funds will lead to lower debt levels as companies will then use their own funding to finance investments and operating activities (Karadeniz et al., 2013; Güner, 2016; Wahyuding and Salsabila, 2019). Therefore, a negative effect of profitability on the change in long-term debt is expected. The interaction effect between financial deficit and digital scores captures the effect of digitalization on the consistency of the second assumption of the pecking order theory. Same as hypothesis 1, there is again mixed empirical evidence regarding the effect of digital maturity on the consistency of the pecking order theory. Therefore, the second hypothesis will also be tested with a two-sided t-test. Profitability is added as a control variable and is measured by operating revenues. Companies use their profits as internal financing. As already mentioned above, high internal funds will lead to lower debt levels (Karadeniz et al., 2013; Güner, 2016; Wahyuding and Salsabila, 2019). Therefore, the effect of profitability on the change in long-term debt is expected to be negative. The interaction effect between financial deficit and profitability captures the effect of profitability on the consistency of the pecking order theory. Ooi (1999) argues that profitable firms have easier access to debt than less profitable firms due to fewer debt constraints. In the case of financial deficit, profitable firms tend to prefer debt over equity. This is consistent with the second assumption of the pecking order theory. A positive interaction term is thus expected. Tangibility shows the level of tangible assets compared to the book value of total assets. Colombo and Grilli (2007) argue that firms with a low tangibility level face financial constraints due to few collaterals for issuing debt. Therefore, the effect of tangibility on debt is expected to be positive as a higher tangibility leads to fewer debt constraints. Bharath et al. (2009) argue that firms with a low tangibility level face higher asymmetric information costs compared to firms with a high tangibility level, leading to the expectation that firms with high tangibility act less consistent with the pecking order theory. This effect is captured by the interaction term between financial deficit and tangibility and is expected to be negative. Growth is also added as a control variable and is measured by the growth in operating revenue. Start-ups are often market players with high growth potential. However, due to the newness, these companies in general face difficulties in their first years to build up enough internal capital as their earning potential is in the future (Chong and Luyue, 2014). Therefore, it can be expected that growth has a positive effect on change in long-term debt as these growth firms are in need of additional financing. The value of a firm with a high growth rate is often determined by their future opportunities, which higher their debt constraints (Chen, 2002). This will lead to the expectation of a negative interaction coefficient between financial deficit and growth as growth firms are often forced to rely on equity as financing source in the case of financial deficit. This weakens the second assumption of the pecking order theory. Lastly, firm size is added as a control variable. Large size firms, often mature firms, already have some internal capital reserves which lowers the need for external financing (Karadeniz et al., 2013; Güner, 2016; Wahyuding and Salsabila, 2019). Therefore, a negative coefficient for firm size is expected. In addition to this, larger firms have lower asymmetric information costs than smaller firms, leading to the expectation that large firms act less consistently with the second assumption of the pecking order theory (González and González, 2011). Therefore, the interaction coefficient between financial deficit and firm size is expected to be negative. The regression also contains year fixed effects and industry fixed effects. Adding these fixed effects will help to eliminate annual trends and time-invariant industry characteristics, leading to a variation in the outstanding long-term debt that is on a higher level explained by specific firm characteristics. The epsilon represents the error term of the regression model and is expected to be zero.

The third hypothesis tests the relationship between the digital maturity of a firm and firm performance. The hypothesis states that higher digitalization within firms will lead to higher firm performance. To test this hypothesis, two different measures for firm performance will be used. The multivariate OLS regression with ROA as dependent variable looks as follows:

$$ROA_t = \alpha + \beta_1 * Digital\ score_{t-1} + \beta_2 * Firm\ Size_{t-1} + \beta_3 * Digital\ score_{t-1}\ x\ Firm\ Size_{t-1} + \beta_4 * ROA_{t-1} + \beta_5 * Firm\ age_{t-1} + \beta_6 * Digital\ score_{t-1}\ x\ Firm\ age_{t-1} + \beta_7 * Growth_{t-1} + \beta_8 * Digital\ score_{t-1}\ x\ Growth_{t-1} + \beta_9 * Leverage_{t-1} + \beta_{10} * Risk_{t-1} + F_{Year} + F_{Industry} + \varepsilon_t$$

In this equation, α is the intercept with the y-axis and β_x is the slope coefficient for each independent variable. The dependent variable ROA_t stands for the return on assets which is the firm's net income divided by its average total assets. The variable of interest is the digital $score_{t-1}$. This time-lag structure avoids endogeneity problems and causality between the dependent and independent variables by ensuring that the independent variables precede the dependent variables (Aschhoff and Schmidt, 2008). From the literature, there is mixed empirical evidence about the effect of digitalization on firm performance. On the one hand, digitalization within a company often leads to lower costs, higher efficiency, and higher valuations from investors (Martinez-Caro et al., 2020). On the other hand, changing current business processes to digitalized business processes can lead to a clash between the two processes, and resistance to change can arise from employees (Del Giudice, 2019). As it is not yet possible to make a confident expectation regarding the digital score coefficient, this hypothesis will be tested with a two-sided t-test. The lagged firm size variable is added as a control variable. The coefficient for firm size is expected to be positive as larger firms have the capabilities and resources to gain from investment opportunities and therefore, higher their firm performance (Lee, 2009; Hejazi et al., 2016). The interaction effect captures the effect of firm size on the digital score, which can be both negative or positive. On the one hand, large firms are with a higher degree able to react to the digital trend (Weil and Woerner, 2015). On the other hand, it has been come clear from the interviews that it is difficult for large firms to immediately adapt to the digital trend due to the complexity of these firms. Further, the lagged variable of ROA is also added as a control variable, which is expected to have a positive coefficient. The variable firm age, which is also added as a control variable, indicates the number of years since the firm's foundation. Research by Martin-Pena (2019) provides evidence that there is a positive correlation between firm age and firm performance. Therefore, the coefficient for firm age is expected to be positive. Stonehouse and Konina (2020) argue that relatively new firms have a higher capacity to react to digital disruption than mature companies due to their flexible characteristics. Furthermore, with implementing changes, young firms likely adopt new processes easier than companies who have been working with a specific process for already a long time (Masli et al., 2016). The interaction effect between digital score and firm age captures this effect of a firm's maturity on the digital score. The coefficient of this interaction effect is expected to be negative. Growth of operating revenue is also added as a control variable in this regression. Brush et al. (2000) provide empirical evidence that growth positively influences firm performance, leading to the expectation of a positive coefficient for growth. The interaction effect between digital score and growth captures the effect growth has on the digital score. Firms with high growth rates are often start-ups that are flexible and can easily adapt to the digital world. Therefore, a positive interaction coefficient between digital score and growth is expected. The variable leverage indicates the amount of debt within a firm. The leverage coefficient is expected to be negative as Dao and Ta (2000) find empirical evidence that both short-term and long-term debt are negatively related to firm performance. The variable risk stands for the company's stock return volatility. The higher the stock return volatility, the higher the risk related to a firm. According to Dutt and Humphery-Jenner (2013), low volatility stocks will result in higher operating performance. Therefore, the coefficient for risk is expected to be negative. The year fixed effects and industry fixed effects that are added to the regression will capture the variation on the ROA which are determined by annual trends and time-invariant industry characteristics. The estimated variation in the dependent variable is then mainly determined by specific firm characteristics. The value of the epsilon is expected to be zero and represents the error term of the regression.

The other firm performance measure used to test the effect of digitalization on firm performance is Tobin's Q. The multivariate OLS regression, with Tobin's Q as the dependent variable, looks as follows:

$$Tobin's\ Q_t = \alpha + \beta_1 * Digital\ score_{t-1} + \beta_2 * Firm\ Size_{t-1} + \beta_3 * Digital\ score_{t-1}\ x\ Firm\ Size_{t-1} + \beta_4 * ROA_{t-1} + \beta_5 * Firm\ age_{t-1} + \beta_6 * Digital\ score_{t-1}\ x\ Firm\ age_{t-1} + \beta_7 * Growth_{t-1} + \beta_8 * Digital\ score_{t-1}\ x\ Growth_{t-1} + \beta_9 * Leverage_{t-1} + \beta_{10} * Risk_{t-1} + F_{Year} + F_{Industry} + \varepsilon_t$$

In this equation, α is the intercept with the y-axis and β_x is the slope coefficient for each independent variable. The dependent variable in this regression is Tobin's Q_t, expressed as the firm's market value divided by the replacement cost of assets. The variable of interest is the digital $score_{t-1}$. Previous literature provides mixed empirical evidence about the effect of digitalization on firm performance, which also specifically relates to the performance measure Tobin's Q. On the one hand, as digitalized firms gain value from intangible assets and digital knowledge, investors could undervalue the firm's stock as they are unknown about the potential of these digital intangibles (Beutel et al., 2019). This undervaluation of the stocks leads to a lower Tobin's Q. On the other hand, digitalized firms often have high growth potential due to the future opportunities digitalization brings which would automatically higher Tobin's Q as Tobin's Q is a measure of growth opportunities. Further, investors are increasingly taking into account digitalization in their investment decisions (Salvi et al., 2021). Therefore, it can be expected that investors recognize the digital firm's growth potential and are willing to pay a relatively high price for its stocks, which leads to a higher Tobin's Q. Due to these mixed expectations, the hypothesis will be tested with a two-sided t-test. The expectations regarding the sign of the coefficients for the control variables are the same as described in the model with ROA as dependent variable. Thus, the coefficient of the lagged variable of firm size is expected to be positive. There can be made no reliable expectation regarding the sign of the interaction coefficient between digital score and firm size as literature provides mixed expectations. The signs of the coefficients for ROA and firm age are expected to be positive. In addition, it is expected the interaction coefficient between digital score and firm age to be negative. The coefficient for growth and the interaction coefficient between digital score and growth are both expected to be positive. Lastly, leverage and risk are expected to have a negative effect on firm performance and therefore a negative sign for this coefficient is expected. The regression contains year fixed effects and industry fixed effects to capture annual trends and time-invariant industry characteristics. The epsilon represents the error term in this model and the value of this term is expected to be zero.

4.2 OLS assumptions

To obtain unbiased estimates using ordinary least square regressions, several assumptions are considered. First of all, as already mentioned in section 3.5, all variables are adjusted by taking the cube root of the variables in order to normalize the data. Furthermore, robust standard errors are added to the regressions to avoid heteroskedasticity. According to Stock and Watson (2015), there are only a few cases where the standard errors are homoscedastic. The authors see homoskedasticity as the expectation and therefore argue always to use robust standard errors. Furthermore, multicollinearity is controlled by a correlation matrix, which can be found in Appendix Table A4. According to Tabachnick and Fidell (2007), a correlation higher than 0.80 indicates multicollinearity. There is no value higher than 0.80 in the correlation matrix, indicating no multicollinearity. Another OLS assumption that must hold is the value of the error term expected to be zero which is forced by adding the constant in every regression. Lastly, the OLS assumption of endogeneity is considered. Endogeneity is an important issue related to corporate finance studies and can be described as the phenomenon where the explanatory variables are correlated with the error term in the regression (Roberts and Whited, 2013). In the case of endogeneity, OLS is not able to deliver consistent parameter estimates (Woolrich, 2010). In order to ensure the reliability of the results, attention is given to these endogeneity problems. There are four different forms of endogeneity; omitted variable bias, simultaneity, measurement error, and selection bias (Roberts and Whited, 2013). Omitted variable bias occurs when variables that should be included in the model as an explanatory variable are not included. Endogeneity arises when these omitted variables correlate with the explanatory variables included in the model (Roberts and Whited, 2013). To address this problem, two steps have been undertaken in this research. Due to the panel data in this research, it is possible to use fixed-effect models, which is a way to ameliorate endogeneity problems (Roberts and Whited, 2013). Second, based on the literature, many control variables are included in the regression models, which lowers the chance that explanatory variables are missing. Simultaneity arises when both the independent and the dependent variable influence each other. Many researchers have avoided this problem by using lagged variables (Aschhoff and Schmidt, 2008; Bania et al., 2007; Brinks and Coppedge, 2006). In this way, it can be ensured that the independent variables precede the dependent variables. Therefore, the robustness check regressions for hypotheses 1 and 2, and the main regressions for hypothesis 3 contain lagged variables. The third endogeneity problem can arise due to measurement errors, indicating a difference between the actual value of a variable and the measured value of a variable. In order to minimize measurement error in this research, the use of proxy variables is limited (Wickens, 1972). Furthermore, high-quality databases, such as Bloomberg and DataStream, are used to ensure having updated data of trustable quality. The last endogeneity problem is selection bias, appearing when the randomization of the sample is not sufficient. In that case, the sample is not representative for the population. In this research, a certain selection bias could arise as only public firms are incorporated in the dataset. However, it could be still representative for public firms in other countries.

5. Results

In this section, the results that have been found in this research will be discussed and related to the theoretical framework. Furthermore, robustness checks will be performed to ensure the reliability of the results.

5.1 Main results

Several regressions are performed to test the first hypothesis, which assumes digitalized firms act consistently with the first assumption of the pecking order theory and thus prefer internal financing above external financing. The results of the univariate regression without fixed effects and control variables can be found in column 2 of Table 3. The main results can be found in column 3 of Table 3, where all control variables and both fixed year and fixed industry effects are added to the regression. The results of the regression with only fixed year effects can be found in Appendix Table B1 and Table B2 in the Appendix contains the results of the regression with only fixed industry effects. The results of the univariate regression, shown in column 2 of Table 3, give the digital score a positive, insignificant coefficient of 0.20. However, it is likely to have omitted variable bias as there are no control variables added. Therefore, this coefficient is not interpretable. In column 3 of Table 3, the multivariate regression with added control variables, fixed year effects, and fixed industry effects is shown. The digital score has a positive coefficient of 1.06, indicating that the ratio between internal financing and total financing increases by 1.06 when the digital score increases by one point. The first assumption of the pecking order theory states that digitalized firms act consistently with the pecking order theory and thus prefer internal financing above external financing. As a higher digital score leads to a higher amount of internal financing, it can be concluded that high digital mature firms act more consistently with the first assumption of the pecking order theory compared to lower digital mature firms. This can be explained from theory. Digitalization within a company can lead to high asymmetric information costs due to the unknown potential of digital technologies. Furthermore, it can lead to financial constraints due to the uncertainty associated with digitalization (Kedzior et al., 2020). Therefore, the cost of external financing will be higher than the cost of internal financing, which leads to digital mature firms relying more on internal financing. However, as the coefficient is statistically insignificant, hypothesis 1 cannot be accepted with certainty. The average amount of internal financing relative to total financing is -2.46. The effect of having an increase in digital score of one point represents an increase in the ratio Internal financing/Total financing of 43.09% compared to the average. Therefore, the economic significance is high.

The interaction effect between digital score and firm size is significant with a negative coefficient of -0.03, meaning that the positive effect of digitalization on the level of internal financing will be lowered by 0.03 if the firm size increases by one unit, indicating one million euros increase in the book value of total assets. This implies that large firms act less consistently with the first assumption of the pecking order theory compared to small firms. Chen and Chen (2011) also confirm this. They argue that smaller firms are more reluctant to external financing as they wish to minimize the intrusion of outsiders, which leads to the tendency for small firms to prefer internal financing over external financing. The adjusted R^2 of the multivariate regression is 0.02, indicating that 2% of the variation in the ratio between internal financing and total financing is explained by the model. The adjusted R^2 is chosen because it considers how many independent variables are added to the model, which is not the case with the standard R^2. In this way, the adjusted R^2 can provide a more detailed view of the model as more independent variables usually increase the model's reliability. Further, the F-statistic is added to Table 3 which tests whether the explained variance is higher than zero. The F-statistic for the main multivariate regression is 1.78, indicating that the model with added independent variables fits the data better than a model without these independent variables.

Table 3: Linear OLS regression on internal financing relative to total financing with Year and Industry-fixed effects and Robust Standard Errors

Internal financing/Total financing	Univariate	Control variables and fixed effects added
Constant	-1.212 [1.322]	-5.073* [2.973]
Digital score	0.202 [0.328]	1.060 [0.948]
Profitability		-0.217 [0.332]
Digital score * Profitability		-0.005 [0.089]
Tangibility		2.033 [3.529]
Digital score * Tangibility		-0.432 [1.030]
Growth		-0.610 [1.386]
Digital score * Growth		0.227 [0.382]
Firm size		0.212 [0.109]
Digital score * Firm size		-0.028* [0.028]
Year-fixed effects	No	Yes
Industry-fixed effects	No	Yes
Adjusted R^2	-0.003	0.021
F-statistic	0.03	1.78
Number of observations	389	389

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

The second hypothesis states that digitalized firms follow the pecking order theory and thus prefer debt over equity when there is a financial deficit. To test the second hypothesis, multiple regressions are performed. The results of the univariate regression without fixed effects and control variables can be found in column 2 of Table 4. The main results can be found in column 3 of Table 4, where all control variables and both fixed year and fixed industry effects are added to the regression. The results of the regression with only fixed year effects can be found in Appendix

Table B3 and Table B4 in the Appendix contains the results of the regression with only fixed industry effects. The result of the univariate regression, shown in column 2 of Table 4, has a positive coefficient of 0.32 for financial deficit at a 10% significance level. The interaction effect between financial deficit and the digital score has a negative coefficient of -0.12. This coefficient is significant at a 5% level. However, as no control variables are added, it is likely to have omitted variable bias leading to endogeneity problems. Therefore, these results are not interpretable. The results for the main regression of financial deficit and digital score on the outstanding long term debt can be found in Table 4, column 3. The coefficient for financial deficit has increased to 0.35 and is still statistically significant at a 10% level. This result indicates that, on average, 35% of the financial deficit is covered by newly issued debt. The pecking order theory assumes that debt is preferred over equity in the case of financial deficit. Therefore, this result does not align with the pecking order theory, as 65% of the financial deficit is covered with equity. The effect of digitalization on the consistency of the pecking order theory is captured with the interaction effect between financial deficit and digital score, which has a negative coefficient of -0.13, significant at a 5% level. This coefficient indicates that the pecking order coefficient will be lowered by 0.13 when the digital score increases by one point, implying that the financial deficit is covered with a lower level of debt and a higher level of equity. This result is not only statistically significant, it also indicates economic significancy. A decrease of 0.13 in the coefficient for financial deficit represents a decrease of 37.14% compared to the financial deficit coefficient of 0.35. From these results, it can be concluded that a high digital mature firm acts less consistently with the pecking order theory than a less digital mature firm. The results are thus not in line with hypothesis 2. However, this result can be explained from theory. Investors are increasingly considering the level of digitalization with their investment decisions (Salvi et al., 2021). Investors who realize the growth potential of digitalized firms and their unique expertise will highly value these firms. A higher valuation will decrease the equity cost of capital, making it cheaper for firms to issue equity instead of debt. Several researchers have confirmed this (Audretsch and Lehmann, 2004; Coleman and Robb, 2012). Furthermore, the interviews showed that companies express their degree of digitalization to the outside world to gain a higher valuation. This confirms that higher digitalization could lead to a higher investor valuation. Hereby, the lower equity capital costs will compensate for the higher asymmetric problem costs involved with issuing equity.

Column 3 of Table 4 also shows a significant, negative coefficient for the interaction effect between financial deficit and growth. A 1% increase in growth leads to a decrease of the pecking order coefficient of -0.11, indicating that the financial deficit is covered with less debt at a firm with high growth potential than a firm with low growth potential. Thus, a firm with high growth potential acts less consistently with the pecking order theory than a firm with low growth potential. This result is in line with the theory. It can be explained by the fact that firms with high-growth potential need additional external financing to benefit from valuable investment opportunities. They then can be forced to issue new equity (Michaeles et al., 1999). The adjusted R^2 of the main multivariate regression in column 3 is 0.10, meaning that the model explains approximately 10% of the variation in the change in long-term debt. The F-statistic of the main multivariate regression is 2.55, indicating that the model including independent variables fits the data better than the model without independent variables.

Table 4: Linear OLS regression on change in long-term debt with Year and Industry-fixed effects and Robust Standard Errors

Change in long-term debt	Univariate	Control variables and fixed effects added
Constant	0.208 [1.303]	0.951 [1.381]
Financial deficit	0.322* [0.189]	0.352* [0.181]
Digital score	0.252 [0.397]	-0.425 [0.465]
Financial deficit * Digital score	-0.120** [0.057]	-0.126** [0.057]
Profitability		0.190 [0.172]
Financial deficit * Profitability		0.003 [0.016]
Tangibility		1.220 [1.178]
Financial deficit * Tangibility		0.175 [0.174]
Growth		0.099 [0.374]
Financial deficit * Growth		-0.108* [0.062]
Firm size		0.015 [0.094]
Financial deficit * Firm size		-0.004 [0.006]
Year-fixed effects	No	Yes
Industry-fixed effects	No	Yes
Adjusted R^2	0.036	0.104
F-statistic	2.08	2.55
Number of observations	389	389

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

The third hypothesis states that higher digitalization within firms leads to higher firm performance. To test this hypothesis, two measures for firm performance are used. First, the results of the regression on ROA will be discussed. The result of the univariate regression can be found in column 2 of Table 5. The main results can be found in column 3 of Table 5, where all control variables and both fixed year and fixed industry effects are added to the regression. The results of the regression with only fixed year effects can be found in Appendix Table B5 and Table B6 in the Appendix contains the results of the regression with only fixed industry effects. The result of the univariate regression is shown in column 2 of Table 5. The coefficient of digital score is 0.22 and significant at a 1% level. However, the results are not interpretable as no control variables are added, which will most likely lead to omitted variable bias. In the third column, the results of the main multivariate regression can be found. The digital score coefficient of 0.16 is significant at a 1% level and indicates that the ROA will increase by 0.16 if the digital score increases by one point. The average ROA of this sample is 1.21. If the digital score increases by one point, the ROA will increase 13.22% compared to the average ROA. These results are thus both statistically and economically significant. A positive coefficient for ROA is in line with hypothesis 3, which states that higher digitalization within firms would lead to higher firm performance. The positive relationship between digitalization and firm performance can be explained by Tambe and Hitt (2013), who provide evidence that higher IT spending leads to production reaching higher returns. Chitsaz et al. (2017) argue that digital resources lead to higher efficiency implying higher firm performance. The positive coefficient of the digital score on ROA is also confirmed with the interviews. Companies argue that their digital strategy could lead to higher firm performance due to efficiency and lower costs.

In column 3, the interaction effect between digital score and firm age is -0.08, indicating that long-existing firms will weaken the positive effect of the digital score on ROA compared to short-existing firms. This is in line with Stonehouse and Konina's (2020) theory, which argues that relatively new firms have more flexibility and could therefore benefit with a higher degree from the digital trend compared to mature firms. This could then lead to higher firm performance. However, as this coefficient is insignificant, the negative interaction effect cannot be assumed with certainty. Another interesting control variable is leverage which has a negative coefficient of -0.02. An increase of 1% in debt level will lead to a decrease in the ROA of 0.02. However, this coefficient is insignificant and therefore not interpretable with certainty. The adjusted R^2 of the multivariate regression is 0.39, which indicates that the model explains 39% of the variation in the ROA. The F-statistic is 9.27, indicating that the model with independent variables fits the data better compared to a model without independent variables.

Table 5: Linear OLS regression on ROA with Year and Industry-fixed effects, Robust Standard Errors and lagged independent variables

ROA	Univariate	Control variables and fixed effects added
Constant	0.461 [0.312]	0.652 [0.741]
Digital score	0.223*** [0.076]	0.163*** [0.058]
Firm size		0.017 [0.012]
Digital score * Firm size		-0.004* [0.003]
ROA		0.545*** [0.093]
Firm age		0.044 [0.046]
Digital score * Firm age		-0.081 [0.001]
Growth		0.057 [0.051]
Digital score * Growth		-0.005 [0.106]
Leverage		-0.015 [0.028]
Risk		-1.162 [0.973]
Year-fixed effects	No	Yes
Industry-fixed effects	No	Yes
Adjusted R^2	0.024	0.385
F-statistic	8.55	9.27
Number of observations	307	307

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

Besides the performance measure ROA, Tobin's Q is also used as a performance measure to test the third hypothesis. The main results of the regression of digital score on Tobin's Q can be found in Table 6. The results of the regression with only fixed year effects can be found in Appendix Table B7 and Table B8 in the Appendix contains the results of the regression with only fixed industry effects. The digital score coefficient with the univariate regression is -0.06 and significant at a 1% level. However, this result is not interpretable as no control variables are added, leading to endogeneity problems regarding omitted variable bias. The multivariate regression results are shown in column 3, where the digital score coefficient equals 0.01, indicating a positive relationship between digital score and Tobin's Q. More specifically, an one point increase in digital score leads to an increase of Tobin's Q of approximately 0.01. As existing research provides evidence that a higher Tobin's Q leads to higher firm performance, the positive coefficient of digital score is in line with hypothesis 3, which states that digitalization leads to higher firm performance. The positive relationship between digitalization and Tobin's Q can be explained from theory. The business world is currently dominated by new digital technologies and the future opportunities that digital solutions bring. Firms that adopt digitalization as one of their strategic pillars, due to the digital disruption, are able to gain advantages from these digital growth opportunities (Weil and Woerner, 2015). As Tobin's Q is a measure for growth opportunities, it is interpretable that a higher digital score leads to a higher Tobin's Q. Further, the level of Tobin's Q indicates the investor's expectations about the growth potential of the firm. Investor behaviour has changed in the last few years, and investors are increasingly seeking digital companies (Salvi et al., 2021). This is also confirmed by the practical interviews where it was stated that companies are adding digitalization as one of their strategic pillars to keep their investors and consumers satisfied. Due to the positive attitude from investors towards digitalization, it can be assumed that investors are recognizing the high growth potential of digitalized firms and are willing to pay a relatively high price for stocks leading to a high Tobin's Q. However, the effect of digital score on Tobin's Q is statistically insignificant and therefore hypothesis 3 cannot be accepted with certainty. Further, the average Tobin's Q in this sample is 1.09. An increase in Tobin's Q of 0.01, due to an one point increase in digital score, indicates an increase of 0.92% compared to the average Tobin's Q in the sample. This small percentage shows that the result for the regression on Tobin's Q is also not economically significant.

Comparing the positive relationship between digital score and Tobin's Q with the previous results provides interesting points. The previous results indicate that a higher digital score leads to less consistency of the second assumption of the pecking order theory, indicating that digitalized firms prefer equity over debt. A high Tobin's Q indicates that a firm's stock is worth more than its asset value. Firms prefer to issue equity when their stocks are overvalued as they receive more capital than the stocks are actually worth (Hovakimian, 2016). Therefore, this could explain that firms with a higher digital score, and therefore also a higher Tobin's Q, prefer equity over debt. However, as the positive coefficient of the digital score on Tobin's Q is both economic and statistically insignificant, it cannot be assumed with certainty.

In column 3, firm size provides a significant negative coefficient which is logical as firm size is measured with the book value of total assets, and Tobin's Q is expressed with replacement costs of assets as denominator. The adjusted R^2 in the multivariate regression model is 0.35, indicating that the variation in Tobin's Q is explained for 35% by the model, which is lower than the adjusted R^2 in the model with ROA as dependent variable. The F-statistic for the main multivariate regression is 9.31, indicating that the explained variance is higher than zero.

Table 6: Linear OLS regression on Tobin's Q with Industry and Year-fixed effects, Robust Standard Errors and lagged independent variables

Tobin's Q	Univariate	Control variables and fixed effects added
Constant	1.144*** [0.054]	1.692*** [0.291]
Digital score	-0.058*** [0.015]	0.013 [0.068]
Firm size		-0.011*** [0.003]
Digital score * Firm size		0.001** [0.002]
ROA		0.014 [0.021]
Firm age		-0.025 [0.051]
Digital score * Firm age		-0.006 [0.016]
Growth		-0.019 [0.087]
Digital score * Growth		0.004 [0.022]
Leverage		-0.010 [0.015]
Risk		-0.653** [0.305]
Year-fixed effects	No	Yes
Industry-fixed effects	No	Yes
Adjusted R^2	0.038	0.352
F-statistic	14.24	9.31
Number of observations	307	307

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

5.2 Robustness checks

To further ensure the reliability of the results, several robustness checks are performed. The robustness regression for hypothesis 1 is the same as performed earlier but with a lagged independent variable and lagged control variables. Hereby, the effect of the lagged digital score on the amount of internal financing relative to the total financing should be the same as the no-lagged digital score. In Table 7, the results for the robustness check for hypothesis 1 are shown. With the univariate regression, the digital score has a positive coefficient of 0.38. The coefficient of the digital score on the amount of internal financing relative to the total financing gives the multivariate regression a positive coefficient of 1.61. Although these results are insignificant, they show the same effect as the main regression. Therefore, it can be stated that the results are robust.

Table 7: Linear OLS regression on internal financing relative to the total financing with Industry and Year-fixed effect, Robust Standard Errors and lagged independent variables

Internal financing/Total financing	Univariate	Control variables and fixed effects added
Constant	-1.863 [1.845]	-6.435 [3.885]
Digital score	0.380 [0.492]	1.608 [1.305]
Profitability		0.110 [0.687]
Digital score * Profitability		-0.139 [0.204]
Tangibility		1.264 [4.231]
Digital score * Tangibility		-0.159 [1.385]
Growth		1.841 [2.056]
Digital score * Growth		-0.617 [0.565]
Firm size		0.116* [0.231]
Digital score * Firm size		0.004 [0.065]
Year-fixed effects	No	Yes
Industry-fixed effects	No	Yes
Adjusted R^2	-0.003	0.035
F-statistic	0.01	1.65
Number of observations	307	307

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

In order to do a robustness check for hypothesis 2, a time-lag structure is used. Hereby, the lagged financial deficit and lagged digital score should have a similar effect on the change in long-term debt as the no-lagged variables. In Table 8, the results of the regressions are shown. In column 2, it can be seen that the univariate regression gives a significant positive coefficient of financial deficit on change in long-term debt. The interaction effect between financial deficit and digital score is significantly negative. The multivariate regression is shown in column 3. There is a significant positive coefficient of 0.47 for financial deficit and a significant negative coefficient of -0.13 for the interaction effect between financial deficit and digital score. Even though the financial deficit coefficient is somewhat higher compared to the main regression, it can be concluded that the results are robust.

Table 8: Linear OLS regression on change in long-term debt with Industry and Year-fixed effects and Robust Standard Errors and lagged independent variables

Change in long-term debt	Univariate	Control variables and fixed effects added
Constant	-0.185 [1.349]	0.979 [1.402]
Financial deficit	0.506*** [0.192]	0.472*** [0.182]
Digital score	0.312 [0.428]	-0.119 [0.512]
Financial deficit * Digital score	-0.151** [0.063]	-0.130** [0.058]
Profitability		0.211 [0.205]
Financial deficit * Profitability		0.000 [0.000]
Tangibility		0.345 [1.246]
Financial deficit * Tangibility		0.074 [0.215]
Growth		0.200 [0.219]
Financial deficit * Growth		0.001 [0.000]
Firm size		-0.058 [0.099]
Financial deficit * Firm size		-0.001* [0.000]
Year-fixed effects	No	Yes
Industry-fixed effects	No	Yes
Adjusted R^2	0.025	0.113
F-statistic	0.00	0.63
Number of observations	307	307

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

To perform robustness checks for hypothesis 3, a different method is used. The regression performed for this hypothesis is split into two separate regressions. The first regression measures the effect of digitalization on the performance measure for 2015 up to and including 2017. The second regression measures the same effect, but then for the years 2018 and 2019. The regressions should indicate the same effect of the digital score on the performance measure to assume that it does not matter in which period the regression is performed. In Table 9, the results for the regression of digital score on ROA can be found. The coefficient of ROA in the years 2015-2017 is significantly equal to 0.11 at a 10% level. For regression 2, the coefficient of ROA in the years 2018-2019 is equal to 0.20 and significant at a 5% level. These coefficients indicate the same results as the main regression. Therefore, it can be concluded that the results for ROA are robust. The results for the regression of digital score on Tobin's Q can be found in Table 10. The coefficient of digital score in the years 2015-2017 is equal to 0.30. The digital score coefficient for the years 2018 and 2019 equals 0.13. Although the results for Tobin's Q are insignificant, the conclusion can be made that the results are robust for different time horizons.

Table 9: Difference-in-difference linear OLS regression on ROA with Industry and Year-fixed effects, Robust Standard Errors and lagged independent variables

ROA	2015-2017	2018-2019
Constant	1.636*	-0.109
	[0.932]	[1.139]
Digital score	0.112*	0.198**
	[0.088]	[0.090]
Firm size	0.004	-0.002
	[0.005]	[0.005]
Digital score * Firm size	-0.006	-0.002
	[0.004]	[0.004]
ROA	0.423***	0.655***
	[0.142]	[0.116]
Firm age	0.077	0.004
	[0.070]	[0.057]
Digital score * Firm age	-0.084	-0.003
	[0.072]	[0.065]
Growth	0.117	-0.102
	[0.084]	[0.134]
Digital score * Growth	-0.374	0.273
	[0.172]	[0.158]
Leverage	-0.039	0.006
	[0.033]	[0.057]
Risk	-2.215*	-0.310
	[1.180]	[1.544]
Year-fixed effects	Yes	Yes
Industry-fixed effects	Yes	Yes
Adjusted R^2	0.379	0.460
F-statistic	6.22	13.75
Number of observations	151	156

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

Table 10: Difference-in-difference linear OLS regression on Tobin's Q with Industry and Year-fixed effects, Robust Standard Errors and lagged independent variables

Tobin's Q	2015-2017	2018-2019
Constant	1.875* [0.980]	1.458 [1.422]
Digital score	0.299 [0.364]	0.125 [0.331]
Firm size	-0.023** [0.011]	-0.028 [0.019]
Digital score * Firm size	0.002 [0.003]	0.005 [0.03]
ROA	-0.227 [0.184]	0.679 [0.110]
Firm age	0.162 [0.225]	0.057 [0.233]
Digital score * Firm age	-0.069 [0.080]	-0.067 [0.072]
Growth	1.146** [0.489]	-0.702 [0.459]
Digital score * Growth	-0.294** [0.127]	0.141 [0.105]
Leverage	-0.020 [0.036]	-0.100 [0.062]
Risk	-1.325 [1.308]	0.501 [1.756]
Year-fixed effects	Yes	Yes
Industry-fixed effects	Yes	Yes
Adjusted R^2	0.190	0.134
F-statistic	4.39	1.72
Number of observations	151	156

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

6. Conclusion and discussion

In this section, an answer to the main research question will be formulated. The answer to the research question is supported by the three hypotheses that are investigated in this thesis. The conclusion of the results is followed up by a discussion where the limitations of this research are given. Further, possible suggestions for future researchers and practical implications will be discussed.

The research concerns the companies included in the AEX/AMX/AScX from 2015 to 2019. The focus in this thesis was either on the relationship between digitalization and the consistency of the pecking order theory and the effect of digitalization on firm performance. This has been studied based on three hypotheses and the following research question:

''Are digitalized firms making financial decisions that are in line with the pecking order theory, and what is the effect of this digital disruption on the firm performance?''

Hypothesis 1 states that digital firms will hold onto the first assumption of the pecking order theory, indicating that internal financing is preferred over external financing. The regression shows a positive relationship between digital score and the level of internal financing relative to total financing. This result is in line with hypothesis 1. However, the coefficient does not show a statistically significant effect. Therefore, it is not possible to form a valid conclusion related to the effect of digitalization on the consistency of the first assumption of the pecking order theory. In contrast, the results do show an economic significant relationship between digitalization and the level of internal financing relative to total financing. The interaction effect between digital score and firm size gave a significant negative coefficient. Therefore, it can be concluded that large firms act less consistently with assumption one of the pecking order theory compared to smaller firms.

Hypothesis 2 states that digital firms will hold onto the second assumption of the pecking order theory, indicating that debt is preferred over equity when there is a financial deficit. The regression shows a statistically significant coefficient less than 0.50 indicating that equity is preferred over debt when there is a financial deficit. Furthermore, the interaction effect between financial deficit and digital score provides a statistically and economically significant negative coefficient indicating that a higher digital score will lead to a lower use of debt in the case of financial deficit. Therefore, it can be concluded that a high digital mature firm is acting less consistent with the pecking order theory than a less digital mature firm. This conclusion is not in line with hypothesis 2. There is also some noticeable effect of the control variable growth, which shows a negative significant interaction coefficient with financial deficit. Therefore, it can be concluded that a firm with high growth potential is acting less consistently with the pecking order theory than a firm with low growth potential.

Hypothesis 3 states that higher digitalization within firms will lead to higher firm performance. The regression on ROA provides a statistic and economic significant positive coefficient for the digital score, indicating a positive relationship between the digital score and ROA. Therefore, it can be concluded that digitalization within firms leads to higher firm performance, which is in line with hypothesis 3. Further, the digital score coefficient for the regression on Tobin's Q is insignificant positive, indicating a positive relationship between digitalization and Tobin's Q. However, due to the insignificance, no valid conclusion can be made from this.

With the support of the above views, a final answer to the research question can be given. Firms with a higher digitalization degree are making capital structure decisions that are not in line with the second assumption of the pecking order theory. In other words, digital mature firms prefer equity over debt when there is a financial deficit. Furthermore, there is a positive effect of digitalization on the firm performance measure ROA. Thus, firms with a higher priority for digitalization gain a higher financial value. Due to the insignificant result of hypothesis 1 which is related to the first assumption of the pecking order theory, this hypothesis is not included in the final answer.

This research also has some limitations. One of the most important limitations is the number of observations as there are only 80 companies included over five years. The 11 deleted missing values have resulted in 389 as the number of total observations. The relatively low number of observations may have caused the insignificant result of hypothesis 1 and the insignificant effect of digitalization on Tobin's Q. Another limitation is the selection bias as there are only companies included in this research listed on the AEX/AMX/AScX index. There are high requirements for a company to be listed on the stock exchange. These requirements create a selection bias because, for example, smaller firms are not included in the research.

Follow-up research might focus on the different effects of digitalization on the pecking order theory and firm performance between different countries and continents. It might be the case that the level of digitalization within countries or continents differs from each other, leading to other findings. Furthermore, follow-up research could add more observations to this research, possibly leading to more statistically significant results. Lastly, it is highly interesting to repeat this research over five years to see the development of digitalization within firms.

The outcome of this research has also led to some practical implications. As a higher level of digitalization within a firm leads to less consistency of the second assumption of the pecking order theory, it is important for economists and researchers not to underestimate the effect of new trends within the economy. It also shows that the practical applications of these prominent corporate finance theories have become less undeniably. Further, the interviews and theoretical framework show the high urgency for companies to react to digital disruption to retain their market value. Managers need to recognize this and add digitalization as one of their strategic pillars. Lastly, there is a statistically significant result indicating a positive effect of digitalization on firm performance. In practice, firms could benefit from these results by incorporating a higher degree of digitalization in their firm.

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Appendix A

Table A1: Keywords for measuring the digital score

Keywords
Internet
Website
Software
Computer
Cyber
Online
Information system
Information technology
Web
Virus
Digital
Hardware
Cloud
IT
Database

Table A2: Categories of Industries based on the different SIC codes

Industry code	Range of SIC codes	Division
1	100 – 999	Agriculture, Forestry and Fishing
2	1000 – 1499	Mining
3	1500 – 1799	Construction
4	2000 – 3999	Manufacturing
5	4000 – 4999	Transportation, Communications, Electrics, Gas and Sanitary Service
6	5000 – 5199	Wholesale Trade
7	5200 – 5999	Retail Trade
8	6000 – 6799	Finance, Insurance and Real Estate
9	7000 – 8999	Services
10	9100 – 9999	Public Administration

Table A3: Hausman test for regression on change in long-term debt, ROA and cash flow/sales

	Change in long-term debt	ROA	Cash flow/sales
P-value	0.000	0.0140	0.000

Table A4: Correlation matrix with all variables

	Change in long-	**ROA**	**Cash flow/sal**	**Digital score**	**Financial deficit**	**Profitability**	**Tangibility**	**Growth**	**Firm size**
Change in long-	1								
ROA	0.024	1							
Cash flow/sales	0.028	0.515	1						
Digital	0.001	0.134	0.080	1					
Financial deficit	-0.031	-0.027	-0.084	0.052	1				
Profitability	0.066	0.378	0.282	0.367	0.371	1			
Tangibility	0.068	-0.015	-0.015	0.183	-0.335	-0.023	1		
Growth	-0.081	0.040	0.010	0.049	0.055	0.094	0.044	1	
Firm size	-0.016	0.075	0.020	0.350	0.639	0.786	-0.250	0.059	1
Liquidity	0.006	-0.099	-0.145	-0.211	0.070	-0.186	-0.032	0.016	-0.138
Capital	0.045	0.011	0.164	0.024	0.214	0.269	-0.074	0.011	0.253
Risk	-0.082	-0.384	-0.333	-0.003	-0.033	-0.265	0.062	-0.050	-0.126
Firm age	0.021	0.131	0.111	0.010	-0.195	0.045	0.224	-0.098	-0.053

Liquidity	**Capital structur**	**Risk**	**Firm age**
1			
-0.143	1		
0.174	-0.087	1	
-0.205	-0.041	-0.259	1

Appendix B

Table B1: Linear OLS regression on internal financing relative to total financing with Year-fixed effects and Robust Standard Errors

Internal financing/Total financing	
Constant	-3.614
	[2.742]
Digital score	0.532
	[0.804]
Profitability	-0.261
	[0.312]
Digital score * Profitability	0.018
	[0.082]
Tangibility	1.483
	[3.723]
Digital score * Tangibility	-0.195
	[1.032]
Growth	-0.593
	[1.350]
Digital score * Growth	0.220
	[0.370]
Firm size	0,.225
	[0.108]
Digital score * Firm size	-0.031
	[0.027]
Adjusted R^2	0.013
F-statistic	1.77
Number of observations	389

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

Table B2: Linear OLS regression on internal financing relative to total financing with Industry-fixed effects and Robust Standard Errors

Internal financing/Total financing	
Constant	-4.607
	[2.888]
Digital score	0.889
	[0.914]
Profitability	-0.216
	[0.334]
Digital score * Profitability	-0.006
	[0.089]
Tangibility	1.812
	[3.579]
Digital score * Tangibility	-0.325
	[1.049]
Growth	-0.640
	[1.361]
Digital score * Growth	0.236
	[0.376]
Firm size	0.216
	[0.112]
Digital score * Firm size	-0.028
	[0.028]
Adjusted R^2	0.027
F-statistic	2.04
Number of observations	389

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

Table B3: Linear OLS regression on change in long-term debt with Year-fixed effects and Robust Standard Errors

Change in long-term debt	
Constant	1.600 [1.259]
Financial deficit	0.196* [0.161]
Digital score	-0.614 [0.388]
Financial deficit * Digital score	-0.083* [0.053]
Profitability	0.171 [0.163]
Financial deficit * Profitability	0.004 [0.016]
Tangibility	0.612 [1.062]
Financial deficit * Tangibility	0.175 [0.166]
Growth	0.066 [0.347]
Financial deficit * Growth	-0.100 [0.058]
Firm size	0.026 [0.089]
Financial deficit * Firm size	-0.004 [0.006]
Adjusted R^2	0.100
F-statistic	2.60
Number of observations	389

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

Table B4: Linear OLS regression on change in long-term debt with Industry-fixed effects and Robust Standard Errors

Change in long-term debt	
Constant	-0.225 [1.374]
Financial deficit	0.207** [0.169]
Digital score	-0.054 [0.413]
Financial deficit * Digital score	-0.077* [0.055]
Profitability	0.166 [0.177]
Financial deficit * Profitability	0.003 [0.017]
Tangibility	0.701 [1.174]
Financial deficit * Tangibility	0.163 [0.173]
Growth	0.014 [0.361]
Financial deficit * Growth	-0.111** [0.061]
Firm size	0.011 [0.100]
Financial deficit * Firm size	-0.004 [0.006]
Adjusted R^2	0.068
F-statistic	2.62
Number of observations	389

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

Table B5: Linear OLS regression on ROA with Year-fixed effects, Robust Standard Errors and lagged independent variables

ROA	
Constant	0.793 [0.701]
Digital score	0.117* [0.063]
Firm size	0.017 [0.012]
Digital score * Firm size	-0.004 [0.002]
ROA	0.553*** [0.090]
Firm age	0.052 [0.044]
Digital score * Firm age	-0.059 [0.042]
Growth	0.054 [0.051]
Digital score * Growth	-0.015 [0.104]
Leverage	-0.008 [0.029]
Risk	-1.248 [0.907]
Adjusted R^2	0.390
F-statistic	8.13
Number of observations	307

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

Table B6: Linear OLS regression on ROA with Industry-fixed effects, Robust Standard Errors and lagged independent variables

ROA	
Constant	0.643 [0.739]
Digital score	0.148* [0.058]
Firm size	0.018 [0.012]
Digital score * Firm size	-0.004 [0.002]
ROA	0.547*** [0.092]
Firm age	0.045 [0.046]
Digital score * Firm age	-0.049 [0.044]
Growth	0.055 [0.051]
Digital score * Growth	-0.001 [0.105]
Leverage	-0.018 [0.029]
Risk	-1.068 [0.962]
Adjusted R^2	0.391
F-statistic	9.28
Number of observations	307

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

Table B7: Linear OLS regression on Tobin's Q with Year-fixed effects, Robust Standard Errors and lagged independent variables

Tobin's Q	
Constant	1.844***
	[0.292]
Digital score	0.009
	[0.068]
Firm size	-0.015***
	[0.003]
Digital score * Firm size	0.001*
	[0.001]
ROA	0.017
	[0.021]
Firm age	-0.053
	[0.047]
Digital score * Firm age	0.003
	[0.016]
Growth	-0.054
	[0.093]
Digital score * Growth	0.012
	[0.023]
Leverage	-0.019
	[0.014]
Risk	-0.608*
	[0.312]
Adjusted R^2	0.389
F-statistic	31.31
Number of observations	307

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.

Table B8: Linear OLS regression on Tobin's Q with Industry-fixed effects, Robust Standard Errors and lagged independent variables

Tobin's Q	
Constant	1.647*** [0.278]
Digital score	0.007 [0.067]
Firm size	-0.011*** [0.003]
Digital score * Firm size	0.001** [0.001]
ROA	0.015 [0.021]
Firm age	-0.027 [0.050]
Digital score * Firm age	-0.005 [0.016]
Growth	-0.047 [0.082]
Digital score * Growth	0.010 [0.020]
Leverage	-0.009 [0.014]
Risk	-0.568** [0.276]
Adjusted R^2	0.349
F-statistic	8.95
Number of observations	307

Robust standard errors in brackets; *p < 0.10, **p < 0.05, ***p< 0.01.