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Innovation Output and Capital Structure

-A new determinant?

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Abstract

Title: Innovation Output and Capital Structure- A new determinant?

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Key words: Capital structure**,** Trade-off, Pecking order, Information asymmetry**,** Innovation output, Leverage

Purpose: The purpose of this study is to determine if innovation output influences the capital structure of Swedish listed companies and to understand if the effect is different on OMXS and First North

Methodology: The study follows a deductive approach, and quantitative data is used to conduct two multiple regression analysis. The results from the regressions are analyzed based on the relevant theoretical frameworks.

Theoretical perspective: The theoretical perspective of this study is based on capital structure theories, including the trade-off and pecking order theory, as well as previous research related to innovation.

Empirical foundation: The sample consists of 423 firms and 2549 data points. The data is gathered from PAtlink, FinBas, and Retriever Business.

Conclusions: Innovation output has a statistically significant negative impact on the leverage ratio of firms listed on Nasdaq First North Growth Market. The channel in which it has an effect is through a reduction in the information asymmetry a firm faces in the equity market. The effect is statistically significantly greater than on Nasdaq Stockholm, explained by a difference in the information asymmetry between the two markets. Innovation output is however not found to significantly impact the leverage ratio of firms listed on Nasdaq Stockholm

Sammanfattning

Titel: Innovation Output and Capital Structure - En ny determinant?

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Författare: Isak Bark, Linus Lindh, Oscar Stålhök

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Nyckelord: Kapitalstruktur, Trade-off teorin, Pecking order teorin, Informationsasymmetri, Innovation output, Skuldsättningsgrad

Syfte: Syftet med studien är att undersöka ifall innovation output påverkar kapitalstrukturen på publika svenska bolag samt att förstå ifall effekten skiljer sig mellan OMXS och First North.

Metod: Studien följer en deduktiv ansats, och kvantitativ data används för att genomföra två multipel regressioner. Resultat från regressionerna analyseras utifrån relevanta teoretiska ramverk.

Teoretiska perspektiv: De teoretiska perspektiv studien baseras på är teorier om kapitalstruktur, däribland Trade-off och Pecking order teorin, samt tidigare empirisk forskning relaterad till innovation används.

Empirisk grund: Urvalet består av 423 bolag och 2549 datapunkter. Datan hämtades från PAtlink, FinBas och Retriever Business.

Slutsats: Innovation output har en statistisk signifikant negativ effekt på skuldsättningsgraden för bolag på Nasdaq First North Growth Market. Kanalen genom den har en effekt argumenteras vara genom en minskning i informationsasymmetrin på marknaden för aktiekapital. Effekten är statistiskt signifikant större på First North än vad den är på Nasdaq Stockholm, förklarat av skillnaden i informationsasymmetri mellan marknaderna. Innovation output har emellertid ingen signifikans på skuldsättningsgraden för bolag på Nasdaq Stockholm

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Table of contents

1. Introduction

The following chapter provides an overview of the research area and argues why the subject area is interesting to investigate. Then the purpose and relevance of the research are presented, along with the limitations of the research.

1.1 Background

Capital structure is a field of corporate finance literature that has been researched within academia for almost 70 years. It aims to understand how different companies make decisions about how they finance their operations. Capital structure can be defined as what mix of equity, debt, and other securities a firm has outstanding to its investors (Berk & Demarzo, 2020). Although there is a consensus in the literature on the definition of capital structure, there is not one simple theory or explanation that can single-handedly solve the mystery of how a firm chooses its capital structure. Generally considered, issuing debt is seen as a cheaper option than issuing equity. However, as the leverage of a firm increases, the required rate of return from equity holders increases due to the increased risk, which balances out this difference (Berk & Demarzo, 2020). Many have attempted to solve this mystery, and while some researchers suggest that capital structure is something that managers dedicate a larger amount of resources for, others find that capital structure naturally develops with time and changes from day to day (Berk & Demarzo, 2020).

Miller and Modigliani's theory on optimal capital structure can be seen as the foundation of modern research on capital structure. The authors theorized that in a perfect market with no friction, a firm's capital structure does not impact the value of a firm but merely alters the cash flows (Miller & Modigliani, 1958). Although Miller and Modigliani's research revolutionized the field and their findings have been widely accepted (Myers, 2001), it is still important to consider the impact of firms' capital structure due to the presence of market imperfections such as agency costs, taxes, and information asymmetries.
Derived from the three market inefficiencies is the pecking order and trade-off theory of capital structure. The two theories are the most prominently used in literature, and they differ in emphasis on what market imperfection affects a firm's capital structure decisions. The trade-off theory suggests that a firm's optimal structure is a trade-off against tax and agency benefits of debt and costs of financial distress as well as agency costs (Myers, 2001). Jensen and Meckling (1976) discuss agency costs and benefits, and the authors suggest an agency theory where debt has a disciplinary role and can lower agency costs until excessive debt increases agency costs. The pecking order theory is presented by Myers and Majluf (1984) and instead emphasizes the influence of information asymmetry in the decision of capital structure and suggests that managers have a preferred order of financing based on the level of information asymmetry facing the firm.

However, empirical research suggests that neither of these theories can fully explain capital structure decisions (Baker & Wurgler, 2002; Myers, 2001). Extensive research has been conducted to find and understand possible determinants in the form of firm characteristics that could explain how a firm chooses its capital structure (see Harris & Raviv, 1991). One possible determinant that has not been given much consideration in corporate finance literature is how a firm's innovative capabilities could influence its capital structure decisions.

"Just as energy is the basis of life itself, and ideas the source of innovation, so is innovation the vital spark of all human change, improvement, and progress"- Theodore Levitt, American Economist

As the quote from Theodore Levitt, the famous American economist, reads, innovation plays a crucial role not only in business but for humanity as a whole. Innovation has been studied by several fields of research, including economics and management science, to understand the importance and how to utilize innovation best to grow businesses or the economy as a whole. Research on innovation's benefits on a firm, regional and national level are examples of the studies conducted and is summarized by Neely & Hii (1998). On a firm level, literature agrees that innovation facilitates improved financial performance as new products or processes can strengthen a firm's competitive position through increasing market shares and profits. Although innovation is a rather explored subject in some research fields, its impact in the field of corporate finance is not as apparent, and existing literature is more limited. As of later years, studies are more common, and areas researched include Hirshleifer et al.(2013), who found that innovation can predict stock returns, O'brien (2003), who found that the capital structure is influenced by a firm pursuing a strategy based on innovation and lastly, innovation increases the profitability and number of growth opportunities for a firm (Gunday, Ulusoy, Kilic and Alpkan, 2011)

Recently in the literature, Rajaiya (2023) conducted a study where he hypothesized that innovation has an influence on capital structure through reducing the information asymmetry associated with the firm. The author is among the first in corporate finance to find empirical evidence that a relationship exists between innovation output and capital structure. There is a distinction between innovation input and output, where innovation input can be seen as spending on innovation, while innovation output is what you reap from the input. Rajaiya's (2023) results shed new light on innovation output in the corporate finance literature, and the implications of the results are yet to be distinguished.

1.2 Problem Discussion

Preceding Rajaiya's (2023) study, Bartoloni (2013) was among the first to find that innovation significantly impacts capital structure decisions.

More specifically, Bartolini proved that while innovation input had a positive relationship with leverage, innovation output had an inverse effect. Literature prior to Bartolini mainly focused on a reversed causality, where capital structure facilitated innovation, but she proved that the causality runs in the other direction (2013). In addition to the reverse causality, research focused on and found indirect effects between innovation and capital structure through empirically accepted determinants. Examples of the findings include that innovation is related to profitability, number of growth opportunities, tangibility, and firm performance (Gunday et al., 2011; Ataly, Anafarta, and Sarvan, 2013; O'brien, 2003). Unfortunately, we believe Bartoloni's findings did not get the coverage they might deserve. This could be argued since Rajaiya (2023) states that he is the first in academia to find significant empirical results that innovation output influences the capital structure.

Nonetheless, Rajaiya's (2023) findings could have a more significant impact in the field since it proves that innovation output influences a firm's capital structure and defines and argues why this is the case. Rajaiya conducts his study on public US firms and finds support for his hypothesis that through a decrease in information asymmetry, firms more successful in their innovation are more likely to issue equity and therefore are less leveraged. The author quantifies innovation output using patents and argues that firms signaling their successful innovative efforts through innovation output reduce the information asymmetry they face in the equity market.

Although the implications of Rajaiya's (2023) results are yet to be determined due to the short time since his work was published, they are intriguing. Rajaiya's result indicates that innovation output encompasses additional aspects that contribute to a firm's capital structure decisions in cases where other determinants fall short. Specifically, innovation output might be able to explain differences in the relative level of information asymmetry a firm is facing in the equity market, thus rendering firms more successful in their innovation less leveraged.

Rajaiya tested his hypothesis and found support when investigating U.S. firms. Therefore, testing for a similar effect of innovation output on capital structure in a country that is characterized by innovation seems highly relevant. Innovation output as a determinant of capital structure can be expected to be a more prevalent determinant for firms operating in a country, distinguished by its innovative capabilities. The country in question is Sweden, which is known as an innovative powerhouse and is home to firms such as King, Spotify, and Klarna, to name a few unicorns of the north. Sweden is ranked number one in the European Innovation Scoreboard 2022 (EU, 2022) and had the world's second most patent applications per capita during 2020 (Patent- och registreringsverket, 2021). Accordingly, this thesis will study Swedish firms listed on the stock exchanges Nasdaq OMX Stockholm (OMXS) and Nasdaq First North Growth Market.

The difference between OMXS and First North is that the latter faces less regulations, and firms are usually both smaller and younger growth firms, whilst the former is a stricter regulated market where more established, older and larger firms are listed (Nasdaq Nordic, 2023). As noted, firms listed at the two stock exchanges differ in terms of firm age and size, which is considered in the literature to affect the capital structure (Harris & Raviv, 1991; Titman & Wessels, 1988; Rajan & Zingales, 1995). Older and larger firms might be more well-known and have a better reputation, which could decrease the transaction costs when issuing debt and the information asymmetry facing them in the equity markets. Firms listed on First North face fewer disclosure requirements on their financial reporting, and Botosan (2006) presents evidence that increased disclosure leads to lower information asymmetry. Hence, firms listed at OMXS, with more comprehensive disclosure requirements (Nasdaq, 2023), could be expected to face relatively less information asymmetry in the equity market.

Rajaiya's (2023) study suggests that innovation output affects a firm's capital structure by reducing information asymmetry. Given the anticipated differences in information asymmetry on the two stock exchanges, it is of interest to distinguish between them. Therefore, it is relevant to test the hypothesis similar to Rajaiya (2023) on Swedish firms and examine differences in the expected decrease in information asymmetry between OMXS and First North.

1.3 Purpose

The purpose of this study is to determine if innovation output influences the capital structure of Swedish listed companies and to understand if the effect is different on OMXS and First North.

1.4 Relevancy

As far as the authors of this thesis are concerned, we will be among the first in the literature to test if innovation output influences a firm's capital structure and the first to test this relationship on Swedish companies. The study will differentiate from previous studies by including a distinction between regulated and less regulated markets and tests for any differences innovation output may have between the two for the first time in literature.

Our study contributes to an increased understanding of firms’ capital structure decisions and on the relationship between innovation output and capital structure. Finally, we contribute to the understanding of how capital structure decisions might differ between stock markets depending on the market characteristics affecting information asymmetry.

1.5 Limitations and Scope

The study is limited to Swedish firms listed on Nasdaq OMX Stockholm and First North Growth market. We deemed this appropriate since Sweden is characterized by innovation, and necessary data was available. Additionally, including firms listed on the NGM Growth market was considered. Nevertheless, due to challenges in accessing the required data, we acknowledge this limitation, and the focus remains on OMXS and First North, as they offer robust datasets and comprehensive insights into the Swedish financial market.
Moreover, this study has chosen 2010-2019 as the time period because we wanted as relevant data as possible while not including any abnormalities related to the financial crisis of 2008 and the Covid-19 outbreak of 2020.

Lastly, the study does not include firms in the finance and insurance and the utility industry. This is quite usual in the empirical field of corporate finance since their balance sheet and capital structure differ from firms in other industries since specific regulations and laws affect them (Rajan & Zingales, 1995; Frank & Goyal, 2009).

2. Theoretical framework

In this chapter, the three fundamental theories which will be used as a framework for the rest of this paper is presented, with an emphasis on information asymmetry's role in these theories, and its influence on capital structure. Following the theories, we discuss determinants of capital structure and previous research related to our research area. Finally, we summarize the theories and previous research relevant to our thesis.

2.1 Miller Modigliani's Capital Structure Theorem

The capital structure theory, presented by Miller and Modigliani (1958), laid the groundwork for the capital structure theories we know today. Miller and Modigliani proposed that under the assumption of no market imperfections, the value of an unlevered firm is equivalent to the value of a levered firm based on the law of one price; hence, capital structure choices and decisions do not matter, and merely redistribute the cash flows generated by a firm's assets (Miller & Modigliani, 1958).

However, because market imperfections of taxes, agency costs, and information asymmetry exist, the capital structure does matter (Myers, 2001). In the presence of these market imperfections, a firm's leverage level can bring advantages and disadvantages. These include tax benefits, agency costs and benefits, and the level of information asymmetry a firm faces. The trade-off and pecking order theory has been developed from these three market imperfections to guide capital structure decisions.

2.1.1 Trade-off Theory

The trade-off theory has its roots in Miller and Modigliani's (1963) acknowledgment of the market imperfection of taxes and theorizes that both advantages and disadvantages are associated with different capital structure choices. Kraus and Litzenberger (1973) derived from the conclusion of Miller and Modigliani (1963) that adding leverage has the benefit of yielding an interest tax shield since interest expenses are tax deductible. Consequently, the trade-off theory started to take form. The theory suggests that firms seek an optimal capital structure that weighs the benefits of tax advantages against the costs of financial distress to maximize its value (Kraus & Litzenberger, 1973). As firms increase their leverage, the probability of default increases which in turn increases the costs of financial distress (Berk & Demarzo, 2020).

Jensen and Meckling (1976) helped to further develop the trade-off theory by acknowledging agency costs and benefits. The authors define agency relationships in the context of businesses, as a principal (shareholders) assigns an agent (managers) to act in his or her interest and is given decision-making power. Agency costs are a result of this separation of ownership and control.

Jensen and Meckling contend that managers seek to maximize their utility and thus may be inclined to act selfishly and not in the best interest of the shareholders (1976).

Jensen (1986) argues that agency costs are especially problematic for firms with larger free cash flows since this is a source of funding more easily accessible for managers to use for their self-interests.

Agency benefits of leverage are based on debt's disciplinary effect on managers. As debt holders have a stake in the company's ability to pay back debts, Jensen (1986) contends that debt financing can help lower agency costs by reducing free cash flow and increase the implicit control debt entails. This added control and supervision can reduce agency costs associated with equity financing while signaling the market an indication of financial stability. Acquiring additional debt is often considered a credible signal of financial stability. This is because a firm would not willingly commit to significant future debt payments if it did not believe it could afford them. Such a decision could potentially lead to financial distress (Berk & Demarzo, 2020). However, excessive debt may encourage managers to put debt holders' interests ahead of shareholders', which may result in additional agency costs (Jensen, 1986). The agency costs of excessive debt include debt overhang, which is the inability to fund new NPV-positive projects for the firm due to the restraint on issuing new equity when facing financial distress (Berk & Demarzo, 2020).

Moreover, because of the seniority debtholders have over shareholders in the case of default, when a firm has excessive debt, shareholders might substitute assets with more risky ones that do not benefit the debtholders. This is referred to as risk-shifting or asset substitution (Berk & Demarzo, 2020).

In conclusion, according to the trade-off theory, the optimal capital structure is achieved when the incremental benefits of increasing leverage, such as agency and tax advantages, are balanced by the corresponding increase in the costs of financial distress and agency conflicts. This trade-off predicts that firms seek to balance the tax benefits of higher leverage and the potential costs associated with financial distress and agency problems.

2.1.2 Pecking Order Theory

Myers and Majluf's pecking order theory hypothesizes that firms finance their new investments and operations following a pecking order, ranging from prioritizing internal funding over debt and issues equity as a last resort due to the adverse selection of funding (1984). The theory is based on the market imperfection of asymmetric information, where adverse selection is based on the premise that management has access to more knowledge about a company's actual worth. As a result, new shareholders might suspect the equity to be overpriced.

According to Myers and Majluf (1984), the natural inclination of businesses is to finance their investments using internal capital since it is most often the cheapest option. When the internal capital is insufficient, firms are most likely to take on debt. Debt is more expensive and raises the financial risk of the firm. However, it is still more favorable than issuing new equity. Equity financing is the least favorable option because it involves giving up ownership and control of the company to new shareholders along with the issue of adverse selection, which reduces current shareholder value through dilution.

A corporation's capital structure is significantly influenced by information asymmetry, and Myers and Majluf conclude that a company's cost of issuing equity rises when the degree of information asymmetry increases (1984). Debt financing is considered less sensitive to information asymmetry than equity financing since it does not need the same amount of information disclosure from the firm (Rajan & Zingales, 1995). By the very contractual nature of debt, it adds a monitoring effect and increased security. (Berk & Demarzo, 2020).

Before Mayers and Majluf's paper, the concept of adverse selection due to asymmetric information was proposed på Akerlof in "Market of Lemons" (1970). Akerloof uses the metaphor of lemons to demonstrate that an asymmetrical distribution of information among buyers and sellers might create the impression that the lemons are overpriced. As a result, customers could request a lower price to prevent being taken advantage of by the vendor. Conceptualized in the context of capital structure, if a firm issues new equity, the market has reasons to believe that the equity is overpriced since the managers may have private information about the firm's true value. This information asymmetry can lead to adverse selection in the equity market, as potential investors may fear that they are being offered shares at a higher price than what they are truly worth.

2.2 Previous Research

2.2.1. Innovation Output

Innovation in the context of corporate finance can be interpreted as the ability a company has to discover, develop and adopt new concepts from which new investment opportunities are derived. This statement is supported by Rajaiya (2023), who states that innovation is an important factor in enabling growth through new investment opportunities for companies. In the literature, some articles use the term innovation in a broader sense, including innovation input and output, while others separate the two. Innovation input could be seen as the total spending on generating knowledge and developing new concepts, innovation output instead refers to what firms manage to reap and capitalize on from the input.

While the exact definitions have some discrepancies, it is generally accepted that innovation output refers to generating and communicating the results of innovative efforts. In contrast, innovation input refers to the resources used to create innovation output (Rogers, 1998).

Studies on innovation, and more specifically innovation output, and how it relates to corporate finance have steadily increased and been given more room in literature. Examples include: Hirshleifer et al. (2012), who found that innovation can predict future stock return, O'brien (2003) who studied the implications on capital structure following an innovation-based strategy and innovation drives growth, profitability, and firm performance (Gunday et al., 2011; Ataly et al., 2013) which previously have been found to be important determinants of capital structure. These studies can be considered indirectly linked to how innovation output affects capital structure decisions, whilst Rajaiya's (2023) study instead focuses more on the existence of a causal relationship between the two.

He contributed to the field of study by being one of the first who found empirically significant results on how innovation output influences capital structure decisions and why this is the case. Rajaiya found support for his hypothesis that innovation success has a negative relationship with leverage for firms in the U.S. market.

In conclusion, this thesis will study the effect innovation output has on capital structure. However, it is worth mentioning that Rajaiya (2023) focused on a firm's innovation success rather than the output. The two share several similarities, but they differ in that proxies for innovation success better manage to capture the quality of a firm's innovation output by, for example, taking the number of citations into account.

2.2.2 Measuring Innovation Output

Griliches (1984), Schmookler (1966), and Scherer (1965) were among the pioneers of using patent data in economic research. They used the number of patents granted as a measure of innovation output. It is well known that innovation varies significantly in terms of both its technological and economic value, and an innovation exhibiting technological value does not necessarily mean that it is of economic significance. As a result, capturing the entire scope of the deviations is inherently difficult when depending only on the count of patents granted.

Hall, Jaffe, and Trajtenberg (2005) criticize the measurement of only using patents granted. They found that patent citations were the main driver for the value of a patent. A patent citation is a reference made by a newly granted patent to previously granted patents related to a similar subject matter. It serves as a measure of the significance of an innovation, indicating that the new invention acknowledges and builds upon it (Hall et al., 2005). If a patent receives one extra citation, its market value will increase by 3% (Hall et al., 2005).

However, there is another problem with citations as a measurement; due to the fact that patents can receive citations long after a study is conducted, there is a risk that newer patents with fewer citations may not be recognized as having high value.

O'Brien (2003) suggests that innovativeness can be determined by comparing a firm's research and development (R&D) investments to that of other companies within the same industry. This method, however, cannot show if the money spent on R&D is successfully used or results in output. Thus it could be seen as a measurement of a firm’s innovation input, whilst patents granted aim to proxy the innovation output. Consequently, one could argue that proxying for innovation output by patents granted is a sufficient metric since firms successful with their innovation would want to protect it by filing for a patent (Jaffe, 1986)

2.2.3 Innovation Output and How It Affects Capital Structure

Rajaiya (2023) proves in his recently published research the hypothesis that innovation output has an impact on the capital structure of a firm through the channel of information asymmetry. Rajaiya measures a firm’s information asymmetry using proxies such as a firm’s analyst following, forecast error, and dispersion. He argues that innovation success decreases the information asymmetry a firm faces in the equity market since innovation success, measured through patents, signals intrinsic value and credibility of the research and development to external parties of the organization. Rajaiya’s discovery can be explained by Myers and Majluf's (1984) pecking order theory which states that managers are more inclined to issue debt in firms with high information asymmetry since equity is the financing most sensitive to information.

Conversely, firms facing relatively less information asymmetry on the equity market instead tend to issue more equity. Hence, the pecking order theory assists in understanding the relationship between innovation output and leverage, where firms more successful in their innovation have less information asymmetry in the equity market and, accordingly, have lower leverage ratios. Before Rajaiya’s (2023) discovery, Bartoloni (2013) also conducted a study where the author tested for causality and the relationship between innovation and capital structure. Bartoloni found using panel data on Italian firms that leverage does not cause innovation but rather that the capital structure is influenced by innovation.
More specifically, similarly to Rajaiya (2023), she finds that innovation output has a negative relationship with leverage.

Whilst both Rajaiya (2023) and Bartoloni (2013) suggest a negative relationship between innovation output and leverage, their reasoning as to what causes this relationship differs. Bartoloni (2013) means that the negative relationship implies that firms successful in their innovation are more prone to use internal rather than external funds due to the difficulties of externally financing their projects. While this suggestion agrees with the pecking order, intuitively, this should rather be the case for innovation input than output.

The possible shortcomings of this argument from Bartolini are supported by Rajaiya (2023), who finds significant support for the fact that firms with higher innovation output are more likely to issue equity. Bartolini (2013) also states that she is unable to test whether firms are more likely to issue equity. Building on this, Rajaiya (2023) suggests that innovation output lowers the information asymmetry a firm faces in the equity market and thus concludes that it is why firms more successful in their innovations have lower leverage ratios.

2.2.3.1 Innovation's indirect effect on capital structure

Except for Rajaiya (2023) and Bartoloni (2013), the literature is scarce regarding innovation output as a possible determinant of capital structure. However, there is empirical work based on the opposite casualty that financing affects innovation (Bartoloni, 2013), as well as studies relating innovation to empirically proved capital structure determinants such as profitability.

O'brien (2003) examines the impact of a firm's strategy, centered around being an industry innovator, on its capital structure.The author derives his hypothesis from previous empirical work, which has found that R&D intensity leads to lower leverage. O'brien finds empirical support for his hypothesis that firms with a higher relative R&D intensity to the industry have lower leverage. Unlike Rajaiya (2023), O'brien instead argues that the strategy of being an innovator has a channeling effect on the capital structure through the importance of keeping a comfortable level of financial slack, which essentially translates into a lower leverage ratio in order to facilitate this strategy (O'brien, 2003).

Moreover, it is important to understand that innovation is linked to the capital structure of a firm through also having an impact on other more empirically common determinants of capital structure. Innovation is considered one of the cornerstones in creating growth opportunities for firms (Gunday et al., 2011). Furthermore, Neely & Hii (1998) and Atalay et al. (2013) argue that innovation leads to higher profitability by continuously introducing new products that face less market competition. Neely & Hii (1998), Gunday et al. (2011), and Ataly et al. (2013) are only a few examples of the strand of literature linking innovation to growth, profitability, and financial performance. As described in *2.2.5.4 Growth*, growth is an empirical common determinant of capital structure and most often proved to have a negative relationship with leverage.
Focusing on the link between innovation and growth, it would then intuitively make sense that innovation would share the same relationship and an indirect effect of innovation on a firm's leverage is considered. A similar relationship could be argued for applies to profitability as well.

A firm's tangibility is another example of a determinant that innovation impacts. Innovative firms are more likely to have a larger share of intangible assets (O'brien, 2003), and intangible assets usually face higher information asymmetry and cannot be used as collateral for debt (Titman & Wessels, 1988).

A firm's tangibility has been empirically proven to have a positive relationship with leverage, whilst the relationship between innovation and tangibility is a negative. Hence, we could expect that firms successful in innovation would have lower leverage ratios.

2.2.4 Summary of Theories

Table 1

Articles	Subject	Results
Miller & Modigliani (1963), Kraus & Litzenberger (1973), *Berk & Demarzo (2020)*	Trade-off theory	Optimal capital structure is when the agency and tax benefits are equal to the cost of financial distress and agency costs of increasing leverage.
Jensen & Meckling (1976), Jensen (1986), Berk & Demarzo (2020)	Agency benefits and costs	There are agency benefits and costs. Debt has a disciplinary effect and thus can help lower agency costs. Excessive debt can lead to risk-shifting or underinvestment issues.
Myers & Majluf (1984), Åkerlöf (1970)	Pecking-order theory	Capital structure follows a pecking order ranging from internal resources first, to issuing new equity last. If the information asymmetry decreases, firms are more prone to issue equity rather than debt.
Rajaiya (2023), Bartoloni (2013)	Innovation output and capital structure	Authors found that innovation output has a negative relationship with leverage. Innovation output has a channeling effect on capital structure through a decrease in information asymmetry.
Griliches (1984), Schmookler (1966), Scherer (1965), Jaffe (1986)	Measuring innovation output	Patent application and patent granted is a good proxy to measure innovation output since firms want to protect their innovation if it shows promise.

Summary of theories.

2.2.5 Determinants of Capital Structure

Extensive research has been conducted within academia to capture various variables that affect firms' capital structure. The two leading theories are the trade-off and pecking order theories (Fama & French, 2002). However, the two theories do not agree on the relationship between different determinants and capital structure. Empirical results differ to what degree the theories can explain differences in the capital structure and what determinants are most impactful (Harris & Raviv, 1991; Frank & Goyal 2009).

Although information asymmetry has a role in some of the determinants and theories, it alone can not explain why a firm's capital structure differs. In empirical studies regarding capital structure, several different determinants are used as proxies to control for effects following either the trade-off, pecking order, or agency theory, and how these are measured differs in some cases. In the following section of this paper, we will present some of the most prominent determinants which will be accounted for in our paper, and their expected influence on capital structure based on previous research.

2.2.5.1 Size

Fama and French (2002) highlight that smaller firms might face greater transaction costs in the debt market which Titman & Wessels (1988) similarly argues for. However, Titman and Wessels also theorize that smaller firms may face even greater costs while issuing new equity (1988). Frank & Goyal (2009) argue that larger firms should have more retained earnings and be better known by the equity market, thus facing less information asymmetry. From a pecking order perspective, this would implicate a negative relationship between firm size and leverage since small firms would, to a greater extent, issue debt due to the transaction costs and the information asymmetry they face in the equity market.

Moreover, Rajan & Zingales (1995) and Titman & Wessels (1988) argue that larger firms are usually more diversified, leading to a lower risk of default and a higher capacity to take up new debt. Frank & Goyal (2009) argues for a similar point and states that larger firms with better reputation might have lower debt-related agency costs. Because of this, Frank & Goyal argue that according to the trade-off theory, firm size has a positive relationship with leverage.

Kayo & Kimura (2011) explains that empirical results regarding the firm size vary, but a majority have shown a positive effect (Harris & Raviv, 1991; Frank & Goyal, 2009), while de Jong, Kabir, and Nguyen (2008) found that size did not have a significant impact on Swedish firms.

2.2.5.2 Age

Firm size and age are two determinants that are closely linked, where the former is more commonly controlled for in the empirical literature (See Harris & Raviv, 1991).

However, proxies for size measure additional attributes besides just the size of the firm, like reputation and history. Some of these additional attributes are also strongly related to a firm's age (Titman & Wessels, 1988). From a pecking order perspective, older firms would face less transaction costs and lower information asymmetry in the equity market like larger firms do, following the argument of Titman & Wessels (1988) and Frank & Goyal (2009). Thus, an older firm would be predicted to be less leveraged.

Conversely, the trade-off and agency theories predict a positive relationship between firm age and capital structure. Chen and Strange argue that older firms likely have a better credit history while there is a lower risk for these firms having agency costs relating to risk-shifting (2005). Ergo, older firms should have a lower cost of debt and therefore be more prone to issue debt rather than equity.

Empirical results on this determinant are more scarce, but existing results include Chen and Strange (2005), who find that age increases leverage, while Rajaiya (2023) finds that it instead decreases it.

2.2.5.3 Tangibility

Since tangible assets can be used as collateral for debt, the trade-off theory predicts that firms with more tangible assets should be more leveraged (Titman & Wessels, 1988; Kayo & Kimura, 2011). Furthermore, Frank & Goyal provides a similar argument with the addition that the agency cost of debt decreases with tangibility since shareholders can not as easily partake in risk-shifting when a majority of the firm's assets are tangible (2008). Kayo & Kimura (2011), Titman & Wessels (1988), and Frank & Goyal (2008), all argue that since tangible assets can be used as collateral, the agency cost of debt is reduced, and the assets would suffer less loss of value under financial distress, the trade-off theory suggests that tangibility should have a positive relationship with leverage.

On the contrary, the pecking order theory suggests a negative relationship between tangible assets and debt (Frank & Goyal, 2008). The theorem predicts a negative relationship because of the lower information asymmetry related to tangible assets (Titman & Wessels, 1988; Harris & Raviv, 1991), which leads to firms with a higher degree of tangible assets being more prone to issue equity since the lower information asymmetry leads to a lower cost of equity.

More empirically significant results have been found for tangibility to have a positive relationship with leverage. See Harris & Raviv (1991), Frank & Goyal (2009), and de Jong et al. (2008).

2.2.5.4 Profitability

The pecking order and trade-off theory predictions are conflicted when it comes to how profitability is related to capital structure (Frank & Goyal, 2003). The pecking order theory is quite clear in its prediction and suggests that past profitability should lower debt levels since it should reflect the available retained earnings (Titman & Wessels, 1988).

Contrariwise, the trade-off theory predicts that profitability should positively correlate with high debt ratios to offset high tax levels (Frank & Goyal, 2003). Furthermore, Frank & Goyal (2009) argues that from an agency cost perspective, more profitable firms should have higher leverage to utilize debt's disciplinary effect when free cash flows are high.

Empirical results are generally similar, showing a negative relationship between profitability and leverage (Harris & Raviv, 1991; Frank & Goyal, 2009).

2.2.5.5 Growth

Fama & French (2002) states that the trade-off theory predicts a negative relationship between investment opportunities measured as a market-to-book ratio, a common proxy for growth (Myers, 1977; Harris & Raviv, 1991; Rajan & Zingales, 1995). The authors base their argument on the fact that firms with many growth opportunities are incentivized to avoid underinvestment arising from agency problems, which Myers (1984) also illustrates. Shareholders of these types of firms are more prone to risk-shifting, and debtholders have a tougher time recognizing this, hence debt is more costly (Frank & Goyal, 2008). Additionally, Kayo & Kimura (2011) argue that when a firm is in a high growth phase, there are several growth opportunities with positive NPV, leading to a lower level of free cash flow. The lower free cash flow levels for firms with abundant growth opportunities means that the debt's disciplinary effect is not necessarily pointing toward that the trade-off theory should predict a negative relationship (Fama & French, 2002).

The pecking order theory differs and suggests a positive relationship between leverage and growth (Frank & Goyal, 2008; Fama & French, 2002; Frank & Goyal, 2003) since managers needing new capital to fund investments would issue debt if there are no retained earnings instead of issuing equity since it is cheaper (Meyer & Majluf, 1984). Thus, firms with high growth would increase their leverage if there are inadequate internal funds (Kayo & Kimura, 2011).

Empirically, growth proxies have shown a negative relationship with debt levels (Rajan & Zingales, 1995; Frank & Goyal, 2009; Fama & French, 2002).

2.2.5.6 Non-debt Tax Shields

The theory of Non-debt Tax shields, or NDTS, as a determinant of capital structure is presented by DeAngelo and Masulis (1980) on the basis that the benefit of increasing leverage is to reduce taxable income, thus generating an interest tax-shield. The authors argue that other tax shields, generated by, for example, R&D expenditure and depreciation, should have a direct negative correlation with leverage since they can be interpreted as a substitution for increasing leverage to reduce the taxable income (DeAngelo & Masulis, 1980). The prediction by DeAngelo and Maslius is theoretically supported as Fama & French (2002) argue that from a trade-off perspective, the value of the interest tax shield is reduced for firms having a larger magnitude of NDTS as a result of the lower tax rate; thus these firms would decrease their leverage.

From a pecking order perspective, where a focus is on the market imperfection of information asymmetry rather than taxes, it is difficult to make a solid prediction on how NDTS would affect the capital structure. This is supported by Fama & French's (2002) paper, where they discuss predictions of pecking order and trade-off theory on determinants in which they refrain from predicting NDTS from a pecking order perspective.

Empirically significant results indicate that NDTS has a negative relationship with leverage (DeAngelo & Masulis, 1980; Fama & French, 2002). However, Titman & Wessels could not find that NDTS has a significant effect on the capital structure at all (1988).

2.2.5.7 Summary of Determinants and Predictions

Illustrated in Table 2 is a summary of the different determinants of capital structure and their predicted effect according to theory and empirical results.

Table 2

Determinant	Pecking Order	Trade-Off	Empirical results
Size	**-**	+	+
Age	**-**	+	+/-
Tangibility	**-**	+	+
Profitability	**-**	+	-
Growth	+	-	-
NDTS	**N/A**	-	-

2.3 Hypothesis

Given the theoretical background and current state of capital structure research relating to innovation, there is reason to believe that innovation output affects a firm's leverage. Previous empirical findings support that innovation indirectly affects capital structure decisions through an increase in growth opportunities and profitability and a decrease in tangible assets, which all are common determinants in capital structure research (Harris & Raviv, 1991; Rajan & Zingales, 1995; Fama & French, 2002; Frank & Goyal, 2009). However, following Rajaiya's (2023) approach, the authors hypothesize that when controlling for the above indirect effects and other common determinants of capital structure, there is still a significant relationship between innovation output and leverage to be found. The authors believe that firms with higher innovation output will have lower leverage due to reduced information asymmetry the firm faces in the equity market.

Through the perspective of Myers and Majluf's (1984) pecking order theory, in which information asymmetry leads to adverse selection of funding, our hypothesis is supported. The pecking order theory suggests that equity is the source of funding most sensitive to information asymmetry. Thus a relative decrease in information asymmetry would mean managers are more prone to issue equity. Similarly to Rajaiya (2023), the authors consider that innovation output reduces information asymmetry because when a patent is granted, the firm can better disclose its innovative efforts to the public. Therefore, the pecking order theory would predict a negative relationship between innovation output and leverage. Rajaiya's (2023) results on the U.S. market are in line with this prediction.

The trade-off theory provides another perspective on the contingent effect of innovation output on capital structure. Rajaiya (2023) argues that innovation output may reduce the expected costs of financial distress, and the channel is a reduction in the probability of default due to success in their innovative efforts. This would mean that innovation output would increase leverage. On the other hand, firms with a higher level of innovation output can be anticipated to have greater growth opportunities (Gunday et al., 2011), leading to incentives to avoid underinvestment (Myers, 1984). Moreover, creditors may believe more shareholders of innovative firms with abundant growth opportunities are more prone to risk-shifting and accordingly assign a higher cost of debt resulting in managers being more inclined to issue equity (Rajaiya, 2023). These two agency-related issues suggest that innovation output negatively affects leverage. Hence, the trade-off theory could be argued to be conflicted in predicting innovation output, and a negative and positive coefficient can be explained through the theory.

Lastly, the authors hypothesize that there is a difference in the effect of innovation output on OMXS and First North. This hypothesis is derived from the expected differences in the level of information asymmetry between firms listed on the respective stock exchanges due to the former having stricter regulations. According to Nasdaq, the regulated market OMXS has strict listing requirements, with established norms for corporate governance, financial performance, profitability, and firm size (Nasdaq, 2023). Conversely, Nasdaq First North is not a regulated market; instead, it is a Multilateral Trading Facility (MTF) with lower listing requirements and different regulations on what information has to be disclosed in the financial reporting. Botosan (2006) presents in her literature review that research suggests that disclosure decreases a firm's information asymmetry in the equity market. From Botosan's findings, the two different markets are hypothesized to differ in the degree of information asymmetry firms face in the equity market due to the more comprehensive disclosure requirements at OMXS. Hence, we believe that innovation output will have a greater effect on the leverage of a firm listed on First North than on OMXs due to the expected differences in information asymmetry.

Derived from the above discussion, our hypotheses are the following:

H1a: Higher innovation output leads to lower leverage for firms listed on Nasdaq First North Growth Market

H1b: Higher innovation output leads to lower leverage for firms listed on Nasdaq Stockholm

H1c: The negative effect of innovation output on the leverage of a firm is greater on Nasdaq First North Growth Market than on Nasdaq Stockholm

No hypotheses are made for the empirically significant determinants of capital structure, and these should be regarded as control variables in our study.

3. Method

In this chapter, we begin by describing the scientific approach and choice of theories before detailing the data gathering, processing, and sample selection. Then follows a description of our variables before we discuss and describe our regression model. After describing the regression model, the underlying assumptions are discussed. Finally, we critically discuss our methodology, reliability, and validity.

3.1 Scientific Approach

The study follows a deductive approach by developing a set of hypotheses based on existing theories and prior research, which are tested by a quantitative method by empirical data through operationalizing theoretical concepts into measurable terms (Bryman & Bell, 2015). A quantitative method is the natural choice given the research question.

3.2 Choice of Theories

This thesis hypothesizes that organizations with high levels of innovation output are more likely to have lower levels of debt. It is vital to have a thorough grasp of capital structure theories in order to evaluate this hypothesis. The bedrock of the capital structure theory is Miller and Modigliani's work, which has been widely recognized and cited (Berk & DeMarzo, 2020). The two prevalent theories within capital structure are rooted in Miller and Modigliani's work, namely, the pecking order by Myers and Majluf (1984) and the trade-off theory. The latter explains a firm's capital structure by balancing the benefits of the tax shield with the costs of financial distress and agency costs. While the pecking order, on the other hand, explains that the choices of a firm's capital structure can be derived from information asymmetry between managers and investors, leading to certain preferences of leverage. Given the hypothesis that innovation output reduces the information asymmetry a firm is facing in the equity market, the pecking order theory appears particularly appropriate for this study. Additionally, the trade-off theory is useful and can help illuminate aspects of capital structure decisions where the pecking order theory falls short. The trade-off theory and the pecking order theory offer insights into various capital structure decision-making processes. Therefore, while examining a firm's capital structure, it is essential to consider a range of theoretical viewpoints and empirical evidence.

The trade-off theory and the pecking order theory are two well-established theoretical frameworks in corporate finance, but they are not without their limitations. The pecking order has been criticized for being too simple and not considering several important factors (Baker & Wurgler, 2002). Myers (2001) criticizes his work and states that the pecking order does not explain why managers would care if the issued equity is over- or undervalued. Overall there is mixed empirical evidence on both the trade-off theory and the pecking order, and the usual case is that other explanations are needed to grasp why a firm chooses its capital structure fully.

However, the theories are well cited and offer great insight into firms' capital structure decisions and are therefore used in this study.

Because existing literature on the relationship between innovation output and capital structure is relatively scarce, the authors decided to include all the empirical evidence they could access. Raijaya (2023) and Bartoloni (2013) are the pioneers in this field, and the authors of this thesis hope to contribute to further developing this field of research. Innovation, however, is a more researched topic, and as such, numerous definitions and measurement methods exist among scholars in the field. The authors believe explaining the different methods of measuring innovation in case others want to replicate our study is highly relevant.

3.3 Data

3.3.1 Data Gathering

The authors of this thesis have used quantitative secondary data retrieved from various databases to receive the necessary data to conduct our study. Our main variable of interest, innovation output proxied by the number of patents granted, is retrieved from PAtlink. PAtlink is provided by the Swedish House of Finance and includes all patents granted to Swedish firms since 1990 (Swedish House of Finance, n.d). PAtlink matches patent data with unique patent identifiers from Patstat, a database provided by the European Patent Office (Patstat, n.d), with the firm’s unique organization number. The data for a majority of our other variables are gathered through the use of Retriever Business. Retriever Business is connected with several Swedish government agencies and has data on Swedish firms collected directly from annual reports since the 2000s (Retriever Business, n.d). Lastly, the use of FinBas, which the Swedish House of Finance also provides, was needed to extract data for the market capitalization of our firms.

One of the main benefits of using secondary data is the large amounts of resources saved in terms of money and time in the data-gathering process whilst also accessing data with high quality (Bryman & Bell, 2015). However, Bryman and Bell note that it is crucial not to take the credibility of secondary data for granted. The fact that PAtLink and FinBas are provided by the Swedish House of Finance at the Stockholm School of Economics, Sweden’s national research center for financial economics, signifies a high level of credibility due to the data being used in a vast amount of research. Retriever Business, being a well-established database and cooperating with Swedish government agencies, also signals high credibility. Thus, we consider our data to be of high quality and credible.

3.3.2 Data Characteristics

Our research uses panel data. Panel data, also called longitudinal data, are data for multiple entities in which each entity is observed at two or more time periods where the data are pooled on a cross-section over several time periods (Stock & Watson, 2022; Baltagi, 2021; Hsiao, 2021). The pooling of cross-sections and time periods leads to more data points, increasing the degrees of freedom and reducing collinearity among independent variables (Hsiao, 2021). Moreover, Hsiao (2021) describes an array of benefits from the use of panel data in handling heterogeneity, as it provides a comprehensive understanding of the dynamics of adjustment over time, capturing inter-individual differences and intra-individual dynamics while effectively controlling for unobserved heterogeneity (Hsiao, 2021). The issue of unobserved heterogeneity in our research will be further discussed in *3.5 Regression Model.*

Panel data with some missing data for at least one time period for at least one entity is called an unbalanced panel (Wooldridge, 2012). As is typical in an economic empirical setting (Baltagi, 2021), this is the case with our panel data. Since our sample is dependent on two stock exchanges, any changes to their composition would also impact our panel data. There are multiple plausible reasons for changes to the composition of the exchanges, e.g., a new listing, a delisting, a bankruptcy, or a merger, which we assume is the reason for the missing data points. As a result, altering the sample to achieve a balanced panel by removing entities where data is missing for one or several years would risk heavy bias.

Even if there are plausible reasons for attrition, if these reasons are correlated with the idiosyncratic error, the regression model can become biased; that is, if the reasons for entities leaving the sample are related to unobserved specific characteristics or qualities of the companies, it might cause bias. This will be discussed further in section *3.6.2.3 Exogeneity,* under *Endogeneity*.

3.3.3 Sample Selection

The sample is selected based on the limitations and scope of this thesis presented in section 1.5, and the limitations will be further discussed and argued for below. After limiting the population based on time, country, and marketplace, there were 588 firms and 3743 data points. Following the limitations, an attrition analysis will be presented.

When Rajaiya (2023) conducted his study, he highlighted the influence of innovation output on firms' leverage ratio in the U.S. This research aims to replicate and expand upon those findings by investigating a different country, namely Sweden. Sweden is an ideal choice for this study due to its rich history of successful innovations and superior position in patent applications per capita, as evidenced by data from the Patent- & Registreringsverket (2021).

Moreover, conducting the study on Sweden benefits from the availability of comprehensive databases specifically focused on the Swedish financial market, facilitating accurate and reliable data analysis.

Although the European Union might be viewed as a potential alternative, it is important to concentrate on one particular country rather than the entire EU due to the existence of country-specific factors that have a major impact on a firm's capital structure (de Jong, Kabir, & Nguyen, 2008). The Nordic countries are quite often clustered together in the empirical literature. However, the authors of this thesis were both satisfied with the amount of data points recovered from Sweden, and de Jong, Kabir, & Nguyen (2008) criticize clustering due to the named country-specific factors. The authors of this thesis believe it is interesting to broaden the focus beyond the U.S. and look at the particular setting of Sweden to gain a further understanding of how generalizable Rajaiya's (2023) results are.

The time period selected for this study is from January 1st, 2010, to December 31st, 2019, providing us with the most contemporaneous data while considering the time required for the patent application process (Rajaiya, 2023). The start date of 2010 is based on not including the financial crisis of 2008-2009, where Sweden faced a general economic decline (SCB, 2020) which might skew our results and lead to misinterpretations of our findings. Similarly, the end date was based on the fact that patent data was only available up until 2020, which is the year of the Covid-19 outbreak. Even though we only study Swedish firms, there is an expected difference in how the firms were affected during the pandemic. The expected difference is associated with both firms' innovative capabilities during that time and other determinants proxied by sales, ebit, etc. The abnormalities associated with the Covid-19 pandemic might introduce biases in our results. While we will incorporate year fixed effects in our models, it does not adequately control for changes in how the chosen explanatory variables impact leverage. Accordingly, we have chosen to study the years 2010-2019 since this is a time of relatively stable economic conditions in terms of GDP growth in Sweden (SCB, 2020).

Furthermore, the study examines the connection between a firm's innovation output and leverage ratio while studying potential market variations. First North and OMXS are the two major markets of interest in Sweden. These markets display noteworthy differences regarding their listing criteria and corporate governance norms. As discussed in *1.5 Limitations and Scope*, a third market was of interest, but due to data availability, this thesis will focus on OMXS and First North.

3.3.3.1 Attrition Analysis

Our sample is based on the above mentioned limitations. However, other than time, country, and market, a set of criteria have been followed to get our final sample for our regression analysis. Before applying the criteria, the original sample consists of 3743 data points, 588 firms, and ten years with an average of 6.37 years of data per entity. The criteria set is as follows:

1. Following previous empirical literature in corporate finance, we have removed firms in the finance, insurance, and utility industry using Retriever Business industry classifications. It is common to exclude firms within these industries since their capital structure characteristics differ, and they face different regulations and laws than firms in other industries (Rajan & Zingales, 1995; Frank & Goyal, 2009; Rajaiya, 2023).
2. All companies with a negative value or zero in total assets are dropped for the year following Rajaiya (2023).
3. All firms must have data on all variables. Firms are only excluded for the years for which they have missing values, and we keep their data for the other years.
4. Lastly, all firm-year observations with negative values for the variables sales and total debt are removed, as Rajaiya (2023) advocates. All firm-year observations where the leverage ratio exceeds the value of one are also removed, per Halling, Yu, and Zechner (2012).
5. Dropping all singleton observations due to the use of lagging variables.

The steps culminate to a regression on 423 firms and 2549 data points. As a result of using lagged variables, step five includes a reduction in the total amount of data points due to the first year for all firms being removed. The amount of data points removed, and left, after each step is shown in Table 3.

Table 3

	Removed		**After Removal**	
Step	**Firms**	**Data Points**	**Firms**	**Data Points**
1	91	582	497	3161
2	0	8	497	3153
3	7	60	490	3093
4	1	33	489	3060
5	66	511	423	2549

3.3.4 Data Processing

In order for us to use the gathered data for analysis, we applied a comprehensive data processing routine. The data processing was done using Python, an all-purpose programming language where we make use of programs called packages (Magallanes Reyes, 2017). Packages are reusable and shareable code in Python containing various functions to perform specific tasks (Beuzen & Timbers, 2022). A majority of the tasks conducted in our data processing are done using *pandas*, a tool that aims to facilitate working with data sets common to finance and statistics (McKinney, 2010). A systematic procedure was established to guide the data processing workflow. This involved breaking down the overall process into smaller, manageable steps, each with its defined objectives. By doing so, it became possible to assess the accuracy of the data processing at various stages and identify potential errors or inconsistencies through manual sample checks after each step. The procedure included:

1. Structuring and reshaping the data per source
2. Cleaning and formatting the data
3. Integrating the data

3.3.4.1 Reshaping the Data

The output data from Patlink, FinBas, and Retriever Business was received in varying shapes and split between multiple files and sheets; thus, the first step of data processing was to merge the sheets and files into one file with one sheet per database (Appendix I). While the data from FinBas and Retriever Business was retrieved in a long panel data format, the data from Patlink was not. Hence the second step was to reshape the data to a long panel data form. The latter included generating a count variable for the number of granted patents per organization per year to generate a firm's innovation output according to eq 1 (Appendix II).

Eq 1.

$$Innovation\ output_{i,t} = \Sigma_{i,t} Patent\ granted$$

.i= Firm, and t= Year

The innovation output is calculated in a short format panel data structure, where multiple rows can exist for each patent, by counting the unique combinations of firm and patent identifier per year to determine the number of unique patents granted to each firm in each specific year.

3.3.4.2 Cleaning and Formatting the Data

The different databases vary in formatting missing values, units, and decimal marks. In order to integrate the data, the formatting needs to be consistent; therefore, we clean the data in these regards (Appendix III).

3.3.4.3 Integrating the Data

Since we use panel data, we need two common identifiers to match the data, one identifying different entities and one identifying different times. The year will be used as the sole key for time, whereas the organization number and ISIN code will be used as entity keys. Two keys are needed for the entity since FinBas did not provide a firm's organization number but instead only the ISIN code. However, this issue was mitigated by PAtlink providing both the organization number and ISIN code. Therefore we were able to first merge the FinBas file with PAtlink and lastly merge the Retriever Business data using a firm's organization number (Appendix IIII). Finally, we saved it as both an Excel and Stata file. The process is summarized in Table 4

Table 4

Data set 1	**Data set 2**	**Time Identifier**	**Entity Identifier**	**Matching**
FinBas	PAtlink	Year	ISIN	Year=Year, ISIN=ISIN
PAtlink	Retriever Business	Year	Org.Nr	Year=Year, Org.nr=Org.nr

3.4 Variables

3.4.1 Dependent Variables

To study the effect of innovation output and other determinants on capital structure, a measurement is needed. Titman & Wessels discusses that using market values instead of book values of leverage may indeed better capture the effect different determinants have on the capital structure, although they have a high correlation (1988). Nevertheless, it is common in empirical studies to have both proxies for leverage, one ratio using book values and one using market values (Fama & French, 2002; Kayo & Kimura, 2011). Rajan & Zingales also shed light on the various ratios used to proxy leverage, and examples include total liabilities over total assets and total debt over total assets (1995). We chose the latter since the first proxy mentioned total liabilities over total assets, accounting for accounts payable and other liabilities that can overestimate the firm's leverage. Total debt over total assets is also widely accepted and supported in previous literature (Fama & French, 2002; Frank & Goyal, 2009).

Following the literature, book leverage and market leverage will be calculated, where the latter will help us to nuance our analysis and further test the robustness of our results. In order to proxy for the market leverage, we will follow Rajaiya (2023) and use the ratio of the book value of total debt over the market value of assets.

The market value of assets is calculated as the book value of assets subtracted by the book value of equity and, lastly, adding the market capitalization. The predictions for the determinants discussed in section *2.2.5 Determinants of Capital* Structure are expected not to be impacted by the use of either market value or book value of leverage based on previous empirical findings (Rajan & Zingales, 1995; Fama & French, 2002; Frank & Goyal, 2009).

3.4.2 Independent Variables

Below, all the independent variables of the regression model are presented and discussed in terms of how they are proxied and transformed in the models. The independent variables of interest for this research are the innovation output of a firm and the market dummy; the other independent variables are to be interpreted as control variables and are based on previous empirical research within the field.

3.4.2.1 Innovation Output

Innovation output is our primary variable of interest as it allows us to test our hypotheses. As discussed in *2.2.2 Measuring Innovation Output*, there are various proxies for innovation output, including patents granted (Griliches, 1984; Schmookler, 1966; Scherer, 1965), the natural logarithm of the stock of patents (Rajaiya, 2023) and R&D intensity (O'brien, 2003). In the model, innovation output will be proxied by the natural logarithm of patents granted plus one. ln(1+INNO) is used since it normalizes and stabilizes the data, reducing the influence of extreme values and skewed distribution and avoiding undefined values.

3.4.2.2 Market Dummy

To test H1c, a dummy variable for which the market a firm is listed is introduced to the model. The dummy assumes the value one if a firm is listed on OMXS that specific year and assumes the value zero if the firm instead is listed on First North. The use of the dummy variable is further discussed in section *3.5, Regression Model*.

3.4.2.3 Size

In the literature, two frequent ways are used to measure the firm's size. One of these, which Frank & Goyal (2003) uses is the natural logarithm of sales. This way of quantifying the size of a company has proven to yield significant empirical results relating to capital structure (Rajan & Zingales, 1995; Titman & Wessels, 1988). The alternative proxy for firm size is instead to take the natural logarithm of total assets (Fama & French, 2002; Frank & Goyal, 2009). In the models, size will be proxied by the natural logarithm of sales (in SEK) following Frank & Goyal (2003), Rajan & Zingales (1995), and Titman & Wessels (1998).

3.4.2.4 Age

As mentioned in section *2.2.5.2 Age*, age as a determinant is not as common in empirical studies compared to, for example, Size, which grasps similar attributes. However, age has been found to significantly impact capital structure in empirical studies (Rajiya, 2023; Chen & Strange, 2005). Literature is not consistent with one measurement, and examples include the natural logarithm of the years a firm has available data points (Rajaiya, 2023), years listed on a stock exchange (Chen & Strange, 2005; Kieschnick & Moussawi, 2018), and years between initial creation and present time (Kieschnick & Moussawi, 2018). We have chosen to use the natural logarithm of age based on data available on Retriever Business, which is the years since it was registered with the Swedish Companies Registration Office.

3.4.2.5 Tangibility

Tangibility's impact on the capital structure has proven to be important (Kayo & Kimura, 2011), and it is proxied similarly in empirical studies. The impact of tangibility is the possibility of using the asset as collateral for debt (Frank & Goyal, 2008). In empirical studies, tangibility is proxied by fixed assets/total assets (Titman & Wessels, 1988; Kayo & Kimura, 2011; Frank & Goyal, 2008)

3.4.2.6 Profitability

Profitability has been empirically found to be an impactful determinant of capital structure (Frank & Goyal, 2009; Rajan & Zingales, 1995; Harris & Raviv, 1991). Profitability has various measurements, including operating cash flow to book value of assets (Rajan & Zingales, 1995) and EBIT to total assets (Rajaiya, 2023). We used EBIT to total assets in the models to test if Rajaiya's findings are transferable to other regions.

3.4.2.7 Growth

A proxy for growth commonly used in the literature is the market-to-book ratio of a company (Myers, 1977; Harris & Raviv, 1991; Rajan & Zingales, 1995; Rajaiya, 2023). For our model, we have followed prior literature's use of the market-to-book ratio in order to control for growth in our model.

3.4.2.8 Non-debt Tax Shields

Proxies for NDTS aim to capture all non-debt related tax shields, and examples of measurements are investment tax credits over total assets, depreciation over total assets, and R&D expenditure over total assets (Titman & Wessels, 1988; Fama & French, 2002). In our models, we will use depreciation over total assets to proxy NDTS following previous literature and based on available data.

3.4.3 Summary of Variables

Illustrated in Table 5 is a summary of the dependent and independent variables, their abbreviation, and the proxy used to measure them.

Table 5

Variables	**Abbreviations**	**Proxies**
Book Leverage	BVLEV	Book value of Total Debt/ Total Assets
Market Leverage	MVLEV	Book Value of Total Debt/ Market Value of Total Assets
Independent Variables		
Innovation Output	INNO	Ln (1+#Patents Granted)
Size	SIZE	Ln (1+Sales)
Age	AGE	Ln (1+Age)
Tangibility	TANG	Fixed Assets/ Total Assets
Profitability	PROF	EBIT / Total Assets
Growth	GRTH	Market Capitalization/ Total Assets
Non-Debt Tax Shield	NDTS	Depreciation/ Total Assets
Dummy Variables		
Market Dummy	MrktD	1 for OMXS, 0 for First North
Interaction Terms		
Innovation Output * MrktD	INNO#MrktD	INNO*MrktD

Variable list

3.4.4 Descriptive Statistics

In table 6 descriptive statistics is provided, illustrating the key characteristics of our data. A considerable amount of outliers diverge from the mean, as evident in Table 6. This is specifically noticeable for ratios. Intuitively, a ratio runs a more considerable risk of being an outlier since either the denominator or the numerator could have an extreme value, thus distorting the proxy value. Worth mentioning is that the values in Tables 6 and 7 for variables INNO, SIZE, and AGE are already log-transformed. These variables are transformed with the natural logarithm following previous literature discussed in *3.4.2 Independent Variables*. One might log-transform variables if there is reason to believe that a non-linear relationship exists between two variables or if the data is highly skewed and is expected to follow a log-normal distribution (Stock & Watson, 2022).

Lastly, to deal with any outliers in the data, we will follow Frank & Goyal (2009) and winsorize all variables that are ratios at a one percent level. This includes BVLEV, MVLEV, TANG, PROF, GRTH, and NDTS. Winsorizing is used to replace any outliers with observations at a determined percentile (Frank & Goyal, 2009), hence limiting any distortion of the results because of outliers. There is no set theoretical nor empirical rationale of what percentile serves the purpose best.

Winsorizing the variables at a lower percentile of one percent is deemed suitable by the authors with support from prior literature (Frank & Goyal, 2008).

Table 6, descriptive statistics before winsorization.

VARIABLE	MEAN	MEDIAN	STD. DEV.	MIN	MAX
BVLEV	.4537	.4759	.2212	0	.9998
MVLEV	.4204	.4267	.2228	0	.9615
INNO	.5328	.0	1.273	0	9.497
SIZE	19.28	19.19	4.071	0	26.79
AGE	2.959	2.996	.9160	0	4.812
TANG	.1649	.0496	.2526	0	.9987
PROF	-.0591	.0384	.3003	-1.986	.8279
GRTH	2.256	1.217	2.926	.0339	27.86
NDTS	.0243	.0002	.0524	0	.6859

The post winsorization data are displayed in Table 7, and the variables calculated as ratios now differ in their min and max values as expected. However, there was no considerable impact on the mean of the different variables. Moreover, BVLEV, MVLEV, and INNO are also included for each of the separate markets to highlight potential differences and will be used to standardize the coefficients in section *5. Analysis.* Since these variables were not winsorized, the minimum value is still zero for age, size, and innovation output since these variables were not winsorized. To accommodate the numerous occurrences of zero values, the natural logarithm plus one was applied to retain the data points.

Table 7, descriptive statistics post winsorization.

VARIABLE	MEAN	MEDIAN	STD. DEV.	MIN	MAX
BVLEV	.4534	.4759	.2304	.0596	.9582
BVLEV (FN)	.3771	.3412	.2473	.0596	.9458
BVLEV (OMXS)	.5123	.5302	.1974	.0596	.9582
MVLEV	.4129	.4267	.2195	.0459	.9221
MVLEV (FN)	.3366	.2950	.2298	.0459	.9221
MVLEV (OMXS)	.4717	.4854	.1915	.0459	.9084
INNO	.5176	.0	1.256	.0	9.497
INNO (FN)	.3805	.0	.8478	.0	4.025
INNO (OMXS)	.6235	.0	1.488	.0	9.497
SIZE	19.58	19.90	3.148	6.908	26.79
AGE	2.959	2.996	.9160	0	4.812
TANG	.1648	.0496	.2523	0	.9820
PROF	-.0569	.0384	.2791	-1.194	.3536
GRTH	2.205	1.217	2.625	.1336	14.41
NDTS	.0226	.0002	.0401	0	.2276

3.5 Regression Model

In order to conduct a statistical analysis of the relationships between the dependent and explanatory variables, we will be using an ordinary least squares regression (OLS regression). As justified by the Gauss-Markov Theorem, OLS is the best linear unbiased estimator as long as the theorem holds (Wooldridge, 2010). The theorem is further explained in 3.5.1 *Assumptions.*

Intuitively and empirically (Coles, Lemmon & Meschke, 2012; Roberts & Whited, 2013), an array of factors in addition to our explanatory variables affect the capital structure of a firm and may be correlated with our explanatory variables and is referred to as unobserved heterogeneity. Expanding on the aforementioned possibility of attributed to panel data to handle unobserved heterogeneity or omitted variable problems, we will be applying an unobserved effects model.

Since we assume that unobserved heterogeneity is correlated with our explanatory variables, which is common in corporate finance research, including studies on capital structures (Lemmon, Roberts & Zender, 2008), we opt for a fixed effect estimator (Wooldridge, 2010). We assume unobserved heterogeneity that is constant over time but varies across firms (such as corporate culture) and unobserved heterogeneity that is constant across firms but varies over time (such as the central bank interest rate) and consequently includes both entity (firm) and time (year) fixed effects.

In practice, the fixed effects estimator can be viewed as an extension of the OLS estimator that can handle unobserved heterogeneity rather than a different estimator. It uses OLS as the estimation method after a within-transformation; however, delving into the econometric technicalities is beyond the scope of this thesis and does not directly address our research question. For a comprehensive understanding of the econometric technicalities, interested readers are encouraged to refer to the work of Wooldridge (2010) in his book "Econometric Analysis of Cross Section and Panel Data."

Going forward, we assume that the Gauss-Markov Theorem holds when accounting for unobserved heterogeneity; a detailed summary of the relationship between the OLS and fixed effects assumptions can be found in Appendix V.

To understand the interaction effect between market and innovation output, we include an interaction term between the continuous variable innovation output and the binary variable market. By including this interaction regressor along with the individual variables, we allow for different intercepts and slopes for the two variables.

The purpose of introducing the interaction term is to examine how the relationship between market and innovation output varies based on the values of these variables.

The population regression line we establish relates our dependent variable to innovation output, and the slope of this regression line is contingent upon the value of the binary variable market. In simpler terms, the interaction term helps us investigate whether the impact of innovation output on the dependent variable differs depending on whether the firm is listed on OMXS or First North.

Finally, we apply a lag of one year to all our explanatory variables in line with much of the earlier empirical research in the area (Fama & French, 2002; Frank & Goyal, 2003; Frank & Goyal, 2009; Rajaiya, 2003) We do this to account for the fact that a change in the value of one of the explanatory variables will not affect the dependent variable immediately during one time period, but rather with a lag. Changes in the capital structure are a complex and often slow process, and we assume that our explanatory variables affect our dependent with a lag. More generally, many variables in economics and finance will change only slowly (Brooks, 2008). Moreover, adding lagging variables can help address one source of endogeneity, namely reversed causality (Brooks, 2008).

The decision and considerations of this section leave us with the following model:

Eq 2

$$LEV_{i,t} = \beta_1 INNO_{i,t-1} + \beta_2 MrktD_{i,t-1} + \beta_3 (INNO_{i,t-1} * MrktD_{i,t-1}) + \beta_4 SIZE_{i,t-1} + \beta_5 AGE_{i,t-1} + \beta_6 TANG_{i,t-1} + \beta_7 PROF_{i,t-1} + \beta_8 GRTH_{i,t-1} + \beta_9 NDTS_{i,t-1} + a_i + \lambda_t + u_{i,t}$$

LEV= BVLEV and MVLEV

3.6 Assumptions

The assumptions outlined in this section are later tested in section *4.1 Statistical Evaluation of the Model.*

3.6.1 Gauss-Markov Theorem

The Gauss-Markov Theorem referred to in section 3.5 *Regression Model* proves that under a set of assumptions, the OLS estimator is the best linear unbiased estimator (Wooldridge, 2012).

Table 8

Identifier	Assumption	OLS
OLS 1	**Linearity**	The model in the population can be written as $y = \beta_0 + \beta_1 x + u$
OLS 2	**Random Sampling of Observations**	The sample is random.
OLS 3	**No Multicollinearity**	There is variation over time in each explanatory variable (for at least some observations), and there are no perfect linear relationships among the explanatory variables.
OLS 4	**Exogeneity**	The error u has an expected value of zero given any value of the explanatory variable: $E(u\|X) = 0$
OLS 5	**Homoscedasticity**	The error terms ui should all have the same variance: $Var(u_i\|X) = \boldsymbol{\sigma}^2$
OLS 6	**Autocorrelation**	The error terms are uncorrelated, conditional on all explanatory variables: $Cov(u_i u_j\|X) = 0$
OLS 7 (Optional)	**Normality**	Conditional on X_i, the $u_{i,t}$ are independent and identically distributed as Normal

The Gauss-Markov Theorem (Brooks, 2008; Wooldridge, 2012).

Henceforth, the assumptions will be referred to according to their identifiers in Table 8, and the Gauss-Markov Theorem will be referred to as the OLS assumptions. Under OLS one through four, the estimator is unbiased. If OLS five and six are satisfied, the error term is independent and identically distributed. In that case, OLS is the best unbiased linear estimator. (Brooks, 2008; Stock & Watson, 2022; Wooldridge, 2012).

3.6.2 Assumptions

3.6.2.1 Linearity

Linearity refers to the model being linear. More specifically, the model must be linear in the parameters so that the relationship between the dependent and the explanatory variables fits a straight line (Brooks, 2008). In line with the OLS one, we assume this holds. If the assumption does not hold, the estimators will be biased. Non-linearity would then be an indication of misspecification.

We perform a Link test, also known as a functional form test to test the assumption. If the Link test indicates non-linearity, polynomial variations of the already included variables can be incorporated into the model to test if we can prove linearity since fixed effects only require linearity in the model's parameters (Brooks, 2008).

3.6.2.2 Multicollinearity

Multicollinearity is when explanatory variables are highly correlated with other explanatory variables (Wooldridge, 2012). In line with OLS three, we assume that the explanatory variables are not highly correlated and that there is no multicollinearity. In practice, the correlation between explanatory variables will never be zero, but if the correlation is weak, it will not cause any issues (Brooks, 2008).

Multicollinearity leads to high standard errors, making individual coefficients insignificant and confidence intervals wide, leading to inappropriate conclusions and impeding accurate inference drawing (Brooks, 2008). If multicollinearity exists, OLS is not unbiased (Wooldridge, 2012).

We test for multicollinearity by creating a correlation matrix. If the absolute value of the Pearson correlation coefficient is less than 0.8, we assume that multicollinearity is not an issue (Shrestha, 2020) while acknowledging that this only allows us to detect possible pairwise correlation. There are multiple feasible solutions if the assumption of no multicollinearity is not satisfied. Besides alternative estimation techniques, more ad hoc methods can be used, such as dropping one of the collinear variables or transforming the correlated variables into a ratio (Brooks, 2008).

3.6.2.3 Exogeneity

Exogeneity refers to the assumption that the explanatory variables in a regression model are uncorrelated with the error term. The opposite is referred to as endogeneity. When the exogeneity assumption holds, it means that the explanatory variables are not endogenous to the error term and are considered independent of the unobserved heterogeneity. Endogeneity is a central issue in empirical corporate finance and can lead to biased and inconsistent results (Roberts & Whited, 2012). The OLS four assumption assumes exogeneity.

As discussed earlier, we assume that there are, in fact, unobserved effects and that these are correlated with our explanatory variables based on the nature of our research and earlier empirical work, as argued in section *3.5 Regression Model*. This is referred to as omitted variable bias, which, as we have argued, is our reason for using a fixed effects model, which helps us handle this.

Another possible source of endogeneity is reverse causality which is also briefly mentioned in section *3.5 Regression Model*. Lagged explanatory variables, which are already incorporated in our model based on theoretical justifications unrelated to endogeneity, also help us mitigate the problem of endogenous variables, albeit ruling out reversed causality does not solve endogeneity problems (Brooks, 2008; Reeb, Sakakibara & Mahmood, 2012).

Like often the case in corporate finance research, we use proxies for some variables that are difficult to quantify. If these are inconsistent with the true variable of interest, it leads to measurement error. The proxies used in our regression are based on earlier empirical research, and we assume that any possible measurement error is not systematically related to any of our explanatory variables (Roberts & Whited, 2012; Wooldridge, 2012).

A fourth common source of endogeneity problems in corporate finance research is simultaneity bias which occurs when the explanatory variable is determined simultaneously with the dependent variable (Roberts & Whited, 2012; Wooldridge, 2012). Bartoloni (2011) and Rajaiya (2023) test for possible causality and simultaneity patterns between innovation output and leverage, our variable of interest and our dependent variable, and find no simultaneity problem.

Finally, as discussed in *3.3.2 Data Characteristics*, an unbalanced panel could cause bias if the attrition is correlated with the error term. We assume this is not the case. A simple test was suggested by Nijman and Verbeek (1992 cited in Wooldridge, 2010), where we add the lagged selection indicator to our model and estimate it, and then do a t-test. Under the null hypothesis, selection in t-1 should not be significant at time t.

We will use a Hausman test to test whether the individual characteristics are correlated with the regressors. Then, we will run a joint F-test to see if coefficients for the years are jointly equal to zero to decide whether to include year fixed effects.

3.6.2.4 Homoscedasticity

Homoscedasticity refers to when variance in the error terms is constant. If this is not the case, the error term is said to be heteroscedastic. In other words, homoscedasticity implies that the spread or dispersion of the residuals is the same throughout the range of the predictors (Wooldridge, 2012). Per OLS five, we assume this is the case when accounting for unobserved effects.

While heteroscedasticity does not lead to unbiased estimates in OLS, we can not assume it is the best linear estimate if there is unhandled homoscedasticity (Wooldridge, 2012) since the formula for the coefficient standard errors no longer holds (Brooks, 2008).

To test for homoscedasticity, we calculate a modified Wald statistic for groupwise heteroskedasticity in the residuals of our model. To handle heteroscedasticity in regression analysis, several approaches can be employed. One method involves transforming the variables by taking their logarithms or using other scaling measures to reduce the impact of extreme observations. All our variables are transformed by taking their logarithm or by winsorization as described in section *3.4.4 Descriptive Statistics*. Another common approach if the assumption of homoscedasticity is violated is to use heteroskedasticity-robust standard error estimates utilizing modified standard error estimates (Brooks, 2008).

3.6.2.5 Autocorrelation

Autocorrelation, or serial correlation, occurs when the error terms in a regression model are highly correlated. OLS six assumes there is no unhandled autocorrelation (Brooks, 2008).

Formal statistical tests are necessary for a conclusive assessment of the assumption (Wooldridge, 2012), and therefore, we conduct a Woolridge test of autocorrelation to test the assumption. If there is serial correlation in the model, one solution is to apply fully robust standard errors. These are standard errors that are robust to both heteroscedasticity and autocorrelation by an approach known as clustering (Wooldridge, 2012).

3.6.2.6 Normality

Normality refers to the concept that the regression residuals are normally distributed. According to Wooldridge (2012), normality is often included when discussing the Gauss-Markov Theorem. He states, however, that normality is not needed for OLS to be the best unbiased linear estimator and Brooks (2008) argues that normality, at the very least, for large sample sizes is negligible.

As discussed in *3.4 Variable List* we winsorize all ratios and take the natural logarithm of our other variables. These are both typical measures to deal with non-normality. We conduct a Shapiro-Wilks test after transforming the variables to test for normality. To compare normality before and after transformation, we visually inspect the residuals.

3.7 Discussion of Methodology

3.7.1 Data and Regression Discussion

In our study, we only include one measurement for innovation output: the number of patents granted. While we find support in previous research for our choice of the proxy, it would have been beneficial to test the robustness by using alternative proxies as well. It would have also been valuable to include a measure of innovation input, such as R&D, as used by Raiaiya (2023), to analyze the relationship and differences between innovation input and output regarding capital structure, but the necessary data is unavailable.

While our research question seeks to investigate differences between OMXS and First North, it would have also been valuable to include a pure measure of information asymmetry to both controls for the relation between our market dummy and information asymmetry and further to understand the relationship between innovation output and information asymmetry. Unfortunately, no such data was available.

To gain a more nuanced understanding of the channel for effect on innovation output on leverage, it would have been useful to test firms' propensity to issue equity as Rajaiya did (2023). Finally, in line with the considerable relevance of endogeneity in corporate finance research, one shortcoming is that no strong instrument was identified for which necessary data was available. Including instrumental variables would have allowed for an instrumental variable approach in further handling and testing of endogeneity issues, such as measurement errors and reverse causality, while enabling robustness checks using IV models. We do, however, argue that we follow a long line of prominent researchers in the field who have conducted significant research without including instrumental variables.

3.7.2 Critical Evaluation of the Sources

In this study, we have relied solely on secondary data, which means that the information used has been collected and written by other people, not the researchers themselves. In this case, it is crucial to carefully evaluate the sources to ensure that they meet the desired quality requirements. In order to find relevant articles and studies, LUBsearch and Google Scholar were mainly used. There it was possible to see if the article was peer-reviewed, published in an academic journal, and its citations were reported.

Most of our sources have been published in reputable academic journals, such as The Journal of Finance, The Journal of Corporate Finance, and The Journal of Financial Economics. The sources are well-cited and often refer to each other. This is positive since the authors of this study can by themselves see the first-hand source and avoid any misinterpretation. Throughout the study, the objective has been to utilize original sources of information, known as primary sources. The origin of the information has been the main emphasis rather than just accessing the most recent sources. For instance, original theories from Jensen & Meckling (1976) have been used to discuss information asymmetry since they are still relevant today and are often used in various literature.

Our thesis draws inspiration from a peer-reviewed article published in the Journal of Corporate Finance by Rajayia (2023), where we found insightful ideas and concepts that shaped the foundation of our research. We will be the first researchers to refer to his study. One could argue it is because the article is newly published; on the other hand, the absence of citations leaves room for uncertainty regarding its unique contribution to the field. Since it was first published 24th of January 2023, and this field of study is quite niched, we believe his findings greatly contribute to the field and will be cited once others conduct similar studies. The Journal of Corporate Finance assures that all articles published are peer-reviewed to ensure the highest quality and maintain its reputation.

In addition to the reputable journals, the authors have used several books and handbooks in econometry and Python programming to ensure that the data processing was made without errors, as well as multiple regression. When discussing the methodology, academic literature such as Bryman and Bell (2015), Skärvad and Lundahl (2016), and Wooldridge (2010, 2012) were used. These sources are of high quality and written by professors, doctoral economists, and docents with extensive knowledge about properly conducting research within academia. *Appendix XV summarizes* the number of articles used per journal and shows if it is peer-reviewed.

3.7.3 Reliability

Reliability refers to the study's ability to be trustworthy and replicable by other researchers, producing the same results (Bryman & Bell, 2015). The study's methodology and methods have been thoroughly and precisely detailed in this report to enhance trustworthiness. Chapter *3.3 Data* presents a comprehensive overview of the data processing to ensure that other researchers can replicate the study.

When it comes to stability, meaning that the study can be repeatable over time, the authors do not see any risk for why this would not be true for other years. The authors discussed other measurements for innovation output, for example, patent citations, as suggested by Hall et al.

(2005). However, measuring by patents granted was deemed to be more appropriate as a result of data availability.
Furthermore, patent citations can have a lagging effect and receive additional citations after this study was conducted. This could lead to different results. Hence measuring innovation output through patent citations would reduce the reliability of our study.

Bryman and Bell (2015) assert that it is more difficult to replicate qualitative data than quantitative data. This is due to the underlying nature of qualitative research, which seeks to understand subjective experiences that can be interpreted differently. Quantitative data, in contrast, is based on numerical measures that are less liable to errors due to subjectivity. The data in our study is completely quantitative and could therefore be argued to have higher stability.

Researchers typically follow standardized procedures in their studies to guarantee the reliability, aiming to eliminate random errors (Skärvad & Lundahl, 2016). The critique of this study in terms of its reliability is the extensive data processing since it might lead to diminishing data points due to unobserved human errors. Inadequate data transmission during the processing step is referred to as a processing error (Byström & Byström, 2011). Mistakes made during data inspection, coding, transfer, and programming might result in processing errors. However, we followed our procedures carefully, made manual sample checks of the data continuously, and noted every step that was made. Hence, we do not believe that any type of randomness has affected the study and decreased its reliability.

3.7.4 Validity

In terms of validity, it is essential to consider how effectively the chosen measurement instrument aligns with the study's intended purpose and whether the collected data is relevant to the research question (Bryman & Bell, 2015).
Ensuring validity goes beyond merely collecting and processing data accurately and without errors; it also necessitates the data's direct relevance to the intended inquiry. The authors have gathered data from several databases for our research.
In order to answer the research question, data on firms' capital structure and proxies for innovation output were needed. In order to study innovation output's direct effect on capital structure, data was gathered for previously found determinants of capital structure to control for their respective effect. Moreover, a theoretical framework was put together using well-cited capital structure theories to interpret our results.

According to Bryman and Bell (2015), conceptual validity relates to how well a measure, in this instance, variables, conveys the intended meaning. Nevertheless, when some variables cannot be fully measured, proxies are common. Using proxy variables might reduce validity since they can unintentionally capture unintended attributes of the variable; issues with proxies are also discussed in *3.6 Assumptions.*

The choice of proxies, in general, is further discussed in *3.4 Variables,* and the proxy for innovation output, in particular, is comprehensively discussed in *2.2.2 Measuring Innovation Output*.

Internal validity focuses on determining if the observed relationship is indeed due to the factors being researched. A comprehensive discussion on this, including causality, is found in *3.6 Assumptions*. Sufficient sample size is necessary for the study's validity to be established. A greater sample size improves the study's validity (Bryman & Bell, 2015). This study encompasses 2549 data points from 423 firms over ten years. The authors believe this is sufficient data to test the hypotheses derived in section *2.3 Hypothesis*.

Bryman and Bell (2015) also discuss external validity, which refers to whether the study's findings can be generalized. Since the research is conducted on all companies listed on OMXS and Fist North, it can be said that the external validity of the study is relatively high within the context of publicly listed Swedish companies, and the findings can reasonably be generalized to this population of companies. However, the study's external validity might be limited when it comes to generalizing the findings to companies outside of Sweden or companies that are not publicly listed.

4. Results

In the following section of the thesis, a statistical evaluation of the model will be conducted where the test results from the various assumptions are presented, along with any adjustments called for by the diagnostic tests. Then the regression outputs for our models are presented, before finally presenting the outcome of our hypotheses.

4.1 Statistical Evaluation of the Model

All Stata output is found in *Appendix VI through XIII*.

4.1.1 Testing for Linearity

To test the linearity assumptions, a Link test was conducted. The null hypothesis is that the model is linear. As shown in Table 9, the p-value exceeds the 5% significance level, and therefore we fail to reject the null hypothesis, and the assumption of linearity holds.

Table 9

Link Test	
Book leverage	**Market leverage**
F-distribution	**F-Distribution**
.71	**.91**
P-value	**P-VALUE**
.40	**.93**

4.1.2 Test for Multicollinearity

To test for multicollinearity we create a correlation matrix and look for Pearson correlation coefficients greater than 0.8 in Table 10.

The correlation matrix is displayed below, and no Pearson correlation coefficient is at or above 0.8; thus, the assumption of no multicollinearity is satisfied.

The largest pairwise correlation is between our independent variables size and market dummy. This comes as no surprise considering the typical firm characteristics on OMXS compared to First North, where firms listed on the former usually are larger and more established (Nasdaq, 2023). However, the correlation between the two variables is not alarmingly high at 0.5936.

Table 10

Correlation matrix

VARIABLE	INNO	SIZE	AGE	TANG	PROF	GRTH	NDTS	MrktD
INNO	1.000							
SIZE	.0365	1.000						
AGE	.1502	.5102	1.000					
TANG	-.1153	.2422	.2048	1.000				
PROF	.0872	.5466	.3569	.1676	1.000			
GRTH	.1654	-.3232	-.2497	-.2569	-.3030	1.000		
NDTS	-.0904	-.1510	-.1691	-.0516	-.3559	.0521	1.000	
MrktD	.0936	.5936	.4898	.2127	.4235	-.2438	-.3195	1.000

4.1.3 Test for Endogeneity

To test if the unobserved effects are correlated with the regressors we conduct a Hausman test. The null hypothesis is that they are not (Wooldridge, 2010). We reject the null hypothesis for both models and conclude that fixed effects are appropriate (see Table 11).

Table 11

Hausman test	
Book leverage	**Market leverage**
χ**^2**	χ**^2**
96.65	**137.35**
P-value	**P-VALUE**
.00	**.00**

To decide if time fixed effects are indeed needed, we run a joint F-test where the null hypothesis is that time fixed effects are needed. We fail to reject the null hypothesis and conclude that time fixed effects are indeed needed.

Table 12

Joint F-test for Time Fixed Effects	
Book leverage	**Market leverage**
Joint F-Distribution	**Joint F-Distribution**
1.43	**.91**
P-value	**P-VALUE**
.177	**.504**

To test if the attrition is correlated with the error term, we add a lagged selection indicator, that is, a variable assuming value one if the entity was present in the data for t - 1 and 0 otherwise, to our regression model and then ran a t-test on the lagged selection indicator.

The null hypothesis is that the reason for attrition is uncorrelated with the error term. We fail to reject the null hypothesis.

Table 13

T-test for Selection Bias

Book leverage	**Market leverage**
T-Distribution	**T-Distribution**
.41	**1.09**
P-value	**P-VALUE**
.524	**.297**

4.1.4 Test for Homoscedasticity

To test for homoscedastic residuals, a modified Wald test was used. We reject the null hypothesis of homoscedasticity. Therefore, the model is adjusted to include robust standard errors to account for the heteroscedastic residuals in accordance with the econometric theory presented in *3.6, Assumptions*.

Table 14

Modified Wald Test

Book leverage	**Market leverage**
χ**^2**	χ**^2**
5649	**4085**
P-value	**P-VALUE**
.00	**.00**

4.1.5 Test for Autocorrelation

We perform a Woolridge test for autocorrelation. We reject the null hypothesis of no autocorrelation. In order to address any inefficiencies caused by autocorrelation, theory suggests using clustered robust standard errors as discussed in section *3.6 Assumptions*. Accordingly, we will opt for the same method in our model.

Table 15

Wooldridge Test for Autocorrelation

Book leverage	**Market leverage**
F-distribution	**F-Distribution**
17.27	**23.24**
P-value	**P-VALUE**
.00	**.00**

4.1.6 Test for Normality

Lastly, we test for normality using the Shapiro-Wilk test. We reject the null hypothesis of normally distributed error terms. However, considering we have a sample size large enough to yield the violation of normality in the residuals less of an issue (Brooks, 2008).

Shapiro-Wilk Test

Book leverage	**Market leverage**
Z-Distribution	**Z-Distribution**
11.12	**10.62**

4.2 Regression Output

In Table 16, the output for the final regression model is presented. The model is described in eq 2 in *3.5 Regression Model* with clustered robust standard errors to handle autocorrelation and heteroscedasticity as discussed in sections *4.1.4 Test for Heteroscedasticity* and *4.1.5 Test for Autocorrelation.* The output for both of the regression models from STATA can be found in *Appendix XIIII*.

Table 16

Regression output

	BVLEV		MVLEV	
VARIABLE	**Coeff.**	**P-Value**	**Coeff.**	**P-value**
INNO	-.0155	.038	-.0126	.039
MrktD	-.0401	.282	-.0239	.440
INNO*MrktD	.0219	.019	.0156	.049
SIZE	.0143	.011	.0131	.008
AGE	.0004	.988	.0029	.899
TANG	.1637	.011	.1463	.007
PROF	-.0903	.002	-.0798	.001
GRTH	-.0062	.003	-.0069	.000
NDTS	-.0390	.736	-.0390	.701
	Model Specification			
Firms:	**423**		**423**	
Obs:	**2549**		**2549**	
Entity FE:	**Yes**		**Yes**	
Year FE:	**Yes**		**Yes**	
Clust. Rob. SE.	**Yes**		**Yes**	
Adjusted R^2:	**0.8126**		**0.8378**	

BLEV=Book value of leverage, MVLEV= Market value of leverage.

4.2.1 Interpreting the Coefficients

4.2.1.1 Logarithmic Transformation

Discussed in *3.4 Variable List* three variables have been transformed using the natural logarithm following previous literature and practices (Titman & Wessels, 1988; Rajan & Zingales, 1995; Frank & Goyal, 2003; Rajaiya, 2023). The variables in question are SIZE, AGE, and INNO, which all encompass the possibility of assuming a value of zero, reflecting their inherent nature and characteristics. As depicted in *3.4.3 Summary of Variable List* these are transformed using $ln(X + 1)$ in order to retain the data points with a value of zero since the natural logarithm of one is equal to zero, while the natural logarithm of zero is not mathematically defined.

Following Woolridge (2012), these variables will still be interpreted similarly to how a normal level-log regression coefficient is interpreted. Ergo, a 1% change in the independent variable leads to the following unit change in y, ceteris paribus: $\Delta y = \frac{\beta_x}{100} * \%\Delta x$.

4.2.1.2 Interaction Term

As described in *3.5 Regression Model*, an interaction term was included in order to capture the hypothesized differences innovation output has on the capital structure depending on whether a firm is listed on First North or OMXS. Firms listed at First North are denoted by the market dummy as zero, while firms listed at OMXS are denoted by one. To interpret and understand the results of the interaction term, as well as calculate the coefficient for innovation output, we apply eq 3.

Eq 3

$$\beta_{INNO,\,OMXS} = (\beta_1 + \beta_3 * 1)$$

$$\beta_{INNO,\,FN} = (\beta_1 + \beta_3 * 0) = \beta_1$$

Where β_1 *is the coefficient for INNO and* β_3 *is the coefficient for the interaction term INNO*MrktD*

Where β_1 is the coefficient for INNO and β_3 is the coefficient for the interaction term INNO*MrktD

The variable INNO represents the effect innovation output has on firms listed on First North which is mathematically described in the second part of eq 3. As noted, the effect is equal to the coefficient of INNO since the market dummy is equal to zero for these firms. This variable will henceforth be referred to as INNO FN. For firms listed on OMXS which are assigned the value of one by the market dummy, the slope is instead equivalent to the combined slope of INNO and the interaction term as illustrated by the first part in eq 3.

This variable will be referred to as INNO OMXS.

The market dummy coefficient is interpreted as a separate intercept for firms listed on OMXS (MrktD = 1). While the coefficient for this dummy variable explains differences in a firm's leverage ratio depending on which market it is listed on, it does not have to be considered while discussing the slope of innovation output for firms listed at OMXS. Furthermore, a statistically significant interaction term between a continuous and a dummy variable is not rendered statistically insignificant if one of the variables is insignificant in isolation.

When interpreting the significance level, the p-value reported for the interaction term can only conclude whether or not there is a statistically significant difference. In order to test the significance level of $\beta_{INNO,\,OMXS}$ the outcome probabilities are calculated. The respective coefficients and p-values are reported in Table 17.

4.2.1.3 Standardized coefficients

To enable a comparison of between our coefficients, the coefficients will be transformed so they are expressed as a change in standard deviations following Mitton (2022). This also allows for the possibility of comparing our findings with previous literature. The transformation is described in eq 4.

Eq 4

$$Std.Coeff_x = \beta_x * \left(\frac{Std.Dev_x}{Std.Dev_y}\right)$$

Transformation of coefficients. x=Independent variable X and y= BVLEV,MVLEV

That is, the coefficient for the independent variable X is multiplied with the remainder from dividing the standard deviation of the independent variable with that of the dependent variable.

4.3 Hypotheses Outcome

In Table 17, the statistics needed to answer our hypotheses described in *2.3 Hypothesis* is reported. The following section will answer the hypotheses based on the reported statistics. The results will be further analyzed in section *5.1, Innovation Output and its Effect on Capital Structure*. Eq 3 has been applied to calculate the coefficient for innovation output on OMXS.

Table 17

	BVLEV		MVLEV	
VARIABLE	**Coeff.**	**P-Value**	**Coeff.**	**P-value**
INNO FN	-.0155	.038	-.0126	.039
INNO OMXS	.0064	.294	.0030	.594
MrktD	-.0401	.282	-.0239	.440
INNO*MrktD	.0219	.019	.0156	.049

4.3.1 H1A: Innovation Output on First North

The null and alternative hypothesis for H1A is the following:

H0: Higher innovation output does not lead to lower leverage for firms listed on Nasdaq First North Growth Market

Ha: Higher innovation output leads to lower leverage for firms listed on Nasdaq First North Growth Market

The coefficients for innovation output have a statistical significance at the 5% level in both regressions as visible in Table 17. The coefficient is negative indicating a negative relationship between a firm's innovation output and their leverage for firm's listed on First North. Hence, we reject the null hypothesis at a 5% significance level and conclude that innovation output leads to lower leverage for firms listed on First North. Further analysis of the findings will be conducted in section *5.1.1 Innovation output on First North*.

4.3.2 H1B: Innovation Output on OMXS

The null and alternative hypothesis for H1B is the following:

H0: Higher innovation output does not lead to lower leverage for firms listed on Nasdaq Stockholm

Ha: Higher innovation output leads to lower leverage for firms listed on Nasdaq Stockholm

In order to test the hypothesis, eq 3 provided in section *4.2.1.2 Interaction Term* is applied, generating the following slopes for innovation output's effect on the leverage for firms listed on OMXS:

$$\beta_{(BV)INNO,\,OMXS} = (-\,0.0155\,+\,0.0219\,*\,1)\,=\,0.0064$$

$$\beta_{(MV)INNO,\,OMXS} = (-\,0.0126\,+\,0.0156\,*\,1)\,=\,0.0030$$

As illustrated in the above calculations, as well as in Table 17, the coefficient is positive. However, we can note that coefficients are not statistically significant after calculating the outcome probabilities. Therefore, H0 is not rejected at a 5% significance level and we can not conclude that innovation output affects leverage for firms listed on OMXS. The implications of the results are further discussed in section *5.1.2 Innovation Output on OMXS, and the Differences Compared to First North*.

4.3.3 H1C: Difference in the Effect of Innovation Output on First North and OMXS

The null and alternative hypothesis for H1C is the following:

H0: The negative effect of innovation output on the leverage of a firm listed on Nasdaq First North Growth Market is not greater than on Nasdaq Stockholm

Ha: The negative effect of innovation output on the leverage of a firm is greater on Nasdaq First North Growth Market than on Nasdaq Stockholm

The interaction term has a positive coefficient and is statistically significant at a 5% significance level, in both models displayed in Table 17. It should be noted that the interaction term is weakly significant with a p-value of 4.9% in the model with the dependent variable market value of leverage. The statistically significant positive coefficient leads to a rejection of the null hypothesis, and there is an observable difference in the negative effect of innovation output on the leverage ratio comparing the two markets.

5. Analysis

In the following chapter, the results of our hypotheses and regression results for our control variables are analyzed and explained using our theoretical framework. The chapter ends with a summary of our estimated coefficients in the two regression models along with a discussion of economic significance and comparison of coefficients to previous empirical studies.

For a reference on how to interpret log-transformed variables and interaction terms, *a description is given in 4.2.1 Interpreting the Coefficients.*

5.1. Innovation Output and its Effect on Capital Structure

5.1.1 Innovation Output on First North

The null hypothesis was rejected, indicating that innovation has a statistically significant negative effect on the leverage ratio of firms listed on First North. This result is consistent with the pecking order theory's prediction, and a possible theoretical explanation is that innovation output leads to lower information asymmetry. Considering that equity is the most information sensitive source of funding (Myers and Majluf, 1984), a relative decrease in information asymmetry would lead to firms being more prone to issue equity rather than debt.

From a trade-off perspective, the theory instead has conflicted predictions. On the one hand, firms being successful in their innovation could reduce their probability of default and thus also the expected costs of financial distress (Rajaiya, 2023), which would entail a positive relationship between innovation output and leverage. On the other hand, from an agency cost of debt perspective, the theory could predict conflicting results as firms more successful in their innovation have more growth opportunities (Gunday et al., 2011) which could lead to creditors expecting the firm to be riskier and accordingly assign a higher cost of debt. Additionally, firms with abundant growth opportunities would want to avoid underinvestment issues (Myers, 1984). Hence, the trade-off theory could be argued to simultaneously predict a negative relationship. Given the statistically significant negative coefficients for INNO, the agency costs of debt are assumed to be the more prevalent factor for why innovation output influences a firm's leverage.

Our results have support from both the pecking order and trade-off theory and previous literature (Bartoloni, 2013; Rajaiya, 2023). Worth considering is that O'brien (2003) finds empirical evidence that pursuing a strategy of being an industry innovator leads to lower leverage ratios. He concludes that innovative firms need to keep a comfortable level of financial slack to enable this strategy. This alternative channel will be further discussed in *6.2 Discussion.*

Table 18

Variable	Coeff.	P-value	Trade-Off	Pecking Order	Previous Research	Mean	Std.Dev	Std. Coeff.
INNO FN (BV)	-.0155	0.038	+/-	-	-	.3805	.8478	-.0531
INNO FN (MV)	-.0126	0.039	+/-	-	-	.3805	.8478	-.0571

Output of the variable INNO FN on BVLEV, MVLEV

To discuss the variables in terms of economic significance, all variables are transformed per section *4.2.1.3 Standardized Coefficient,* and presented with their respective descriptive statistics. Innovation output is one of the variables that is logarithmized, which leads to the interpretation that a 1% increase in the innovation output for a firm leads to a 0.000155 unit decrease in the book leverage of a firm. Similarly, while regressing on the market leverage, a 1% increase is instead related with a 0.000126 decrease in the market leverage of a firm. For a reference on the coefficients, see Table 18.

In terms of standard deviations, innovation output is transformed using eq 4, similar to the rest of the determinants, with the only difference being that the standard deviation is used from their respective market for the book leverage, market leverage, and innovation output to get the accurate number for the sample following Mitton (2022). A one standard deviation change in INNO leads to approximately a -0.0531 change in the standard deviation of book leverage, while the change is -0.0571 for the market leverage. In *5.3 Summary of Determinants,* this will be compared to our other determinants. Nonetheless, Rajaiya (2023) reported a similar standardized coefficient, albeit a somewhat lower change of -0.036 standard deviations in the book value of leverage.

5.1.2 Innovation Output on OMXS, and the Differences Compared to First North

As displayed in section *4.3 Hypotheses Outcome*, we can not reject the null hypothesis for H1B at a 5% significance level, indicating that innovation output does not have a significant effect on the leverage ratio of firms listed on OMXS. However, the null hypothesis for H1C was rejected with a 5% significance, implying an observable difference in the negative effect of innovation output on the leverage of firms listed on their respective stock exchanges.

The rejection of the null of H1C could imply that innovation output has a larger impact on a firm's leverage ratio if they face relatively more information asymmetry in the equity market. Firms listed at OMXS are expected to face less information asymmetry due to the market characteristics and more extensive disclosure requirements. Botosan (2006) supports this and provides evidence that firm disclosure is negatively correlated with information asymmetry.

Thus, it could be argued that the effect of innovation output is less prevalent for firms listed on OMXS due to the marginal benefit of a reduction in the information asymmetry following a successful innovation is of less value to these firms.

Table 19

Variable	Coeff.	P-value	Trade-Off	Pecking Order	Previous Research	Mean	Std.Dev	Std. Coeff.
INNO OMXS (BV)	.0064	.294	+/-	-	-	.6235	1.488	.0485
INNO OMXS (MV)	.0030	.594	+/-	-	-	.6235	1.488	.0235
INNO*MrktD (BV)	.0219	.019	N/A	N/A	N/A	N/A	N/A	N/A
INNO*MrktD (MV)	.0156	.049	N/A	N/A	N/A	N/A	N/A	N/A

Output of the interaction term and the variable INNO OMXS on BVLEV, MVLEV

While it is not possible to make any conclusions regarding the effect of innovation output on OMXS due to the non-significance illustrated in Table 19, it is still worth analyzing the outcome of the regression. Innovation output is hypothesized to have a channeling effect on a firm's leverage through a reduction in the information asymmetry a firm faces in the equity market. In conjunction with the previously discussed differences in information asymmetry between the two markets, one potential explanation for why the coefficient is insignificant is the reduction in information asymmetry having less of an effect for firms listed on OMXS compared to First North.

Bartoloni (2013) found similar results, only establishing a significance on estimates for smaller firms while splitting her sample based on the size of a firm. Bartoloni explains her findings by arguing that smaller innovative firms are more likely to depend on internal funds rather than issuing debt. However, Rajaiya (2023) proves through an instrumental variable analysis that innovation output has a channeling impact on capital structure decisions through information asymmetry. Hence, there is reason to believe that if the relative information asymmetry is lower for firms listed at OMXS, one could assume that the effect of innovation output will also be diminished, yielding insignificant estimates.

5.1.3 Market Dummy

Table 20

Variable	Coeff.	P-value	Trade-Off	Pecking Order	Previous Research	Mean	Std.Dev	Std. Coeff.
MrktD (BV)	-.0401	0.282	N/A	N/A	N/A	N/A	N/A	N/A
MrktD (MV)	-.0239	0.440	N/A	N/A	N/A	N/A	N/A	N/A

Output of the variable MrktD on BVLEV, MVLEV

As displayed in Table 20, the market dummy is not statistically significant at a 5% level for both of our dependent variables. The dummy variable should be interpreted as a specific intercept for firms listed on OMXS (Dummy=1). As hypothesized, this coefficient should be negative and statistically significant since firms listed on First North are expected to face a higher degree of information asymmetry. Unfortunately, to our knowledge, there is no previous research that has studied the difference in capital structure between firms listed on First North and OMXS. Hence, we do not have a study we can put our results in comparison with.

Furthermore, looking at the descriptive statistics for each of the markets provided in Table 7, the mean for the book as well as the market leverage, is higher for firms listed at OMXS. Nevertheless, it is worth noting that it does not justify the conclusion that our expected difference in information asymmetry between the markets is wrong. It could be an array of feasible factors, including that firms are larger, more tangible, or have fewer growth opportunities on OMXS, that leads to the average leverage ratio being higher in our sample.

5.2 Empirical Determinants of Capital Structure

5.2.1 Size

As illustrated in Table 21, size has a statistically positive coefficient at a 5% significance level. Thus we conclude that firm size increases the leverage of a firm. The relationship is true when size is regressed on both the book and market leverage as it yields similar results. The relationship is consistent with the trade-off theory, and it is concluded that firm size increases the leverage due to larger firms having lower probabilities of default and lower debt-related agency costs (Rajan & Zingales, 1995; Frank & Goyal, 2009).

Contrariwise, the pecking order theory predicted a negative relationship due to the expected lower degree of information asymmetry larger firms face in the equity market and lower transaction costs (Titman & Wessels; Frank & Goyal, 2009). Our results prove this theory wrong, or at least the effect is less prevalent than what the trade-off theory states. Our results are similar to previous empirical findings, which have repeatedly proven size to have a significant positive coefficient for a firm's leverage (Harris & Raviv, 1991; Frank & Goyal, 2009).

Table 21

Variable	Coeff.	P-value	Trade-Off	Pecking Order	Previous Research	Mean	Std.Dev	Std. Coeff.
SIZE (BV)	.0143	.011	+	-	+	19.29	4.072	.2529
SIZE (MV)	.0131	.008	+	-	+	19.29	4.072	.2437

Output of the variable SIZE on BVLEV and MVLEV

Moreover, it is relevant to discuss the economic significance of the coefficient in our model. SIZE is proxied by the natural logarithm of sales, thus the coefficient is interpreted as 1% increase in sales leads to a 0.000143 unit increase in the book leverage, and a 0.000131 unit increase in the market leverage of a firm.

Displayed in Table 21 is the post-transformation of SIZE in terms of standard deviations to discuss its economic significance as discussed in section *4.2.1.3 Standardized Coefficients*. The post-transformation effect, interpreted as a change of one standard deviation of SIZE, is associated with a change of 0.2529 standard deviations in the book leverage or 0.2437 standard deviations in the market leverage. Comparably, Rajan and Zingales (1995) found Size to have a similar effect of 0.23 standard deviations in their research on firms in the U.S. market.

5.2.2 Age

Table 22 displays that the coefficient for age is insignificant in both our regressions. The earlier empirical research on age as a determinant is more limited than other independent variables in our models. However, Chen & Strange (2005) and Rajaiya (2023) found significant results. Upon examining the descriptive statistics presented in Table 7, it is apparent that the values exhibit neither skewness nor errors. The mean value appears rational, while the minimum and maximum values align with expectations. We can not explain the insignificance by looking at the descriptive statistics. Our proxy for age differed from Chen and Strange (2005) and Rajaiya (2023), which also could have led to our insignificant results. Because of the insignificance, no further analysis will be conducted on AGE.

Table 22

Variable	Coeff.	P-value	Trade-Off	Pecking Order	Previous Research	Mean	Std.Dev	Std. Coeff.
AGE (BV)	.0004	0.988	+	-	+/-	2.959	.9160	N/A
AGE (MV)	.0029	0.899	+	-	+/-	2.959	.9160	N/A

Output of the variable AGE on BVLEV, MVLEV.
N/A due to no significance

5.2.3 Tangibility

This study found significant positive coefficients for tangibility while regressing on both the book value and market value of leverage. Moreover, the two models yielded congruous results, as shown in Table 23. The trade-off theory predicts a similar relationship, and the sign of the coefficient can be explained by the fact that tangible assets reduce the possibility of agency conflicts relating to risk-shifting and can be used as collateral for debt (Frank & Goyal, 2008).

An inverse relationship would instead render the pecking order theory prediction accurate. Ergo, tangible assets reduce the information asymmetry and therefore alter a firm's inclination to issue equity, due to the lower cost in the equity market. However, our results, as previous empirical evidence suggests (see Harris & Raviv, 1991), finds that the trade-off theory better explains how and why a firm's tangibility affects its leverage ratio.

Table 23

Variable	Coeff.	P-value	Trade-Off	Pecking Order	Previous Research	Mean	Std.Dev	Std. Coeff.
TANG (BV)	.1637	.011	+	-	+	.1650	.2526	.1795
TANG (MV)	.1463	.007	+	-	+	.1650	.2526	.1684

Output of the variable TANG on BVLEV and MVLEV

As illustrated in Table 23, a 1 % (or a 0.01 unit increase) increase in a firm's tangible assets leads to a 0.001637 unit increase in the book leverage of a firm and a 0.001463 unit increase in the market leverage of a firm. Once more, we transform the coefficient to discuss its economic significance. We can note that a change in the standard deviation of TANG leads to a 0.1795 and 0.1684 change in the standard deviation of the book respectively market leverage. Our results are somewhat similar to previous empirical findings, albeit being of less economic significance compared to Rajan and Zingales (1995), who found a relative change of 0.23 standard deviations.

5.2.4 Profitability

Profitability proved highly significant, estimating negative coefficients in both our regressions, as shown in Table 24. The pecking order suggests that profitability has a negative relationship with leverage since more profitable firms should have more retained earnings, and based on the pecking order of financing, internal funding should be more prevalent than external funding (Titman & Wessels, 1988).

From a trade-off theory perspective, a positive coefficient would be explained by high debt levels to offset the high tax levels (Frank & Goyal, 2003). The empirical evidence is in accordance with the pecking order and our findings (Harris & Raviv, 1991).

Table 24

Variable	Coeff.	P-value	Trade-Off	Pecking Order	Previous Research	Mean	Std.Dev	Std. Coeff.
PROF (BV)	-.0903	0.002	+	-	-	-.0596	.3004	-.1177
PROF (MV)	-.0798	0.001	+	-	-	-.0596	.3004	-.1093

Output of the variable PROF on BVLEV and MVLEV

Based on the coefficient in Table 24, a 1% increase in a firm's profitability (or a 0.01 unit increase) leads to a corresponding 0,000903 unit decrease in its leverage. To delve deeper into its economic implications, we analyze the coefficient transformation. After the transformation to standardized coefficients, we can note that a change in PROF's standard deviation leads to a change of -0.1177 in the standard deviation of book leverage and a -0.1093 change in the standard deviation of market leverage. These results are almost identical to Rajan and Zingales (1995), which showed a change of -0.11 standard deviations.

5.2.5 Growth

A statistically significant negative relationship between growth and leverage can be noted in Table 25. The negative relationship is in line with the trade-off theory's prediction. Firms with relatively more growth opportunities have lower free cash flow, making the use of debt's disciplinary effect less valuable (Kayo & Kimura, 2011). This supports the idea that as growth opportunities increase, reliance on debt financing decreases, resulting in a negative coefficient. It reflects the trade-off between growth and debt usage, where more growth opportunities correspond to reduced leverage (Fama & French, 2002).

The pecking order is contradictory once again and instead suggests a positive relationship between the variables since managers in need of capital prioritize debt over equity when the firm lacks sufficient retained earnings. Previous research by Rajan & Zingales (1995), Fama & French (2002), Frank & Goyal (2009), and Kayo & Kimura (2011) all culminate in the same conclusion that growth has a negative relationship with leverage.

Table 25

Variable	Coeff.	P-value	Trade-Off	Pecking Order	Previous Research	Mean	Std.Dev	Std. Coeff.
GRTH (BV)	-.0062	.003	-	+	-	2.2563	2.9262	-.0787
GRTH (MV)	-.0069	.000	-	+	-	2.2563	2.9262	-.0920

Output of the variable GRTH on on BVLEV and MVLEV

From Table 25, we can read that the coefficients for growth opportunities are -0.0062 and -0.069. This means that if a firm has a 0.1 higher market-to-book ratio, their book and market value of leverage is estimated to be 0.000062 and 0.000069 units lower.

The standardized coefficient for GRTH reads that a change of one standard deviation in the variable has the effect of -0.0787 on the standard deviation of book leverage and -0.0920 change of market leverage. The results can be compared to Rajan and Zingales (1995), who showed a much larger value of -0.37 standard deviations. The difference could be explained by a higher standard deviation in the market-to-book ratio in the sample for U.S. firms used by Rajan and Zingales (1995).

5.2.6 Non-debt Tax Shields

From Table 26, we can note that NDTS does not have a statistically significant coefficient in our models. Previous research has found NDTS to be significant (DeAngelo & Masulis, 1980; Fama & French, 2002), while Titman & Wessels (1988) had similar insignificant results to us. The difference in our results may partly be due to our proxy, depreciation over total assets. For example, Fama & French (2002) found significant results using R&D expenditures over total assets to proxy for NDTS, which might have been a better measurement. However, sufficient data points for R&D expenditure were not available for our sample.

Moreover, judging from our descriptive statistics, we can note that the variable can be considered relatively skewed, with the median being as low as 0.00018, indicating that the sample most likely includes several zeros or arbitrarily small values. Hence, the proxy might not measure the expected effect of NDTS on the dependent variable correctly. Nonetheless, all our coefficient estimates are insignificant, rendering any conclusions or further analysis on the determinant based on our results redundant.

Table 26

Variable	Coeff.	P-value	Trade-Off	Pecking Order	Previous Research	Mean	Std.Dev	Std. Coeff.
NDTS (BV)	-.039	.736	-	N/A	-	.0244	.0525	N/A
NDTS (MV)	-.039	.701	-	N/A	-	.0244	.0525	N/A

Output of the variable NDTS on BVLEV and MVLEV
N/A due to no prediction or no significance

5.3 Summary of Determinants

In Table 27, a summary of the coefficients, significance level, standardized coefficient, and correct theory prediction is presented. Comparing the determinants in terms of the difference in economic significance, we can note that the lowest standardized coefficient for a statistically significant variable is for innovation output for firms listed on First North. A one standard deviation change in innovation output leads to a -0.0531 change in the standard deviation of book leverage, and -0.0571 change of the market leverage. Comparably, size had the largest standardized coefficients of 0.2529 and 0.2437. The difference is quite distinguishable, where the effect of size is almost five times larger than that of innovation output on the standard deviation of leverage.

However, Rajaiya (2023) implies that his results are of economic significance and reported a -0.036 standardized coefficient for his proxy for innovation output. Thus, with support from previous literature, we can conclude that innovation output for firms listed on First North is statistically and economically significant. Considering that innovation output has the lowest standardized coefficient, in conjunction with the broad similarities with Rajan and Zingales (1995) in a majority of the standardized coefficients of our variables, we imply that these are of economic significance as well.

Moreover, de Jong et al. (2008) found in their study that Swedish firms have somewhat similar coefficient estimates as our results. Hence our model estimations could be considered to be reasonable. De Jong et al. (2008) had a sample of 206 firms and researched a total of four years. Hence the smaller differences in the estimates can be explained by differences in sample size and time period compared to our study.

Lastly, as illustrated in Table 27, our results indicate that the trade-off theory better explains more of the determinants compared to the pecking order theory.

Table 27

Variable	COEFF.	STD. COEFF.	Correct Theory Prediction
INNO FN (BV)	-.0155*	-.0531	Pecking Order and Trade-off Theory
INNO FN (MV)	-.0126*	-.0571	Pecking Order and Trade-off Theory
INNO OMXS (BV)	.0064	.0485	N/A
INNO OMXS (MV)	.0030	.0235	N/A
SIZE (BV)	.0143*	.2529	Trade-off Theory
SIZE (MV)	.0131**	.2437	Trade-off Theory
AGE (BV)	.0004	N/A	N/A
AGE (MV)	.0029	N/A	N/A
TANG (BV)	.1637*	.1795	Trade-off Theory
TANG(MV)	.1463**	.1684	Trade-off Theory

PROF (BV)	-.0903**	-.1177	Pecking Order
PROF (MV)	-.0798***	-.1093	Pecking Order
GRTH (BV)	-.0062**	-.0787	Trade-off Theory
GRTH(MV)	-.0069***	-.0920	Trade-off Theory
NDTS (BV)	-.0390	N/A	N/A
NDTS (MV)	-.0390	N/A	N/A

A summary of our independent variables, including economic significance and correct theory prediction.
** 5% Significance level*
*** 1% Significance level*
**** 0.1% Significance level*
N/A due to no significance

6. Concluding Remarks

We conclude this thesis by connecting our findings with the purpose of the study and explaining the contribution of the thesis. Then we critically discuss our conclusion and the research that has been conducted. Finally, we reason about potential research questions for further investigation based on our results.

6.1 Conclusion

The purpose of this study was to determine if innovation output influences the capital structure of Swedish listed companies and to understand if the effect is different on OMXS and First North. We found that for firms listed on First North, there is in fact a significant effect of innovation output on leverage, while we found that there is no such significant effect on firms listed on OMXS. Furthermore, we found that there is a significant difference in the effect between firms listed on OMXS and First North.

Our results have contributed to a greater understanding of how innovation output can influence capital structure decisions in general and how they differ between OMXS and First North in particular. Our results indicate that it can be meaningful to distinguish between regulated and unregulated markets in future capital structure research and that we might be able to explain differences between them with information asymmetry.

6.2 Discussion

Our results are congruent with the pecking order theory, which suggests that firms that reduce their information asymmetry are more inclined to issue equity. One explanation is that innovation output, proxied by patents granted, serves as a channel for reducing information asymmetry. This effect may be explained by innovation output's contribution to increased transparency between the firm and the equity market, leading to a greater inclination for equity issuance.

However, due to insufficient data points for analyst following and forecast dispersion, we could not proxy for information asymmetry. Rajaiya (2023) manages to prove that the channel through which innovation output impacts the capital structure is through a reduction in the information asymmetry using the previously mentioned proxies. Since we were not able to test the direct relationship between innovation output and information asymmetry, we cannot be certain of the channel in which innovation output impacts the capital structure

One alternative explanation could be the trade-off theory prediction, that more innovative firms face higher costs of debt due to agency problems, and therefore are less leveraged. An additional explanation, unrelated to information asymmetry, is proposed by O'Brien (2003). According to O'brien, firms that prioritize innovation as a competitive strategy require a certain level of financial slack, leading to a reduced inclination to leverage. Since we were not able to control for the above channels, our conclusion could be subject to scrutiny.

Yet, our hypothesis that the effect of innovation output is more prevalent on First North than on OMXS was proved correct. Hence, it can be argued that the effect of innovation output is greater in the presence of a relatively higher degree of information asymmetry. These results point that it could be through the channel of information asymmetry that innovation output has an effect, rather than the alternative channels discussed. However, as mentioned before we are not able to proxy directly for information asymmetry, and thus we cannot control for differences in information asymmetry between the market therefore it is possible that other differences between the markets constitute the reason for this difference.

The lack of significance of the control variables for NDTS and age in our regressions raises concerns about the constraints of validity and sufficiency of the chosen proxies. These proxies' explanatory power for the dependent variable may have been constrained by their inability to accurately reflect the underlying effects of NDTS and age.

In our findings, innovation output is not statistically significant for firms listed on OMXS, where one of the explanations could be of similar nature to why NDTS and age did not prove to be significant. Patents granted may have been an insufficient proxy to grasp the effects of innovation output, and the use of for example patent citations following Hall et al. (2005) or the stock of patents following Rajaiya (2023) might have yielded better results. Another possible reason for the insignificant results on OMXS is based on Woolridge (2012), who argues that proxying for variables used $ln(X + 1)$ to retain data points where X is zero could lead to skewness of results. This may in particular prove to be an issue if the variable has a substantial amount of zeros which is the case in our sample judging from the descriptive statistics for innovation output. Although these are feasible reasons for why the effect of innovation output on OMXS may be insignificant, our conclusion that the effect of innovation output on the information asymmetry is diminished in these firms should not be overlooked.

Finally, the absence of instrumental variables discussed in section *3.7 Discussion of Methodology,* is a weakness in our research as it limits our ability to control for and handle endogeneity.Additional variables to measure for information asymmetry and instrumental variables could have helped us tackle the questions of the true channel through which innovation affects capital structure.

6.3 Suggestions for Further Research

As discussed in Chapter 1, innovation output's influence on capital structure is a nascent field, and thus there is a wide range of interesting questions for future research based on our study.

One interesting suggestion for future research is one that allows for a clearer understanding of whether information asymmetry really is the channel through which innovation output affects capital structure. This could be done by including established proxies for information asymmetries as a variable which could be used in an interaction term with innovation output the way we used the market dummy, or by including instrumental variables. In general, a similar study to ours with the inclusion of instrumental variables or additional control variables might be able to contribute to further understanding of and insights into our research question by better establishing causality.

It would also be interesting to test whether the relationship between innovation output and capital structure varies between industries since this is typically an impactful factor in capital structure decisions. Future research could for example test if there is a difference between industries that are characterized by high and low levels of innovation to investigate whether this plays a role in explaining the relationship. Testing for explicit differences between small and large firms is a similar suggestion that might produce interesting results.

An intriguing avenue in regard to our comparisons of firms on OMXS and First North would be to explore how firms listed on unregulated and regulated markets differ in their capital structure in general and delve into understanding the factors that contribute to these differences. This investigation could shed more light on the impact of market regulation on a company's financial decisions.

Finally, conducting similar research with different limitations might generate further insights and understanding. Most prominent is a study that would test our results on different countries, or one that would compare the relationship between innovation output and capital structure depending on the country.

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Appendix

Appendix I, Reshaping the data

```
#Appendix A

import pandas as pd

# Read in the patent data frames
Patent1 = pd.read_excel("/content/drive/MyDrive/Uppsats/First patent set online.xlsx")
Patent2 = pd.read_excel("/content/drive/MyDrive/Uppsats/Second patent set online.xlsx")
Patent3 = pd.read_excel("/content/drive/MyDrive/Uppsats/Third patent set online.xlsx")
Patent4 = pd.read_excel("/content/drive/MyDrive/Uppsats/Fourth patent set online.xlsx")

# merge files vertically while avoiding duplicate Application values
Patent_all = pd.concat([Patent1, Patent2, Patent3, Patent4]).drop_duplicates(subset=["Application"],
keep="last")

Patent_all.to_excel('/content/drive/MyDrive/Uppsats /Patents.xlsx', index=False)

# Read in the FinBasSSE and FinBasSSEFN data frames
FinBasSSE = pd.read_excel("/content/drive/MyDrive/Uppsats/FinBasSSE.xlsx")
FinBasSSEFN = pd.read_excel("/content/drive/MyDrive/Uppsats/FinBasSSEFN.xlsx")

# Create a new data frame for merged data
Merged_data = pd.DataFrame(columns=['ISIN', 'Year', 'Market_value', 'Market',])

# Merge all rows from FinBasSSE
Merged_data = Merged_data.append(FinBasSSE)

# Merge all rows from FinBasSSEFN
Merged_data = Merged_data.append(FinBasSSEFN)

# Drop duplicate rows based on the 'Org_nr' and 'Year' columns
Merged_data = Merged_data.drop_duplicates(subset=['ISIN', 'Year'])

# Write the merged data to a new excel file
Merged_data.to_excel('/content/drive/MyDrive/Uppsats/FinBas.xlsx', index=False)

# Load the Excel file
file_path = "/content/drive/MyDrive/Uppsats /Retriever_business.xlsx"
excel_file = pd.ExcelFile(file_path)

# Create an empty dataframe to store the combined data
combined_data = pd.DataFrame()

# Loop through each sheet in the Excel file
for sheet_name in excel_file.sheet_names:
 # Load the sheet into a dataframe
 sheet_data = pd.read_excel(file_path, sheet_name=sheet_name)
  # Add a new column with the year from the sheet name
 sheet_data["Year"] = sheet_name
  # Append the sheet data to the combined data
 combined_data = combined_data.append(sheet_data)

# Save the combined data to a new sheet in the Excel file
with pd.ExcelWriter(file_path) as writer:
 combined_data.to_excel(writer, sheet_name="Combined Data", index=False)
```

Appendix II, Counting Patents Granted per Firm per Year

```
#Appendix B

import pandas as pd

# Load Patents.xlsx
Patents = pd.read_excel("/content/drive/MyDrive/Uppsats /Patents.xlsx")

# group by Org_nr and Year and get the count of applications
count_df = Patents.groupby(['Org_nr', 'Year']).size().reset_index(name='Count')

# select columns Org_nr, Year, Count and save to a new file
count_df[['Org_nr', 'Year', 'Count']]

# Save the DataFrame to a new file called Merged_count_patent.xlsx
count_df.to_excel('/content/drive/MyDrive/Uppsats /Patents.xlsx', index=False)
```

Appendix III, Data Cleaning and Formatting

```
#Appendix C

import pandas as pd
Patent = pd.read_excel("/content/drive/MyDrive/Uppsats /Patents.xlsx")
FinBas = pd.read_excel("/content/drive/MyDrive/Uppsats/FinBas.xlsx")
Retriever_business = pd.read_excel("/content/drive/MyDrive/Uppsats /Retriever_business.xlsx")

# keep only Org_nr that starts with 55
Patent = Patent[Patent['Org_nr'].astype(str).str.startswith('55')]
FinBas = FinBas[FinBas['Org_nr'].astype(str).str.startswith('55')]
Retriever_business = Retriever_business[Retriever_business['Org_nr'].astype(str).str.startswith('55')]

# keep only Year between 2010 and 2019
Patent = Patent[(Patent['Year'] >= 2010) & (Patent['Year'] <= 2020)]
FinBas = FinBas[(FinBas['Year'] >= 2010) & (FinBas['Year'] <= 2020)]
Retriever_business = Retriever_business[(Retriever_business['Year'] >= 2010) & (Retriever_business['Year'] <=
2020)]

# Read the Patent file
Patent = pd.read_excel("/content/drive/MyDrive/Uppsats /Patents.xlsx")

# Replace "," with "."
Patent.replace(",", ".", regex=True, inplace=True)

# Replace "-" and "N/A" with ""
Patent.replace(["-", "N/A"], "", inplace=True)

# Multiply values in columns with "(tkr)" in column name by 1000
Patent.loc[:, Patent.columns.str.contains("\(tkr\)")] *= 1000

Patent.to_excel("/content/drive/MyDrive/Uppsats /Patent.xlsx")

# Read the FinBas file
FinBas = pd.read_excel("/content/drive/MyDrive/Uppsats/FinBas.xlsx")

# Replace "," with "."
FinBas.replace(",", ".", regex=True, inplace=True)

# Replace "-" and "N/A" with ""
FinBas.replace(["-", "N/A"], "", inplace=True)

# Multiply values in columns with "(tkr)" in column name by 1000
FinBas.loc[:, FinBas.columns.str.contains("\(tkr\)")] *= 1000

FinBas.to_excel("/content/drive/MyDrive/Uppsats /FinBas.xlsx")


# Read the Retriever_business file
Retriever_business = pd.read_excel("/content/drive/MyDrive/Uppsats /Retriever_business.xlsx")

# Replace "," with "."
Retriever_business.replace(",", ".", regex=True, inplace=True)

# Replace "-" and "N/A" with ""
Retriever_business.replace(["-", "N/A"], "", inplace=True)

# Multiply values in columns with "(tkr)" in column name by 1000
Retriever_business.loc[:, Retriever_business.columns.str.contains("\(tkr\)")] *= 1000

Retriever_business.to_excel("/content/drive/MyDrive/Uppsats /Retriever_business.xlsx")
```

Appendix IV, Integrating the Data

```
#Appendix D

import pandas as pd

# Read the Excel files
Patent = pd.read_excel("/content/drive/MyDrive/Uppsats /Patents.xlsx")
FinBas = pd.read_excel("/content/drive/MyDrive/Uppsats/FinBas.xlsx")
Retriever_business = pd.read_excel("/content/drive/MyDrive/Uppsats /Retriever_business.xlsx")

# Merge Patent and FinBas on ISIN and Year
merged_data = pd.merge(Patent, FinBas, on=["ISIN", "Year"], how="inner")

# Merge Retriever_business to the merged file on Org_nr and Year
merged_data = pd.merge(merged_data, Retriever_business, on=["Org_nr", "Year"], how="inner")

# Drop duplicate columns for Org_nr, Year, and ISIN
merged_data = merged_data.loc[:, ~merged_data.columns.duplicated()]

# Save the merged data
print(merged_data)
merged_data.to_excel("/content/drive/MyDrive/Uppsats/Final_data.xlsx")
merged_data.to_stata('/content/drive/MyDrive/Uppsats/Final_data.dta', write_index=False)
```

Appendix V, Gauss-Markov Theorem in Relation to Fixed Effects Assumptions

Identifier	**Assumption**	**OLS**	**FE**
OLS 1 / FE 1	Linearity	The dependent variable y is related to the explanatory variable x and the error term u in the form: y = B0 + B1x + u, Where B0 is the intercept parameters to estimate and B1 is the slope parameters to estimate	The dependent variable y is related to the explanatory variable x, the unobserved effect a, and the error term u in the form: $y_{it} = \beta_1 x_{it1} + \ldots + \beta_k x_{itk} + a_i + u_{it}, t = 1, \ldots, T,$ Where Bj are the parameters to estimate
OLS 2 / FE 2	Random Sampling of Observations	The sample is random.	Same as OLS
OLS 3 / FE 3	No Multicollinearity	There is variation over time in each explanatory variable (for at least some observations), and there are no perfect linear relationships among the explanatory variables.	Same as OLS
OLS 4 / FE 4	Exogeneity	The error u has an expected value of zero given any value of the explanatory variable: E(u|X)=0	For each t, the error u has an expected value of zero given the explanatory variables in all time periods and the unobserved effect: E(uit|Xi, ai)=0
OLS 5 / FE 5	Homoscedasticity	The error terms ui should all have the same variance: Var(ui|X) = σ^2	The error terms ui should all have the same variance: Var(uit|Xi, ai) = σ^2
OLS 6 / FE 6	Autocorrelation	The error terms are uncorrelated, conditional on all explanatory variables: Cov(uiuj|X) = 0	The error terms are uncorrelated, conditional on all explanatory variables and the unobserved effect: Cov(uiuj|Xi, ai) = 0
OLS 7 / FE 7	Normality	Conditional on Xi and, the uit are independent and identically distributed as Normal	Conditional on Xi and ai, the uit are independent and identically distributed as Normal

OLS and FE assumptions (Wooldridge, 2012).

The Assumption of Linearity	While both OLS and FE assume a linear relationship, the FE assumption includes the unobserved effect on top of the explanatory variables and the error terms.
The Assumption of Exogeneity	Both the OLS and FE assume that the term has an expected value of zero, the difference lies in the fact that the latter assumes this is only the case when accounting for the unobserved effect
The Assumption of Homoscedasticity	The OLS and FE assume the error term should have the same variance, once again the difference is the FE assumes this is only the case when accounting for unobserved effects.

The Assumption of No Autocorrelation	While both estimators assume that the error terms are uncorrelated, the OLS conditions this only on the explanatory variables, while fixed effects conditions it on the unobserved effect as well
The Assumption of Normality	Once again the assumption is the same, except that for OLS it is only conditional on the explanatory variables and for FE it is also conditional on the unobserved effect
Summary	As outlined in chapter 3.5 *Regression Model* the assumptions are very similar. What sets them apart if the presence and inclusion of unobserved effects, where fixed effects becmoes the Best linear unbiased estimator.

The differences of the Assumptions (Wooldridge, 2012).

Appendix VI, Hausman test

Book value of Leverage:

```
                             b = Consistent under H0 and Ha; obtained from xtreg.
              B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =  96.65
Prob > chi2 = 0.0000
```

Market value of Leverage

```
                             b = Consistent under H0 and Ha; obtained from xtreg.
              B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            = 137.35
Prob > chi2 = 0.0000
```

Appendix VII, Joint F-distribution

Book Value of Leverage

```
. testparm i.Year

 ( 1)  2012.Year = 0
 ( 2)  2013.Year = 0
 ( 3)  2014.Year = 0
 ( 4)  2015.Year = 0
 ( 5)  2016.Year = 0
 ( 6)  2017.Year = 0
 ( 7)  2018.Year = 0
 ( 8)  2019.Year = 0

       F(  8,  2103) =    0.91
            Prob > F =    0.5039

.
```

Market Value of Leverage

```
. testparm i.Year

 ( 1)  2012.Year = 0
 ( 2)  2013.Year = 0
 ( 3)  2014.Year = 0
 ( 4)  2015.Year = 0
 ( 5)  2016.Year = 0
 ( 6)  2017.Year = 0
 ( 7)  2018.Year = 0
 ( 8)  2019.Year = 0

       F(  8,  2103) =    1.43
            Prob > F =    0.1776

.
```

Appendix VIII, Nijman Verbeek Test

Book Value of Leverage

```
. test L.selection

 ( 1)  L.selection = 0

       F(  1,   428) =    0.41
            Prob > F =    0.5240
```

Market Value of Leverage

```
. test L.selection

 ( 1)  L.selection = 0

       F(  1,   428) =    1.09
            Prob > F =    0.2970
```

Appendix VIIII, Link test

Book Value of Leverage

```
. test sq_fitted = 0

 ( 1)  sq_fitted = 0

       F(  1,   428) =    0.71
            Prob > F =    0.4004
```

Market Value of Leverage

```
. test sq_fitted = 0

 ( 1)  sq_fitted = 0

       F(  1,   428) =    0.01
            Prob > F =    0.9280
```

Appendix X, Modified Wald test

Book Value of Leverage

```
. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (465)  =   5649.39
Prob>chi2 =      0.0000
```

Market Value of Leverage

```
. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (465)  =   4085.21
Prob>chi2 =      0.0000
```

Appendix XI, Wooldridge test

Book Value of Leverage

```
. xtserial res

Wooldridge test for autocorrelation in panel da
H0: no first-order autocorrelation
    F(  1,     349) =     17.268
           Prob > F =      0.0000
```

Market Value of Leverage

```
. xtserial res

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,     349) =     23.327
           Prob > F =      0.0000
```

Appendix XII, Shapiro Wilk Test

Book Value of Leverage

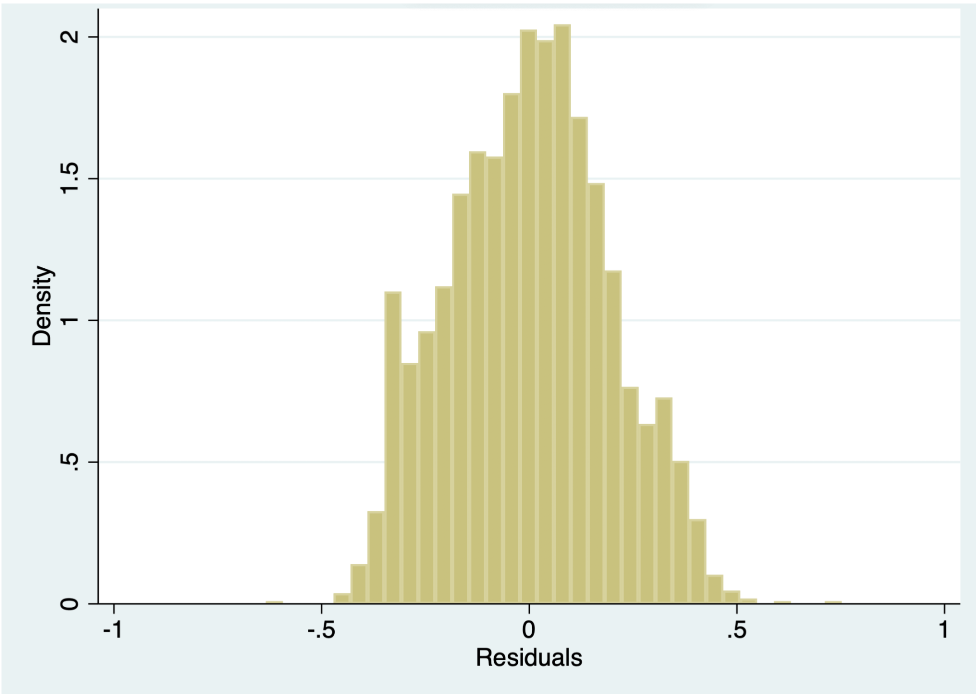
```
. swilk res

                   Shapiro-Wilk W test for normal data

    Variable |        Obs       W           V         z       Prob>z
-------------+------------------------------------------------------
         res |      2,549    0.94847     76.173    11.118    0.00000

Note: The normal approximation to the sampling distribution of W'
      is valid for 4<=n<=2000.

.
```

Market Value of Leverage

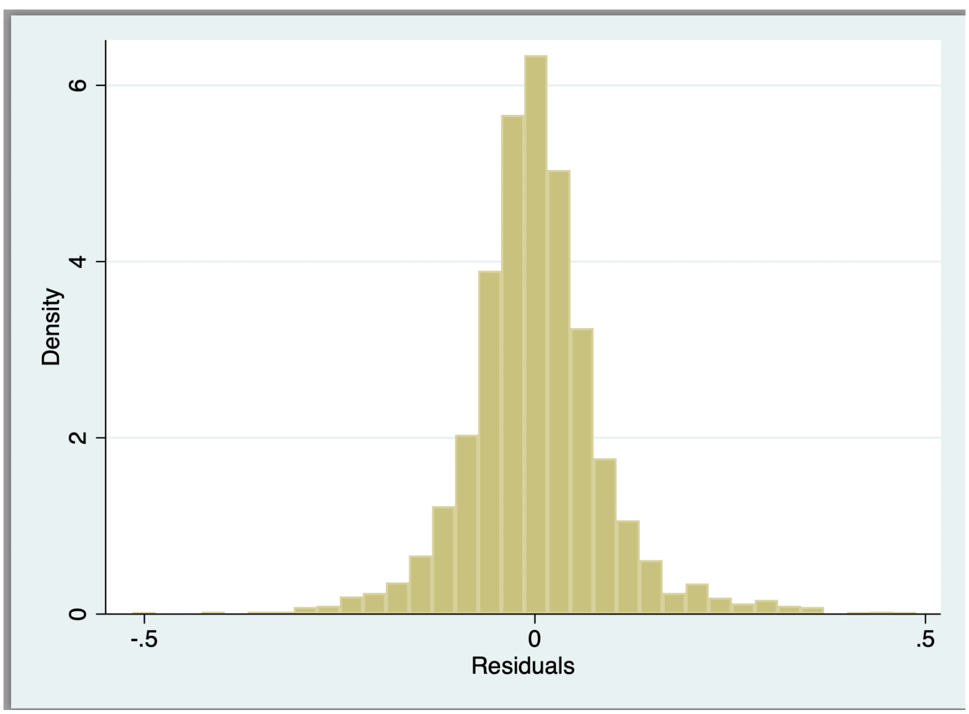
```
. swilk res

                   Shapiro-Wilk W test for normal data

    Variable |        Obs       W           V         z       Prob>z
-------------+------------------------------------------------------
         res |      2,549    0.95753     62.775    10.622    0.00000

Note: The normal approximation to the sampling distribution of W'
      is valid for 4<=n<=2000.
```

Appendix XIII, Histogram Residuals

Before transformation



After transformation



Appendix XIIII, Regression output

Book Value of Leverage

HDFE Linear regression
Absorbing 2 HDFE groups
Statistics robust to heteroskedasticity

Number of obs = 2,549
F(9, 422) = 3.98
Prob > F = 0.0001
R-squared = 0.8453
Adj R-squared = 0.8126
Root MSE = 0.0976

Number of clusters (Firm) = 423

(Std. err. adjusted for 423 clusters in Firm)

BVLEV	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
INNO L1.	-.0154865	.0074563	-2.08	0.038	-.0301419	-.000831
MrktD L1.	-.0400564	.0372163	-1.08	0.282	-.113206	.0330931
L.MrktD#cL.INNO 1	.0219245	.0093206	2.35	0.019	.0036046	.0402445
SIZE_W L1.	.0143103	.0056149	2.55	0.011	.0032741	.0253466
PROF_W L1.	-.0902558	.0290668	-3.11	0.002	-.1473872	-.0331244
TANG_W L1.	.1637212	.0645036	2.54	0.011	.036938	.2905044
GRTH_W L1.	-.0061974	.0020898	-2.97	0.003	-.010305	-.0020898
AGE L1.	.0003915	.0250533	0.02	0.988	-.0488513	.0496344
NDTS_W L1.	-.0390025	.1157575	-0.34	0.736	-.2665264	.1885214

Market Value of Leverage

```
HDFE Linear regression                            Number of obs   =      2,549
Absorbing 2 HDFE groups                           F(   9,    422) =       4.59
Statistics robust to heteroskedasticity           Prob > F        =     0.0000
                                                  R-squared       =     0.8661
                                                  Adj R-squared   =     0.8378
                                                  Root MSE        =     0.0867

Number of clusters (Firm)    =        423

                                 (Std. err. adjusted for 423 clusters in Firm)
```

MVLEV	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
INNO L1.	-.0126085	.0061029	-2.07	0.039	-.024604	-.0006131
MrktD L1.	-.0238865	.0309136	-0.77	0.440	-.0846479	.0368748
L.MrktD#cL.INNO 1	.0156315	.0079247	1.97	0.049	.0000553	.0312077
SIZE L1.	.0131346	.004904	2.68	0.008	.0034957	.0227735
PROF_W L1.	-.0798224	.0246244	-3.24	0.001	-.1282222	-.0314225
TANG_W L1.	.1462933	.0541048	2.70	0.007	.0399491	.2526376
GRTH_W L1.	-.0069002	.0017878	-3.86	0.000	-.0104142	-.0033861
AGE L1.	.0028974	.022754	0.13	0.899	-.0418261	.0476209
NDTS_W L1.	-.0390056	.1015216	-0.38	0.701	-.2385485	.1605373

Appendix XV, Distribution of used Journals

Journal	Count	%	Peer Reviewed
Journal of Finance	6	21.43%	Yes
Review of Financial Studies	1	3.6%	Yes
Financial Management	1	3.6%	Yes
Journal of Corproate Finance	2	7.1%	Yes
Journal of Banking & Finance	1	3.6%	Yes
Int. Journal of Production Economics	1	3.6%	Yes
Procedia- Social and Behavioral Scienses	1	3.6%	Yes
Empirica	1	3.6%	Yes
Economic Change & Restructuring	1	3.6%	Yes
The American Economic Review	4	14.3%	Yes
Journal of Economic Perspectives	1	3.6%	Yes
Journal of Financial Economics	4	14.3%	Yes
Quarterly Journal of Economics	1	3.6%	Yes
Strategic Management Journal	1	3.6%	Yes
Econometrica	1	3.6%	Yes
The RAND Journal of Economics	1	3.6%	Yes
Total	28	100%	