Master's Thesis

Evaluating the Impact of Pre-IPO Financial Metrics on IPO Offer Pricing and Post-IPO Performance in Scandinavian Markets

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Aalborg University Business School

Author
Joseph Charuka Suchendra Babarandage Don
(20221402)

Supervisor
Professor
Cesario Mateus

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Abstract

This thesis critically examines the performance of initial public offerings (IPOs) in the Nordic region, specifically Denmark, Sweden, Norway, and Finland, over the period from 2010 to 2021. The research is structured into two primary segments: the influence of pre-IPO financial performance indicators on IPO offer prices and the post-IPO performance analyzed through the Fama-French five-factor model.

The pre-IPO analysis explores how financial ratios such as Price-to-Earnings (PE), Price-to-Book (PB), Return on Equity (ROE), Net Income to Assets (NIA), and market sentiment indicators influence the IPO offer price. The findings indicate that the PE ratio and NIA exhibit a significant positive relationship with IPO offer prices, suggesting that firms with higher earnings and asset efficiency command higher initial IPO offer prices. In contrast, the PB ratio showed a weak and statistically insignificant positive relationship, and market sentiment surprisingly displayed a significant negative impact on IPO offer prices. These insights diverge from some existing literature, indicating the necessity for further investigation into market sentiment dynamics.

The post-IPO analysis employs the Fama-French five-factor model to elucidate the performance of IPOs in the Scandinavian market. The results affirm the model's applicability, with the market risk premium (MRP) and the size factor (SMB) positively influencing excess returns, while the value factor (HML), profitability (RMW), and investment (CMA) factors negatively affect these returns.

This analysis is further segmented by country, year, and sector to uncover specific performance trends and variations. Swedish IPOs consistently outperformed those in Denmark, with Denmark showing significantly lower post-IPO excess returns. Comparisons between Sweden and Finland and Sweden and Norway did not yield statistically significant differences in IPO performance from 2010 to 2021.

Analysis of annual data revealed that IPOs in earlier years generally yielded higher returns compared to those in 2021, with significant results except for 2012, 2013, 2018, and 2020. Sector-specific analysis indicated that most traditional sectors underperformed relative to a composite 'other' sector, although not all sectors showed statistically significant differences, with the Health and Consumer Durable sectors being statistically insignificant.

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1. Introduction

1.1. Problem Statement and Motivation

The initial public offering (IPO) is an essential milestone in the evolution of any firm, providing insights into how the stock market perceives a new company and its business model as well as the financial structure. Despite extensive research on the pre- and post-performance of IPOs conducted worldwide, there often needs to be a gap in addressing recent developments. This thesis aims to analyze how company financial matrices affect IPO offer prices and the post-IPO performances over the first two years, specifically in Scandinavia. The study covers Denmark, Sweden, Norway, and Finland from 1 January 2010 to 31 December 2021.

Building on the analysis of recent IPO trends in Scandinavia, this thesis examines two aspects of IPOs in the Scandinavian market, aiming to provide a comprehensive understanding of their dynamics and effects in capital markets. The first part of the analysis focuses on pre-IPO financial indicators and their predictive power in determining the offer price when listing. By examining how market-focused financial indicators related to assets and earnings can influence a firm's IPO offer price, this research could potentially enhance forecasting and investment decisions, offering practical benefits to investors, policymakers, and academics.

The second part investigates the factors affecting post-IPO stock performance, employing the Fama-French five-factor model to determine the drivers of returns in the post-IPO period. This model, which includes factors such as market risk, size, value, profitability, and investment, offers a robust framework for understanding the performance of newly public companies relative to broader market expectations. By exploring these elements, the thesis aims to deepen the understanding of the IPO process in the Scandinavian context, providing valuable insights for stakeholders.

1.1.1. Pre-IPO Analysis Based on Company Financial Indicators

This thesis is a deep dive into the relationship between pre-listing financial performance indicators and the resultant IPO offer price. The analysis hones in on primary financial metrics from three years before the IPO date, including the Price to Book Value (PB), Price to Earnings (PE), Net Income to Assets (NIA), and Return on Equity (ROE). These metrics are not just theoretical concepts, but they are practical indicators of a company's financial health and performance, offering actionable insights into its valuation and growth potential. The study by Yadav, Prosad, and Singh (2023) further strengthens this perspective, highlighting the significant impact of financial performance indicators on IPO offer prices. By dissecting these ratios, the thesis aims to gain a practical understanding of how effectively a company utilizes its assets, manages its earnings, and delivers returns to its shareholders, all of which are crucial for assessing its attractiveness to potential investors.

Additionally, this study adopts a macroeconomic perspective by examining the market sentiments of the respective stock exchange 91 days prior to the IPO. This approach evaluates whether prevailing market sentiments have supported or amplified inflation in IPO offer prices. By considering the broader economic environment, this thesis aims to define the degree to which external factors influence IPO pricing. Integrating both firm-specific financial performance indicators and market conditions, this section seeks to provide a comprehensive understanding of the factors affecting IPO outcomes. The combination of detailed financial analysis and broader market trends ensures a robust framework for evaluating the determinants of IPO offer prices. Ljungqvist, Nanda, and Singh (2006) found that positive market return sentiment significantly influences IPO offer prices by increasing demand for new shares, aligning with the approach of incorporating market conditions in IPO evaluation. Furthermore, Chen, Liu, and Zhu (2021) demonstrate that investor sentiment significantly impacts IPO offer prices by affecting demand and market turnover rates.

1.1.2. Post-IPO Returns Analysis Employing the Fama-French Model

This segment of the thesis delves into stocks' performance following their listing on a public board. The analysis employs the Fama-French Five-Factor Model, which includes market risk, size, value, profitability, and investment factors, to identify the critical drivers of post-IPO returns. The aim is to understand post-IPO dynamics and evaluate the model's applicability in Scandinavia.

The study investigates the performance of post-IPO stock returns over a two-year period, comparing actual returns with predictions made by the Fama-French model. This analysis evaluates the effectiveness of the model's factors in explaining the returns. Additionally, the age of the firm is included as a control variable to account for its potential impact on performance.

Furthermore, base case scenarios are developed to compare post-IPO performance across various dimensions, including country, listing year, and sector.

This comprehensive approach assesses stock performance and uncovers broader trends and patterns across different contexts and conditions. Thus, the research provides a detailed and insightful evaluation of the factors influencing post-IPO stock returns in the Scandinavian market.

Guided by the above aims, this thesis addresses two central research questions:

- How do specific pre-IPO financial metrics influence the offer price of companies in the Scandinavian IPO market?
- How effectively does the Fama-French Five-Factor Model explain the returns of IPOs during the post-IPO period within the Scandinavian market?

1.2. Delimitation

This master's thesis investigates the performance of IPOs in Scandinavia, explicitly focusing on Denmark, Sweden, Norway, and Finland. The study examines the primary stock exchanges in Copenhagen, Stockholm, Oslo, and Helsinki.

The thesis is divided into two main parts: the pre-IPO offer price determination and the post-IPO performance. The pre-IPO section covers the period from January 1, 2010, to December 31, 2021, encompassing various market cycles, including the significant impact of the COVID-19 pandemic in 2020. It deliberately excludes the recessionary periods of 2008 and 2009.

The post-IPO performance section meticulously analyzes the period from January 1, 2010, to December 31, 2021. IPOs after December 31, 2021, are deliberately excluded to allow for two years to evaluate aftermarket performance. This rigorous approach ensures a comprehensive and reliable assessment of IPO performance, providing valuable insights into the Scandinavian market.

1.3. Significance of the Study

As highlighted in the introduction section, this master's thesis pursues two primary objectives: first, to examine whether a company's financial performance indicators influence its IPO offer price; second, to investigate whether the Fama-French Five-Factor Model can explain post-IPO market returns over two years following the listing. The analysis is conducted from the perspective of typical investors, with a commitment to providing comprehensive and impartial insights for investors, financial analysts, and researchers.

In the pre-IPO segment, the study constructs an empirical model, a statistical model based on real-world data, linking key pre-IPO financial performance indicators to IPO offer prices. This model assists investors and stakeholders in making informed decisions by systematically evaluating IPO offer prices based on financial metrics. The thesis identifies specific financial performance indicators, including Price to Earnings (PE), Price to Book (PB), Return on Equity (ROE), and Net Income to Assets (NIA) that significantly influence IPO offer prices, supported by statistical evidence.

Moreover, the study offers tangible and actionable implications for both IPO issuers and investors. Issuers can leverage the identified financial indicators to bolster their company's financial performance before an IPO, thereby enhancing valuation and attracting investors (Yadav, Prosad, & Singh, 2023). Conversely, investors can utilize these indicators to compare IPOs and make well-informed decisions to maximize returns. This dual perspective ensures that the findings are not just theoretical, but also practical and beneficial for both parties involved in the IPO process.

Regarding post-IPO analysis, the thesis comprehensively examines IPO returns over two years, using a sample of 196 IPOs in Scandinavia from 2010 to 2021. The study finds that post-IPO market returns in Scandinavia during this period can be explained by the market factor (MRP), size factor (SMB), value factor (HML), profitability factor (RMW), and investment factor (CMA). These findings suggest that investors can use these insights to better assess the potential risks and returns of newly public companies, leading to more optimized portfolio construction. From a risk management perspective, the analysis helps investors anticipate and mitigate risks. For instance, recognizing that smaller, value-oriented IPOs with conservative investment policies tend to perform better enables investors to tailor their investment strategies accordingly (Pitts, 2023; Goldman Sachs Asset Management, 2023).

This research extends the empirical application of the Fama-French Five-Factor Model, demonstrating its relevance in explaining post-IPO returns. This contribution enriches the academic literature on asset pricing models and provides a more comprehensive understanding of market dynamics. The findings open new avenues for academic exploration, suggesting that future research could investigate additional factors, including liquidity or momentum. For instance, a study by Dirkx and Peter (2021) included the momentum factor in the Fama-French Five-Factor Model, creating a six-factor model.

2. Background Theory

This chapter is devoted to an overview of initial public offerings and the process of going public, which are essential concepts in the financial context. Since the Scandinavian market is relatively homogeneous, its characteristic features are similar. It means that in the current study, it is optional to describe the features of each stock exchange, but one can proceed with the listing requirements of the whole Scandinavian market. The process of deciding the listing price and analyzing the aftermarket has been researched significantly, which increased the necessity of focusing on the theoretical background of the IPO process.

2.1. IPO Overview

An initial public offering (IPO) is the procedure by which a private company becomes public by offering its shares to the public for the first time (Berk & DeMarzo, 2017). This event is a significant milestone for a company, providing an opportunity to raise substantial funds for expansion and growth. To thoroughly understand the IPO process and its impact on a company's performance, we will explore the various steps and procedures involved in transitioning to a public company.

The IPO process generally includes several key steps: selecting underwriters, preparing an offering prospectus, and pricing and allocating shares. Underwriters, typically investment banks, assist the company in determining the number of shares to issue and setting the price range for the offering. "underwriters" and "bookrunners" are often used interchangeably, as they perform similar functions. The investment bank acts as an intermediate between the issuing company and potential investors, leading the IPO process. Companies may choose one or multiple underwriters to manage different aspects of the IPO collaboratively. The underwriters are involved in all aspects of the IPO, including due diligence, document preparation, filing, marketing, and issuance. The IPO process encompasses several steps, summarized as follows:

1. **Preparation:**

   Selecting Underwriters: The company hires investment banks and other advisors to help prepare for the IPO, including conducting due diligence, drafting a prospectus, and setting a valuation. This includes choosing underwriters based on reputation, expertise, and distribution capabilities (Berk & DeMarzo, 2017; Corporate et al.; PwC, n.d.).

   Due Diligence and Regulatory Filings: The underwriters perform thorough due diligence on the company's financial, legal, and operational status and prepare necessary regulatory filings to comply with local stock exchange requirements (Berk & DeMarzo, 2017; Wall Street Oasis, n.d.; PwC, n.d.).

2. **Roadshow**: The company and its advisors market the IPO to potential investors through presentations and meetings. The book-building process gathers indications of interest from potential investors to set the optimal price range for the IPO (Berk & DeMarzo, 2017; Euronext, n.d.; Corporate et al.).

3. **Pricing**: The share's final offer price is determined based on investor demand. Underwriters may intentionally underprice the IPO to reduce risk and attract investors (Berk & DeMarzo, 2017; Corporate et al.; 365 Financial Analyst, n.d.).

4. **Allocation**: Shares are distributed to investors, prioritizing institutional investors and high-net-worth individuals. Allocation decisions are based on aspects such as investor interest and investment history (Berk & DeMarzo, 2017; Euronext, n.d.; PwC, n.d.).

5. **Stabilization**: Post-IPO, underwriters may engage in stabilization activities to support the stock price and prevent it from dropping below the offering price, typically for about 30 days (Berk & DeMarzo, 2017; 365 Financial Analyst, n.d.; Corporate et al.).

6. **Trading**: Shares are listed on a stock exchange, allowing public trading. The lead underwriter usually makes a market in the stock and assigns an analyst to cover it, providing research and attracting more investors (Berk & DeMarzo, 2017; Euronext, n.d.; 365 Financial Analyst, n.d.).

7. **Managing the Post-IPO Period**: This includes handling lock-up periods, providing ongoing analyst coverage, and ensuring compliance with new regulatory and transparency requirements as a public firm (Berk & DeMarzo, 2017; 365 Financial Analyst, n.d.; PwC, n.d.).

2.2. Listing Requirements in Scandinavian Countries

The listing requirements in Scandinavia are fairly consistent across Sweden, Denmark, Norway, and Finland, with minor deviations among the stock exchanges. Nasdaq Nordic, the primary stock exchange, outlines several prerequisites for companies seeking to be listed (Nasdaq Nordic, 2024):

- **Operating History**: Companies must have three full calendar years of published annual reports before assessment by the Listing Auditor.
- **Audited Financial Statements**: Audited financial statements for the past three years are required, with certain exceptions for closed-ended investment companies.
- **Financial Standards**: Companies must meet minimum revenue, profit, and equity requirements.
- **Shareholders and Public Float**: A minimum of 25% of shares must be in public hands, with exceptions for 10% if the shares are worth at least EUR 43.6 million (SEK 500 million) and there are at least 300 qualified shareholders.
- **Management Competence**: Board and management must demonstrate necessary competence, having been active for at least three months and involved in preparing at least one financial report.
- **Listing Adviser**: Companies must appoint a listing adviser to ensure compliance with the exchange's rules.

3. Literature Review

3.1. Overview

An initial public offering (IPO) is a pivotal event in a company's lifecycle, marking its transition from private ownership to public trading. This critical juncture has garnered considerable scholarly attention due to its role in corporate evolution and its strategic significance for business expansion and shareholder value enhancement (Ritter, 1987; Zingales, 1995; Guo, 2011). Understanding the factors influencing IPO pricing and post-IPO performance is particularly crucial in the Scandinavian market, where unique economic and market conditions prevail. This literature review explores how specific pre-IPO financial metrics influence the offer price of companies and how effectively the Fama-French Five-Factor Model explains post-IPO returns within the Scandinavian market.

3.2 Early Studies on IPO Performance

Historically, research has focused on the initial returns and long-term performance post-IPO. Early studies, such as those by Reilly and Hatfield (1969), highlighted the higher yet unstable systematic risk associated with newly public firms. Ibbotson (1975) noted the difficulty in drawing definitive conclusions due to significant standard errors in performance data while observing a higher likelihood of initial gains from IPO investments, which he referred to as "money left on the table." Subsequent research by Ritter (1984, 1991) indicated that IPOs in "hot" markets experience high initial returns but often suffer poor long-term performance, suggesting that market conditions play a crucial role in IPO outcomes.

Further studies expanded on understanding IPO performance by examining the factors influencing initial returns and underpricing. For example, Ibbotson, Sindelar, and Ritter (1988) observed that underpricing varies over time and across industries, influenced by market conditions and investor sentiment. Additionally, Loughran and Ritter (1995) found that IPOs during periods of high investor enthusiasm tend to be more underpriced initially but often underperform in the long run, reinforcing the impact of market sentiment and timing on IPO success. Research in the 1990s, such as that by Beatty and Ritter (1986), examined the role of investment banking reputation in IPO underpricing, finding that underwriters with better reputations tend to underprice less because they can more accurately gauge market demand. Loughran, Ritter, and Rydqvist (1994) provided a comprehensive international perspective, showing that IPO underpricing and subsequent long-term underperformance are consistent across different markets, albeit with varying degrees.

3.3. Pre-IPO Financial Performance and IPO Pricing

Building on the foundational understanding of IPO performance, research has delved into specific financial metrics influencing IPO prices. Metrics such as return on investment (ROI), earnings from different business segments, and operational efficiency indicators like cost management and asset utilization have been established as critical determinants of IPO pricing (Hove et al., 2020; Firth & Rui, 2008; Halonen et al., 2013; Narullia & Subroto, 2018; Brau & Fawcett, 2006). These findings emphasize the critical role of detailed financial evaluations in assessing the potential value of new stocks. Other researchers have explored the impact of issue size, profitability, operational cash flow, and leverage on IPO pricing, revealing a complex interplay among these factors (Hedau, 2016; Ong et al., 2020).

The significance of the price-to-earnings (PE) ratio and past earnings as forecast tools by investment bankers has also emerged as pivotal in the IPO process (Sahoo & Rajib, 2012; Ghicas et al., 2000). Additionally, non-financial factors such as management quality, company reputation, and market conditions significantly influence IPO pricing, highlighting the multidimensional nature of IPO valuation (Aggarwal et al., 2009). The influence of external parties, particularly investment bankers, on IPO pricing and underpricing is well-documented, with their role closely linked to reputational concerns (Beatty & Ritter, 1986). This section of the literature indicates the complexity of the IPO process, which is influenced by a combination of financial, operational, and market-driven factors.

3.3.1. Empirical Evidence and Recent Developments in IPO Pricing

Recent studies have continued to refine our understanding of these metrics. Loughran and McDonald (2021) explored textual analysis in finance, demonstrating that sentiment and tone in financial documents can predict IPO offer prices, introducing a modern analytical technique to the existing body of knowledge. Similarly, Bessler and Thies (2022) provided new evidence from European markets, highlighting the determinants of IPO underpricing and their relevance to Scandinavia.

Non-financial factors also play a vital role in IPO pricing. Gomolka and Schönfeld (2021) examined the impact of corporate governance on IPO pricing, finding that solid governance practices can enhance investor confidence and lead to higher IPO offer prices. Additionally, Woolley and Clarke (2023) investigated the influence of social media sentiment, revealing that positive sentiment can significantly boost IPO valuations. These findings highlight the multifaceted nature of IPO pricing, where financial and non-financial factors must be considered.

A recent study by Yadav, Prosad, and Singh (2023) developed an empirical model to explore the relationship between critical financial performance indicators and IPO offer prices, using data from companies listed on the National Stock Exchange of India between 2015 and 2021. Their findings emphasize the significant impact of Net Asset Value, Return on Assets, Profit after Tax, and Return on Net Worth on IPO offer prices. This study supports the idea that thorough financial evaluations are essential for accurate IPO pricing and reducing the gap between offering and listing prices (Yadav et al., 2023).

The influence of non-GAAP measures and key performance indicators (KPIs) on IPO valuation has been increasingly recognized. According to a 2023 report by PwC, non-GAAP measures and KPIs can significantly impact IPO pricing by providing a clearer picture of a company's financial health and growth prospects. These metrics, which often include adjusted earnings, free cash flow, and other customized financial indicators, can offer insights that traditional GAAP measures may not fully capture. This additional transparency can make IPOs more attractive to investors by highlighting the company's underlying performance and future potential (PwC, 2023).

3.3.2. ESG matrices, Long-Term Success and Market Sustainability

The role of Environmental, Social, and Governance (ESG) factors in IPO pricing has also garnered attention. Khan and Serafeim (2023) provided international evidence showing that robust ESG performance can lower the cost of capital and positively influence IPO offer prices. This shift towards incorporating ESG metrics reflects a broader trend in responsible investing, where long-term sustainability and ethical considerations are becoming paramount. Ferri et al. (2023) investigated how strong ESG performance can influence IPO underpricing and short-term post-IPO performance. The study found that companies with robust ESG ratings experience less underpricing and better short-term performance post-IPO. This suggests that investors increasingly value ESG factors as indicators of long-term sustainability and risk management. Including ESG metrics in the IPO evaluation process reflects a shift towards more holistic and responsible investing practices (Ferri et al., 2023).

Post-IPO, the financial indicators provided in IPO prospectuses offer insights into long-term company success, though the correlation is modest (Bhabra & Pettway, 2003). The role of pre-IPO profitability in predicting a firm's market sustainability has been particularly highlighted, especially during the late 1990s tech boom (Peristiani & Hong, 2004). This literature review establishes a foundation for understanding the multifaceted nature of IPOs. It sets the stage for further exploration of how financial and non-financial indicators affect IPO success and long-term performance.

3.4 Post-IPO Performance and the Fama-French Five-Factor Model

3.4.1. Theoretical Framework

Research on companies that have recently completed IPOs primarily focuses on two distinct phenomena: the initial underpricing commonly observed at IPOs and the tendency for these firms to underperform in the long term. Ritter (1991) noted that over the first three years of trading, firms that have conducted IPOs typically see significantly lower stock returns than those that have not undergone IPOs. This observation has proven globally relevant, as subsequent studies by Levis (1993) and Aggarwal et al. (1993) have confirmed. These studies show that low long-term returns on IPOs are not confined to the United States but are also prevalent in other countries, including Great Britain, Chile, and Mexico.

As the second section of this thesis seeks to determine whether the Fama-French Five-Factor Model explains post-IPO stock returns, it is pertinent to discuss the related literature. Fama and French (1993) introduced a three-factor model, incorporating size, book-to-market factors, and market risk factors. Later, Fama and French (2015) expanded this model into a five-factor framework that includes market, size, value, profitability, and investment factors. They demonstrated that this enhanced model offers a more accurate explanation of average stock returns, particularly addressing the previous model's shortcomings in explaining the lower average returns on small, heavily investing stocks with low profitability.

3.4.2. Empirical Evidence on Post-IPO Performance

Further research, such as that by Loughran and Ritter (1995), explored the "new issues puzzle," suggesting that IPOs generally underperform in the long run compared to the market. This provides a context in which the Fama-French model can be tested to see if it accounts for such anomalies. Brav, Geczy, and Gompers (2000) noted that while the Fama-French three-factor model partially explains post-IPO returns, additional factors, such as momentum, included in their four-factor model, are necessary for a more comprehensive explanation of post-IPO performance. They also suggested that while the Fama-French model provides a framework for understanding certain risk factors, it may only partially account for some return variations, mainly if momentum is not considered. Similarly, B. Espen Eckbo and Øyvind Norli (2000) found that while Fama-French factors partially explain post-IPO performance, unique characteristics such as lower leverage and a significant liquidity factor also play crucial roles.

Additionally, there are numerous controversial perspectives, such as those presented by Barberis, Shleifer, and Vishny (1998), who proposed a model of investor sentiment that may explain deviations in stock prices from fundamental values. They noted that these psychological factors could influence investor decisions in ways that traditional rational asset pricing models, like the Fama-French model, do not capture. Similarly, Daniel, Hirshleifer, and Subrahmanyam (1998) discussed the impact of investor psychology on market under- and overreactions, suggesting that behavioral biases could explain deviations from the efficient market hypothesis and the unexpected performance of IPOs not accounted for by traditional risk-based models like Fama-French.

3.4.3. Country-Specific Studies

Several country-specific studies have also been conducted in this domain. Thomadakis, Nounis, and Gounopoulos (2012) analyzed 254 Greek IPOs listed between 1994 and 2002. They applied the Fama-French three-factor and Carhart's four-factor models, discovering that these factors significantly elucidate the post-IPO returns of these stocks. Similarly, Anlin Chen and Li-Wei Chen (2016) expanded the traditional Fama-French three-factor model by incorporating leverage and liquidity factors to evaluate the long-term performance of IPOs in Taiwan. Their study spanned the years 1991 to 2007. It examined a cohort of 261 IPOs issued over the counter, finding that these five factors substantially explain the superior long-run returns of these IPOs compared to the market.

Meanwhile, Poulsen and Nielsen (2017) analyzed long-term IPO performance in the Scandinavian markets, focusing on companies listed in Denmark, Sweden, and Norway from 2004 to 2014. Their research critically assessed the adequacy of the Fama-French three-factor model in capturing the post-IPO returns within these countries, concluding that this traditional asset pricing model only partially reflects the dynamics influencing IPO performance in Scandinavian markets during this time.

3.4.4. Sector-Specific Insights

Sector-specific insights also reveal noteworthy findings. Luisa Anderloni and Alessandra Tanda (2016) analyzed 144 energy firms, including green and traditional sectors, from 2000 to 2014. Their results indicated that post-IPO returns are predominantly influenced by market excess returns and size effects, as described by the Fama-French three-factor model. These factors suggest that they significantly predict performance in the energy sector post-IPO.

3.5. Recent Updates to the Post-IPO Literature

Further updating the literature, Novy-Marx and Velikov (2021) explored new anomalies within the Fama-French framework, offering insights that could enhance its explanatory power in different markets, including Scandinavia. Lin and Zhang (2022) examined factor investing and IPO performance globally, providing evidence that the Five-Factor Model can effectively capture the complexities of post-IPO returns across various regions.

The long-term performance of IPOs remains a critical area of study. Doidge and Karolyi (2022) comprehensively analyzed global IPOs, revealing patterns and performance trends essential for understanding long-term success. Their findings suggest that while initial market conditions are crucial, ongoing financial health and strategic decisions significantly impact long-term outcomes. Similarly, Ewens and Farre-Mensa (2023) discussed the deregulation of private capital markets and its implications for IPO performance, noting a shift towards private funding that affects public market dynamics.

3.6. Other Effects of IPOs

3.6.1. Asymmetric Information

Asymmetric Information, a crucial concept in finance, manifests when one party, such as a company's management, possesses more knowledge about the value or prospects of an asset than another party, such as potential investors (Hoque, 2014). This disparity can create unequal bargaining power, leading to problems like adverse selection and moral hazard. In the context of IPOs, this situation arises because management typically has more detailed Information about the firm's actual value and prospects than potential investors, underscoring the significance of this concept in the IPO landscape.

3.6.2. Signaling Hypothesis

The signaling hypothesis, a theory with practical implications, suggests that actions taken by economic agents often aim to send positive signals to others rather than serving their primary purpose (Oxford Reference, 2023). For instance, an IPO can signal a company's confidence in its prospects, thereby reducing information asymmetry and agency costs. Studies by Leland and Pyle (1977) and Ritter (1984) support this hypothesis, showing that high-quality firms use IPOs to signal their value, which can lead to higher post-IPO returns for these firms, highlighting the practical role of this theory in the IPO market.

3.6.3. Uncertainty Hypothesis

The uncertainty hypothesis evaluates company quality, which can influence post-IPO performance. Beatty and Ritter (1986) propose that high-quality firms exhibit less uncertainty, leading to better outcomes. Loughran and Ritter (2004) found that firms with high information uncertainty face greater underpricing and extended registration periods, impacting their post-IPO performance. Firm size also plays a role; smaller firms often experience higher uncertainty and underpricing (Rock, 1986; Lowry & Schwert, 2002). These insights help explain variations in post-IPO performance based on initial conditions at the time of the IPO.

3.6.4. Advancements in Analytical Techniques

Advancements in analytical techniques are providing new tools for IPO valuation and performance analysis. Kogan and Levin (2022) explored the role of AI and machine learning in predicting IPO offer prices and post-IPO performance, demonstrating that these technologies can uncover patterns and insights beyond traditional methods. Additionally, Rajgopal and Shivakumar (2023) discussed the impact of big data analytics on financial market predictions, highlighting how vast datasets and sophisticated algorithms can enhance the accuracy of IPO valuations and subsequent performance assessments.

4. Data Description

4.1. IPO Data

Scholars across various disciplines increasingly leverage qualitative and quantitative research methodologies to investigate and interpret data thoroughly. Qualitative research typically involves purposeful sampling to enhance understanding of the information-rich case, generating detailed insights rooted in specific contexts. Conversely, quantitative methods employ probability sampling techniques, which facilitate the generalization of results to broader populations and enable robust statistical inferences (Sandelowski, 2000). Quantitative methods are particularly suited to this study because they allow for precise measurement of financial metrics and their effects on IPO offer prices and post-IPO performance, which is crucial for answering the research questions.

Aligned with scholarly precedents (Willenborg et al., Y. A. S. (2015), Nilsson, and Wahlberg, 2006), this thesis employs a quantitative methodology to systematically gather data, guided by the nature of the research questions, which seek to identify and verify patterns across a specified population. This thesis outlines the criteria and methods used for data collection, providing detailed justifications to ensure the approach's credibility and relevance. Moreover, it acknowledges potential limitations within the data collection process, assessing their possible impacts on the research findings and discussing strategies to mitigate these issues.

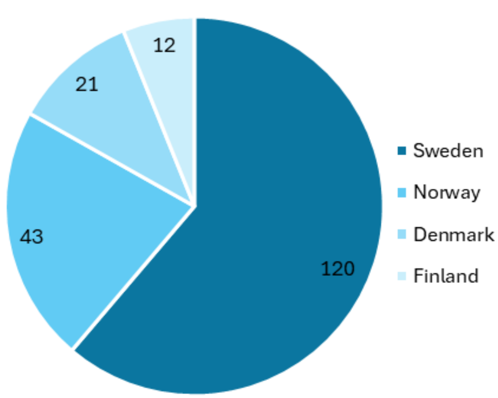
4.2. IPO Data Collection

In the introduction, this thesis outlined two primary objectives: first, to examine the influence of financial performance indicators on the IPO offer prices of Scandinavian companies at the pre-IPO stage, and second, to investigate the factors driving post-IPO share prices using the Fama and French five-factor model. To fulfill these objectives, a comprehensive dataset was compiled from the FactSet database. FactSet is a reputable and comprehensive database for financial data, providing reliable and detailed financial metrics essential for this study.

The study analyzed IPOs successfully launched in Scandinavia, specifically in Denmark, Sweden, Norway, and Finland from January 1, 2010, to December 31, 2021. This timeframe strategically excludes the impact of the 2009 US recession while encapsulating the fluctuations brought about by the COVID-19 pandemic. Significant economic events within this period, such as the post-2009 recovery and the COVID-19 pandemic, are relevant as they influenced IPO activity. During this period, we witnessed a surge in IPOs, particularly in the calendar year of 2021. 349 IPOs were initially identified across key Scandinavian primary stock exchanges, including Denmark's OMX Nordic Copenhagen, Sweden's NASDAQ OMX Stockholm, Norway's Oslo Bors, and Finland's First North. Of these, 153 were excluded from the analysis due to liquidations, unsuccessful IPO launches, and insufficient financial data available in the FactSet database, leading to a count of 196 IPO firms.

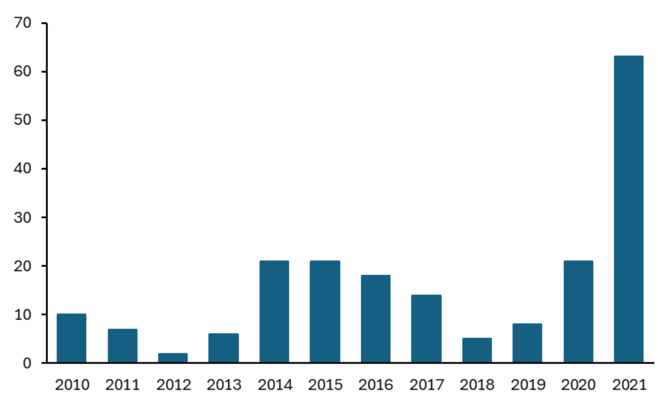
Of 196 firms, 120 (61%) were listed on NASDAQ OMX Stockholm, Sweden. Meanwhile, Oslo Børs in Norway accounted for 43 IPOs (22%), OMX Nordic Copenhagen in Denmark listed 21 (11%), and First North Finland hosted 12 (6%). An analysis of the distribution over recent years reveals that 2021 saw the highest frequency of IPOs, with 63 new listings, representing 32% of the total. Many of these 21 IPOs occurred in 2020, 2014, and 2015. A sectoral breakdown of the 2021 IPOs highlights a dominant trend in the technology sector, where 16 of the 63 listings (25%) were firms involved on the Internet, IT, and software industries. This trend highlights the strong bull market in tech-related stocks during this period, fueled by numerous business opportunities generated by IT-related sectors in response to lockdown strategies implemented by health authorities.

Figure: 1 *- IPOs by Country in Scandinavia*



Source: FactSet Database

Figure: 2 *- IPOs by Year of listing in Scandinavia*



Source: FactSet Database

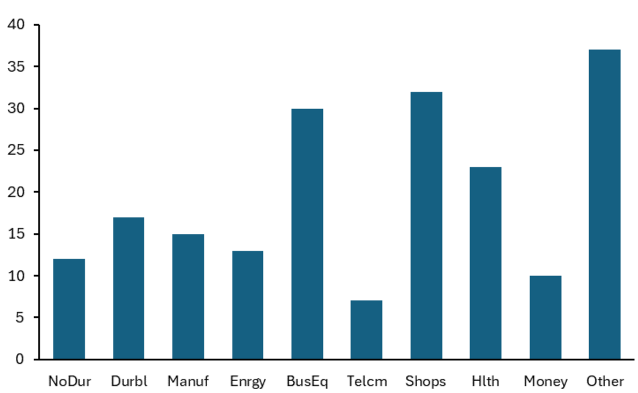
This thesis meticulously categorizes IPO firms into sectors, a complex task due to the diverse sector classifications across four stock exchanges. The 196 new listings have been meticulously organized into 12 main sectors, ensuring a consistent classification. This categorization is a result of careful consideration, drawing inspiration from the sectors used by Fama, E. F., & French, K. R. (1993) in their seminal paper, which adapted sectors from the Standard Industrial Classification (SIC) codes. Of these, the 196 stocks are primarily distributed across ten main sectors. Detailed information on the distribution of stocks into these sectors can be found in Appendix 1 and 2.

Underscore the significance of having complete and standardized financial and stock price data. To mitigate any issues associated with currency fluctuations and inconsistencies in exchange rates, all prices and financial data have been meticulously downloaded and standardized in Euros. This rigorous process ensures a high level of consistency and comparability across different periods and stock exchanges, enhancing the reliability of the findings.

It is of significant importance to note the substantial amount of funds collected from IPOs in Scandinavia between 2010 and 2021. The 196 IPOs tracked in this thesis raised a staggering amount of over 29,364 million euros during this period. Particularly noteworthy is the fact that a majority of these funds, totaling 9,318 million euros, were collected during the pandemic period in 2021. This period witnessed a surge in IPO listings, predominantly by technological companies, underscoring the impact of these findings.

Figure: 3

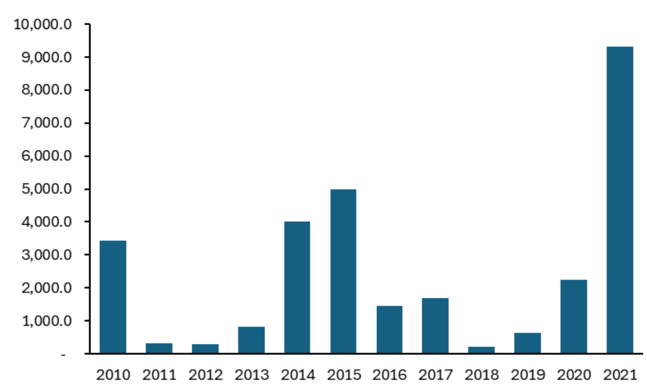
IPOs by Sector



Source: FactSet Database

Figure: 4

Total Proceeds from IPOs by Year (Euro Millions)



Source: FactSet Database

This dataset, comprising 196 firms, is utilized for post-IPO analysis. However, due to the absence of the required financial statements before their IPOs, only a subset of these firms could be included in the pre-IPO analysis. The decline of the observations is listed in table 1 below. Additionally, this thesis excludes bank IPOs from the pre-IPO study due to their distinct reporting structures.

Table 1: Pre IPO-Analysis - Company Count with Available Data Over Three Years

Year of Listing (Y0)	One Year Prior (Y-1)	Two Years Prior (Y-2)
196 firms	157 firms	131 firms

4.3. Standards and Event Period

This thesis analyzes IPOs in Scandinavia, consisting of listings in Denmark, Sweden, Norway, and Finland from January 1st, 2010, to December 31st, 2021. As explained before, the pre-IPO section covers whether the company's financial performance indicators influence the IPO offer price, and the post-IPO segment covers whether the Fama-French five-factor model explains the post-IPO performances.

Financial data is collected three years before the IPO in the pre-IPO segment. This includes the financials for the year of listing, one year prior, and two years before the listing. The specific financial metrics analyzed include the rewards to equity holders, the relationship between book value and earnings to market price, and the earnings-generating capability of assets. In the post-IPO section, stock returns are calculated for two years from the listing date, slightly shorter than the standard long-term evaluation of three years, in line with Ritter's (1991) definition of long-term evaluation. The post-IPO study has been restricted to two years in this thesis to capture the significant number of stock listings reported in Scandinavia in 2021. This surge, driven by technology listings, accounted for 32% of the total listings covered in this thesis.

Figure: 5 *- IPO Company Section Method*

Company Selection Criteria	
Criterion - 1	
Company is listed for the first time between January 1, 2010, to December 31, 2021 (Seasoned public offers are excluded)	
Criterion - 2	
Company should be listed in Scandinavia NASDAQ OMX Stockholm Oslo Børs OMX Nordic Copenhagen First North Finland	
Criterion - 3	
Financial data and stock prices should be available in FactSet database	
Criterion - 4	
Pre - IPO Analysis	**Post IPO Analysis**
Criterion - 4.1	**Criterion - 4.2**
Financials should be available for 3 years prior to the date of listing	Stock prices should be available for 2 years since the date of listing
Criterion - 5	
The company should be actively trading by December 31, 2023	

Each criterion is designed to ensure the dataset's robustness and reliability. For instance, requiring financial data availability three years before the IPO ensures that the analysis can comprehensively assess pre-IPO financial performance. By integrating these criteria, the study aims to provide a concrete foundation for the empirical analysis, facilitating the identification and verification of patterns across the specified population.

5. Methodology and Hypothesis Development

5.1. Methodological Framework for Pre-IPO Analysis

This study examines the relationship between financial performance indicators and IPO offer prices. With the necessary data, we now focus on the design and considerations of the pre-IPO analysis model. The analysis will employ Ordinary Least Squares (OLS) panel regression, concentrating on 131 companies that went public in Scandinavia, covering the leading stock exchanges in Denmark, Sweden, Norway, and Finland from January 2010 to December 2021. This study utilizes financial performance indicators from three distinct time points: the year of listing (Y0), one year prior to listing (Y-1), and two years prior to listing (Y-2).

5.1.1. Ordinary Least Squares Regression

Ordinary least squares (OLS) are a prevalent technique for estimating coefficients in multiple regression analysis. The primary objective of OLS is to reduce the total squared discrepancies between the actual values of the conditional (dependent) variable and the values predicted by the regression model (Kutner et al., 2005). This approach determines the regression coefficients by identifying the values that minimize the sum of squared residuals. OLS is favored for its beneficial attributes, such as being unbiased, consistent, and efficient, contributing to its widespread use in multiple regression estimation (Gujarati & Porter, 2019). Nonetheless, OLS is susceptible to issues like outliers, multicollinearity, and heteroscedasticity, which can undermine the reliability of the regression outcomes. Consequently, we will also incorporate a robust regression model, which will be detailed in the analysis and results chapter.

In the pre-IPO section of this thesis, a fixed effects panel model is used in the OLS regression analysis because each Company possesses unique, time-invariant attributes that could influence IPO offer prices. By employing a fixed effects model, the analysis effectively controls for these unobserved variations, ensuring that the estimated impact of the pre-IPO financial performance indicators on IPO offer prices is not biased by these constant, company-specific effects. This approach provides a more accurate and reliable understanding of how financial performance influences IPO pricing.

Fixed Effects OLS Panel Regression Model

$$Y_{it} = \alpha + \beta_1 x_{it,1} + \beta_2 x_{it,2} + \beta_3 x_{it,3} + \beta_4 x_{it,4} + \beta_5 x_{it,5} + \gamma_1 z_{it,1} + \gamma_2 z_{it,2} + \mu_i + \varepsilon_{it}$$

Y_{it} = Dependent variable

$x_{it,1}$, $x_{it,2}$, $x_{it,3}$, $x_{it,4}$, $x_{it,5}$ = Independent variables

$z_{it,1}$, $z_{it,2}$ = Control variables

μ_i = Company-specific fixed effect

ε_{it} = Idiosyncratic error term

5.2. Pre-IPO Analysis Model Formulation

In the process of formulating the models, we employ OLS panel regression, which extends the traditional OLS method to accommodate panel data involving multiple observations over time for each Company. This approach is beneficial as it allows us to control individual heterogeneity, capturing the unique characteristics of each Company that do not change over time. By using three years of financial data prior to the IPO for each Company, the panel OLS regression can more accurately estimate the impact of financial performance indicators on the IPO offer price. This method is robust for examining relationships between variables, making it especially effective for investigating how pre-IPO financial performance influences IPO offer prices.

This thesis employs three-panel regression models, Model 1, Model 2, and Model 3, to comprehensively analyze how various factors influence IPO pricing. These models are designed to isolate and understand the impact of different control variables on the relationship between financial performance indicators and IPO offer prices.

5.2.1. Regression Models of the Study

This study utilized three regression models to assess the impact of financial performance indicators on IPO offer prices. Model 1 explored the connection between IPO offer prices and performance indicators using a single control variable, "Offer Size". Model 2 analyzed the relationship between IPO offer prices and financial performance indicators with a different control variable, 'Age.' Model 3 incorporated both 'Offer Size' and 'Age' as control variables to examine the relationship between IPO offer prices and financial performance indicators to evaluate the overall effects. The regression equations developed below provide a generalized explanation for these models, designed to empirically test the association between IPO offer prices and financial performance indicators.

Model 1

$$OFP_{it} = \alpha + \beta_1 PB^X_{it} + \beta_2 PE^X_{it} + \beta_3 ROE^X_{it} + \beta_4 NIA^X_{it} + \beta_5 MKS_{it} + \beta_6 OFS_{it} + \varepsilon_{it}$$

(Note that, ^{X} = Y0, Y-1 & Y-2)

Model 2

$$OFP_{it} = \alpha + \beta_1 PB^X_{it} + \beta_2 PE^X_{it} + \beta_3 ROE^X_{it} + \beta_4 NIA^X_{it} + \beta_5 MKS_{it} + \beta_6 AGE_{it} + \varepsilon_{it}$$

(Note that, ^{X} = Y0, Y-1 & Y-2)

Model 3

$$OFP_{it} = \alpha + \beta_1 PB^X_{it} + \beta_2 PE^X_{it} + \beta_3 ROE^X_{it} + \beta_4 NIA^X_{it} + \beta_5 MKS_{it} + \beta_6 OFS_{it} + \beta_7 AGE_{it} + \varepsilon_{it}$$

(Note that, ^{X} = Y0, Y-1 & Y-2)

Note: OFP = Offer Price, PB = Price to Book, PE = Price to Earnings, ROE = Return on Equity, NIA = Net Income to Assets, MKS = Market Sentiments, OFS = Offer Size, AGE = Age of the firm, Y0 = Year of listing, Y-1 = One year prior to listing, Y-2 = Two years prior to listing.

It is important to note that the independent variables, such as PE, PB, ROE, and NIA, have three distinct observations for each firm corresponding to the year of listing (Y0), one year prior (Y-1), and two years prior (Y-2). These observations reflect changes over time in a panel regression analysis. In contrast, the variables MKS, OFS, and AGE remain constant over the observed period for each firm, with the same value repeated for all three years in the panel regression.

The equations provided above use standardized regression coefficients. The offer price (OFP) is the dependent variable, while PB, PE, ROE, NIA, and MKS are independent variables representing financial performance indicators. Additionally, this study includes Offer Size in the IPO (OFS) and the firm's age (AGE) as control variables. All these variables are explained in detail in the following section.

5.2.2. Variables for Regression

This thesis uses five independent (explanatory) variables: Price to Earnings (PE), Price to Book (PB), Return on Equity (ROE), Net Income to Assets (NIA), and Market Sentiments (MKS). Furthermore, two control variables are used: offer Size (OFS) and Age of the firm (AGE), where the dependent variable is IPO Offer Price (OFP). An overview of these variables is given below in table 2.

Table 2: Description of variables

Variables	Description	Notation	Data Source
Dependent variable			
IPO Offer Price	Offer price means the price at which a company's shares are offered during its IPO in Euro Currency.	OFP	FactSet
Independent variables			
Price to Earnings	Ratio is calculated by dividing the IPO offer price by the year-end earnings per share (diluted).	PE	FactSet
Price to Book	Ratio is calculated by dividing the IPO offer price by the year-end net asset value per share.	PB	FactSet
Return on Equity	Total net profits allocated to the average equity value of the company.	ROE	FactSet
Net Income to Assets	Ratio is calculated by dividing the net profits of the company by average assets.	NIA	FactSet
Market Sentiments	Return of the respective benchmark index for the 91 days prior to the company's listing date.	MKS	FactSet
Control Variables			
Size of the Offer	Total number of shares offered to the public at the IPO through a prospectus.	OFS	FactSet
Age	Number of years from the company's incorporation to its public listing.	AGE	FactSet

5.2.3. Independent Variables and Hypotheses

The following are the independent variables used in the regression models and their corresponding hypotheses.

Price to Earnings (PE)

The Price-to-earnings (PE) ratio is a critical financial metric that compares a company's current share price to its earnings per share. This ratio is widely used to gauge anticipated earnings growth, with a higher PE ratio often indicating that investors expect significant future earnings increases (Litzenberger & Rao, 1971; Cragg & Malkiel, 1982). The PE ratio can reflect risk (Ball, 1978) and serve as an earnings capitalization rate (Graham et al., 1962; Boatsman & Baskin, 1981; Alford, 1992). According to derivations from the Gordon model, the PE ratio is influenced by return on equity, highlighting its role in capturing transitory earnings effects, such as the "Molodovsky effect" (Beaver & Morse, 1978; Molodovsky, 1953). Additionally, the PE ratio helps identify mispriced stocks (Basu, 1977; Jaffee et al., 1989) and reflects the influence of accounting principles (Craig et al., 1987). Furthermore, the PE ratio explains average stock returns, and serves as an indicator of risk or financial distress by showing the gap between market expectations and current earnings projections (Penman, 1996). In this thesis, under the pre-IPO section, which studies whether a company's financial performance indicators affect the IPO offer price, we have calculated the PE ratio as the IPO offer price divided by the respective years' diluted EPS before the listing.

Price to Book (PB)

The Price-to-Book ratio is a financial measure used to compare a company's market value to its book value by dividing the market price per share by the book value per share. Traditionally viewed as an indicator of the anticipated return on equity, this ratio aligns price with book value through a standard formula. Although the PB ratio received limited academic attention initially, it gained prominence after Fama and French (1992) introduced their three-factor model. Historically, it was interpreted as reflecting the expected return generated on equity (Graham et al., 1962). Additionally, the PB ratio serves as a marker of growth and is influenced by leverage. Analysts regard it as a "margin of safety," comparing it to liquidation value (Bodie et al., 1989). According to Rosenberg, Reid, and Lanstein (1985), this ratio helps identify mispriced stocks and distinguishes between "value" and "glamor" stocks. Furthermore, it explains average stock returns and is a proxy for risk or financial distress, highlighting discrepancies between market and book leverage or stock mispricing (Penman, 1996). In this thesis, under the pre-IPO section, which studies whether a company's financial performance indicators affect the IPO offer price, we have calculated the PB ratio as the IPO offer price divided by the net asset value per share of the respective years before the listing.

Return on Equity (ROE)

The Return on Equity (ROE) ratio is a vital financial performance metric that indicates how effectively a company generates profit from its shareholders' equity. ROE is commonly used to assess a company's profitability relative to its equity base. Research shows that ROE is highly serially correlated, meaning a high current ROE often forecasts a high future ROE, as Penman (1991) and Fama and French (1995). However, ROE tends to revert to mean values over time, as Beaver (1970) and Freeman, Ohlson, and Penman (1982) noted. This ratio is beneficial for identifying profitability extremes, as extreme ROE values are better predictors of future earnings changes than moderate ones. However, more than relying solely on ROE may be required for evaluating financial ratios like PB or PE, and additional information is often necessary for a more comprehensive analysis. In this section of the thesis, ROE is calculated as net profits allocated to equity holders divided by average equity and is used as an independent variable to understand whether prior ROE values affect the IPO offer price.

Net Income to Assets (NIA)

The Net Income to Assets ratio is an essential financial performance indicator used to evaluate a company's profitability relative to its average assets. This metric is calculated by dividing the annualized net income by the average assets, providing insight into how effectively a company generates profits from its asset base. Studies have demonstrated that Net Income to Assets is closely linked to IPO price adjustments and initial returns. Companies with higher Net Income to Assets ratios often experience positive price revisions and higher initial returns during their IPOs, reflecting solid financial health and investor confidence (Willenborg et al., 2015). Moreover, extreme net income to Asset values, particularly at the distribution's tails, strongly connect with price formation and underpricing. This highlights the significance of Net Income to Assets as a predictor of future performance and its impact on IPO pricing dynamics (Willenborg et al., 2015). In this thesis section, Net Income to Assets is calculated as net income divided by average assets and utilized as an independent variable to examine whether prior Net Income to Assets values affect the IPO offer price.

Market Sentiment (MKS)

Market Sentiment is a vital financial metric used to evaluate the performance of investments compared to the overall market. To understand the market sentiments during the listing period, this thesis calculates the return of the respective indices in which the company is listed. Indexes such as the S&P 500, NASDAQ, or other relevant stock market indexes include both capital gains and dividends for a comprehensive assessment of market performance. Interest in market return, derived from market returns, grew significantly with the introduction of the Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965), which provided a systematic framework for understanding market risks and returns. Historically, market returns have been essential for analyzing the risk-return trade-off in portfolio management, a concept introduced by Markowitz (1952) and fundamentally rooted in Modern Portfolio Theory. Additionally, market return serves as a benchmark for investors to evaluate the performance of individual assets relative to the market, helping identify alpha, the excess return over the market return. Analysts rely on market return to assess investment strategy effectiveness and ensure portfolio returns meet expectations based on market trends. The indices and their 91-day returns used in this analysis are detailed in table 3.

Table 3: Pre-Listing Market return sentiments (91 days)

Listed country	**Market Index**
Sweden	OMX Stockholm 30
Norway	Norway Oslo All-Share TR
Denmark	OMX Copenhagen 20
Finland	OMX Helsinki 25

Source: FactSet Database

In this thesis, the pre-IPO section investigates the impact of a company's financial indicators on its IPO offer price. The market return sentiment is calculated as the change in the relevant market index over the 91 days leading up to the IPO listing.

5.2.4. Control Variables

A control variable, also known as a covariate, is essential to regression analysis. It isolates the impact of the primary explanatory variables on the dependent variable by accounting for potential confounding factors. In the context of IPO pricing models, control variables help minimize bias and improve the accuracy of the results.

Age (AGE)

The age of a company, typically defined as the number of years from its establishment to its IPO, serves as an essential control variable in IPO pricing analysis. It is often viewed as a measure of the firm's maturity and market presence. Having operated for more extended periods, older companies are generally expected to have more established operations and stable revenue streams, which can boost investor confidence and positively impact the IPO offer price. This is because mature firms typically have proven business models, historical financial performance data, and established customer bases, reducing the perceived risk for investors. Studies such as Yadav, Prosad, and Singh (2023) have shown that pre-IPO financial performance indicators, including company age, significantly influence IPO offer prices by providing insights into the firm’s stability and operational efficiency. Additionally, research by Mehmood, Mohd-Rashid, and Ahmad (2020) supports the notion that older firms with longer operating histories are better positioned to command higher IPO prices due to their lower risk profile and established market presence. This study included the firm's age (AGE) as a control variable in the regression models to evaluate its effect on IPO offer prices.

Offer Size (OFS)

The number of shares made available to the public during an IPO, referred to as the size of the offer, is a key control variable. This measure indicates the magnitude of the IPO and the company's fundraising goals. Larger IPOs can garner more interest from institutional investors and market analysts, which might increase the offer price due to heightened demand and perceived market strength. Studies have shown that offer size significantly influences IPO pricing. For instance, research by Weld et al. (2009) and Singh, Bhullar, and Bhatnagar (2014) demonstrate that larger IPOs tend to attract more attention and resources, leading to higher valuations. This study used the offer size (OFS) as a control variable in the regression analysis to evaluate its effect on IPO offer prices.

5.3. Pre-IPO Hypothesis

Historically, research on stock market returns has emphasized the importance of fundamentals related to future cash flows, as Vuolteenaho (2002) highlighted. Investors typically pay higher share prices for companies demonstrating greater profitability. Regarding the IPO offer price influenced by financial indicators, the models mentioned above seek to either reject or fail to reject the null hypothesis (H_0) for their respective independent variables, and the hypothesis summary is given below in table 4.

Table 4: Pre-IPO Analysis Summary of Hypothesis

Number	Hypothesis	Null Hypothesis (H_0)	Alternative Hypothesis (H_1)
1	Hypothesis for PE	There is no significant positive relationship between Price to Earnings and IPO Offer Price.	There is a significant positive relationship between Price to Earnings and IPO Offer Price.
2	Hypothesis for PB	There is no significant positive relationship between Price to Book and IPO Offer Price.	There is a significant positive relationship between Price to Book and IPO Offer Price.
3	Hypothesis for ROE	There is no significant positive relationship between Return on Equity and IPO Offer Price.	There is a significant positive relationship between Return on Equity and IPO Offer Price.
4	Hypothesis for NIA	There is no significant positive relationship between Net Income to Assets and IPO Offer Price.	There is a significant positive relationship between Net Income to Assets and IPO Offer Price.
5	Hypothesis for MKS	There is no significant positive relationship between Market Sentiments and IPO Offer Price.	There is a significant positive relationship between Market Sentiments and IPO Offer Price.

PE = Price to Earning, PB = Price to Book, ROE = Return on Equity, NIA = Net Income to Assets, MKS = Market Sentiments

5.4. Methodological Framework for Post-IPO Performance

This section outlines the methodology and data utilized in the empirical study conducted for this thesis. The initial guidelines and theoretical framework were presented in the introductory section. Here, we delve into the Fama and French Five-Factor Model and the empirical data used in our analysis.

5.4.1. Fama-French 5-Factor Model

The second part of this thesis examines whether the Fama and French Five-Factor Model can explain post-IPO performance. This model, developed by Kenneth R. French and Eugene F. Fama, expands upon the Capital Asset Pricing Model (CAPM). CAPM establishes the relationship between an asset's expected return and the risk associated with investing in that asset (Sharpe, 1964). According to CAPM, the expected return on a security is a function of the risk-free rate, the security's beta, and the market return, expressed as follows.

$$r_i = R_f + \beta_i (R_m - R_f)$$

Fama and French identified limitations in CAPM, particularly its inability to explain certain market anomalies. They observed consistent patterns in stock returns that were not accounted for by the market beta. CAPM does not consider company-specific characteristics such as size or financial metrics, which have been shown to relate to average returns on common stocks (Banz, 1981). To address these shortcomings, Fama and French added two additional factors to the CAPM, creating the Three-Factor Model (Fama & French, 1993). In this model, the Size Factor (SMB) captures the higher average returns of smaller stocks compared to more extensive stocks, while the Value Factor (HML) accounts for the outperformance of value stocks (those with high book-to-market ratios) overgrowth stocks. The Three-Factor Model is represented as follows:

$$r_i = r_f + \beta_1 (r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \varepsilon$$

In 2015, Fama and French introduced an enhanced Five-Factor Model to address additional limitations and better capture variations in stock returns (Fama & French, 2015). The Five-Factor Model incorporates two new factors: the Profitability Factor (RMW - Robust Minus Weak), which differentiates stocks with robust profitability from those with weak profitability, and the Investment

Factor (CMA - Conservative Minus Aggressive), which accounts for the differences in returns based on firms' investment behaviors. Including these factors provides a more comprehensive explanation of expected returns by considering profitability and investment patterns. The Five-Factor Model is formulated as follows:

$$r_i = r_f + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \beta_4(RMW) + \beta_5(CMA) + \varepsilon$$

Through this model, this thesis aims to investigate whether these five factors can effectively explain post-IPO performance, thus providing a deeper understanding of the dynamics at play in this period.

5.4.1.1. Justification for Using the Fama-French Five-Factor Model

The choice of the Fama and French Five-Factor Model for analyzing post-IPO performance is rooted in its ability to provide a more comprehensive and nuanced understanding of stock returns compared to the earlier Three-Factor Model. While the Three-Factor Model, introduced by Fama and French in 1993, incorporates market risk, size, and value factors, it has certain limitations that the Five-Factor Model addresses more effectively.

Enhanced Explanatory Power

The Five-Factor Model includes two additional factors: profitability (RMW) and investment (CMA). These factors capture dimensions of stock returns that are not explained by the Three-Factor Model. Research by Fama and French (2015) demonstrates that the Five-Factor Model explains a larger proportion of the variance in stock returns, thereby offering a more complete picture of the determinants of stock performance (Fama & French, 2015).

Profitability Factor (RMW)

The profitability factor differentiates stocks based on their profitability, distinguishing between firms with robust profitability (high RMW) and those with weak profitability (low RMW). Incorporating this factor is particularly relevant for post-IPO performance analysis as newly public firms often exhibit varying levels of profitability, which significantly impacts on their stock performance. Including RMW helps capture the effect of profitability on post-IPO returns, providing a more detailed assessment than the Three-Factor Model (Novy-Marx, 2013).

Investment Factor (CMA)

The investment factor accounts for differences in returns based on firms' investment behaviors. It distinguishes between conservative firms (low investment) and aggressive firms (high investment). This factor is crucial for post-IPO performance analysis as it reflects the impact of a company's growth strategies and capital expenditure on its stock returns. Newly public companies may adopt different investment approaches post-IPO, and the CMA factor helps capture the associated return patterns, enhancing the model's explanatory power (Titman, Wei, & Xie, 2004).

Addressing Anomalies and Improving Accuracy

The Five-Factor Model is designed to address certain anomalies and shortcomings observed with the Three-Factor Model. For instance, the Three-Factor Model does not adequately explain the performance of stocks with differing profitability and investment characteristics. By incorporating RMW and CMA, the Five-Factor Model reduces unexplained anomalies, thereby improving the accuracy and reliability of the analysis of post-IPO performance (Fama & French, 2015; Ball, Gerakos, Linnainmaa, & Nikolaev, 2016).

Comprehensive Risk Assessment

The Five-Factor Model provides a more thorough risk assessment by considering additional dimensions of risk related to profitability and investment. This comprehensive approach is essential for investors and researchers aiming to understand the full spectrum of factors influencing stock returns, especially in the dynamic post-IPO phase where firms' financial and operational strategies may significantly evolve (Fama & French, 2017; Hou, Xue, & Zhang, 2015).

By choosing the Fama and French Five-Factor Model, this thesis aims to leverage its enhanced explanatory power and comprehensive nature to provide a deeper and more accurate analysis of post-IPO performance. The inclusion of profitability and investment factors allows for a more detailed investigation of the various dimensions influencing stock returns, thereby offering valuable insights into the performance dynamics of newly public companies.

5.4.2. Variables for Regression

In the post IPO performances section, this thesis uses Fama-French five factor model, therefore there are five independent (explanatory) variables they are Market Risk Premium (MRP), Size Factor (SMB), Value factor (HML), Profitability factor (RMW) and investment factor (RMW). An overview of these variables is given below.

When constructing the SMB, HML, RMW, and CMA factors, stocks in a region are sorted into two market cap groups and three groups each for book-to-market equity (B/M), operating profitability (OP), and investment (INV) at the end of June. Big stocks are in the top 90% of the region's market cap in June, while small stocks are in the bottom 10%. The breakpoints for B/M, OP, and INV in a region are set at the 30th and 70th percentiles of the respective ratios for the region's big stocks.

This thesis employs the daily values of European five-factor Fama-French model focusing on developed European countries. Specifically, it includes Sweden, Norway, Denmark, and Finland, representing the main stock exchanges of Scandinavia covered in this study.

Market Risk Premium (MRP)

The Market Risk Premium (MRP) is designed to capture the excess return that investing in the stock market provides over a risk-free rate. This premium is a key component in various asset pricing models, reflecting the compensation investors demand for taking on the higher risk associated with equity investments. The MRP is calculated as the difference between the expected return on a market portfolio and the risk-free rate, Taylor. L. (2021).

Small Minus Big (SMB)

The SMB (Small Minus Big) factors are constructed to capture the average return differences between small-cap and large-cap stocks across various dimensions. SMB(B/M) represents the return difference based on book-to-market ratios by comparing the average returns of small-value, neutral, and growth stocks to those of big-value, neutral, and growth stocks. Similarly, SMB(OP) measures the return difference based on operating profitability by contrasting the returns of small robust, neutral, and weak profitability stocks with those of big robust, neutral, and weak profitability stocks. SMB(INV) reflects the return difference based on investment levels, comparing small conservative, neutral, and aggressive investment stocks to big conservative, neutral, and aggressive investment stocks. Finally, the overall SMB factor is calculated as the average of these three components: one-third of SMB(B/M), one-third of SMB(OP), and one-third of SMB(INV).

SMB = $^{1}/_{3}$ (SMB (B/M) + SMB (OP) + SMB (INV))

High Minus Low (HML)

HML factor is computed as the difference between the average return of the two value portfolios and the average return of the two growth portfolios.

HML = 0.5 (Small Value + Big Value) - 0.5 (Small Growth + Big Growth)

Robust Minus Weak (RMW)

RMW factor is calculated as the difference between the average return of the two robust operating profitability portfolios and the average return of the two weak operating profitability portfolios.

RMW = 0.5 (Small Robust + Big Robust) - 0.5 (Small Weak + Big Weak)

Conservative Minus Aggressive (CMA)

The CMA factor is calculated as the difference between the average returns of the two conservative investment portfolios and the average returns of the two aggressive investment portfolios.

CMA = 0.5 (Small Conservative + Big Conservative) - 0.5 (Small Aggressive + Big Aggressive)

Age of the firm (AGE)

The AGE factor is included as a control variable to account for differences in firm maturity. Generally, older firms have more established operations, advanced business strategies, and stable revenue streams. This maturity often leads to more predictable and stable performance after the IPO. Additionally, older firms tend to have experienced management teams and a strong market presence, which can mitigate operational and financial risks. By including firm age as a control variable, this study seeks to accurately isolate the impact of the Fama-French 5-Factor Model on post-IPO performance. This approach ensures that the varying levels of maturity and stability among firms do not confound the observed relationships, providing a clearer analysis of how the Fama-French factors affect post-IPO performance.

AGE = Date of the IPO - Date of incorporation

5.4.3. Application of the Fama-French Five-Factor Model in OLS Regression Analysis

Based on the variables discussed above, the Fama-French five-factor model with AGE as a control variable can be presented as follows. This model aims to capture the relationship between the excess return of a stock and the various factors influencing it, including market risk, size, value, profitability, and investment, with AGE as a control variable.

$$r_{it} = r_{ft} + \alpha + \beta_1(r_{mt} - r_{ft}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(RMW_t) + \beta_5(CMA_t) + \beta_6(AGE_t) + \varepsilon_{it}$$

5.5. Post-IPO Analysis and Hypothesis

Table 5 presents the hypotheses regarding post-IPO performance, examining the relationship between various financial factors and their impact. For each factor that is MKP, SMB, HML, RMW, and CMA the null hypothesis asserts no relationship with post-IPO performance, while the alternative hypothesis posits a significant relationship.

Table 5: Post IPO Performances Hypothesis

Number	Hypothesis	Null Hypothesis (H_0)	Alternative Hypothesis (H_1)
1	Hypothesis for MKP	There is no relationship between the MKP factor and post-IPO performance.	There is a relationship between the MKP factor and post-IPO performance.
2	Hypothesis for SMB	There is no relationship between the SMB factor and post-IPO performance.	There is a relationship between the SMB factor and post-IPO performance.
3	Hypothesis for HML	There is no relationship between the HML factor and post-IPO performance.	There is a relationship between the HML factor and post-IPO performance.
4	Hypothesis for RMW	There is no relationship between the RMW factor and post-IPO performance.	There is a relationship between the RMW factor and post-IPO performance.
5	Hypothesis for CMA	There is no relationship between the CMA factor and post-IPO performance.	There is a relationship between the CMA factor and post-IPO performance.

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak
CMA = Conservative Minus Aggressive, ER = Excess Return, AGE = Years from incorporation to IPO date

5.5.1. Country-Specific Analysis

This section details the methodology used to assess whether the Fama and French five-factor model, augmented with age as a control variable, explains post-IPO performance in Scandinavian countries. Given the potential differences in market dynamics and economic conditions across Denmark, Norway, Finland, and Sweden, examining whether country-specific effects play a role in post-IPO performance is essential. To do this, we incorporate country-specific dummy variables into our regression model, with Sweden chosen as the base country. Sweden was selected due to the higher volume of IPOs relative to the other countries, which provides a more robust reference point.

This analysis is significant as it aims to uncover variations in post-IPO performance across different Scandinavian markets. Understanding these differences can offer insights into country-specific factors affecting IPO outcomes, which is valuable for investors, policymakers, and companies considering going public in these regions.

5.5.1.1. Country-Specific Model and Description

We use an OLS panel regression model to examine how the Fama and French five factors, along with age and country-specific effects, influence post-IPO performance. The model is formulated as follows:

$$ER_{it} = \beta_0 + \beta_1 MRP_{it} + \beta_2 SMB_{it} + \beta_3 HML_{it} + \beta_4 RMW_{it} + \beta_5 CMA_{it} + \beta_6 AGE_{it} + \beta_7 Denmark_i + \beta_8 Norway_i + \beta_9 Finland_i + \varepsilon_{it}$$

- Dependent variable (ER_{it}) = Post IPO Excess Return
- Independent variables

  $\beta 1$ MRP_{it} = Market risk premium for firm i at time t.

  $\beta 2$ SMB_{it} = Size premium

  $\beta 3$ HML_{it} = Value premium

  $\beta 4$ RMW_{it} = Profitability factor

  $\beta 5$ CMA_{it} = Investment factor

- Control Variable

  $\beta 6$ AGE $_{it}$ = Age of the firm

- Dummy Variables

  $\beta 7$ Denmark $_{i}$, $\beta 8$ Norway $_{i}$, $\beta 9$ Finland $_{i}$ are dummy variables for countries.

- $\beta 0$ = Interceptor
- ε_{it} = Error term.

5.5.1.2. Country Specific Hypothesis

This thesis section aims to determine whether country-specific factors significantly affect post-IPO performance in Scandinavian countries. We can test the following hypotheses by including dummy variables for Denmark, Norway, and Finland, with Sweden as the base country. By analyzing these country-specific effects, we can better understand how different regulatory environments and market conditions impact IPO success. Previous research has shown that country-specific factors, such as legal systems and market maturity, can significantly influence IPO performance (Boulton, Smart, & Zutter, 2011). Country specific hypotheses is given in the following table 6.

Table 6: Country specific hypothesis summary

Country	Hypothesis	Null Hypothesis (H_0)	Alternative Hypothesis (H_1)
Denmark	Hypothesis for Denmark	No significant difference in post-IPO performance between Sweden and Denmark.	Significant difference in post-IPO performance between Sweden and Denmark.
Norway	Hypothesis for Norway	No significant difference in post-IPO performance between Sweden and Norway.	Significant difference in post-IPO performance between Sweden and Norway.
Finland	Hypothesis for Finland	No significant difference in post-IPO performance between Sweden and Finland.	Significant difference in post-IPO performance between Sweden and Finland.

By including the dummy variables for Denmark, Norway, and Finland, we can compare their coefficients to the base category (Sweden). Significant coefficients will prove that post-IPO performance is influenced by the country where the IPO takes place. This analysis is crucial as it can reveal whether local market conditions, regulatory environments, or economic factors in each country play a role in the success of IPOs. The results can help investors and policymakers understand the nuances of post-IPO performance in different Scandinavian countries and guide decision-making processes accordingly.

5.5.2.1. Year-Based Specific Analysis

This section of the thesis details the methodology used to assess whether the Fama and French five-factor model, strengthened with age as a control variable, explains post-IPO performance over different years in the Scandinavian market. Given the fluctuations in market conditions, investor sentiment, and economic environment from 2010 to 2021, examining whether year-specific effects play a significant role in post-IPO performance is crucial. To this end, this thesis incorporates year-specific dummy variables into the regression model, with 2021 chosen as the base year. 2021 is selected due to the higher volume of IPOs relative to other years, providing a more robust reference point.

This significant analysis aims to uncover variations in post-IPO performance across different years. Understanding these temporal differences can offer insights into how yearly changes in market conditions and economic factors impact after-market IPO performances. This information is valuable for investors, policymakers, and companies considering going public, as it emphasizes the importance of timing in the IPO process.

5.5.2.2. Year-Based Model and Description

To examine how the five factors of Fama and French, along with age and year-specific effects, influence post-IPO performance, we analyze the data using an OLS panel regression model. The model is formulated as follows.

$$ER_{it} = \beta_0 + \beta_1 MRP_{it} + \beta_2 SMB_{it} + \beta_3 HML_{it} + \beta_4 RMW_{it} + \beta_5 CMA_{it} + \beta_6 AGE_{it} + \sum_{J=2010}^{2020} \beta_j YEAR_j + \mathcal{E}_{it}$$

- Dependent variable (ER_{it}) = Post IPO Excess Return
- Independent variables

  β1 MRP_{it} = Market risk premium for firm i at time t.

  β2 SMB_{it} = Size premium

  β3 HML_{it} = Value premium

  β4 RMW_{it} = Profitability factor

  β5 CMA_{it} = Investment factor

- Control variable.

  β6 AGE_{it} = Age of the firm

- Dummy Variables = YEAR dummies from 2010 to 2020, with 2021 as the base year
- β0 = Intercept
- $\mathcal{E}_{it}$ = Error term.

5.5.2.3. Year-Based Hypothesis

This thesis section determines whether year-specific factors significantly affect post-IPO performance in Scandinavian countries. It has included dummy variables for each year from 2010 to 2020, with 2021 as the base year, to test the following hypotheses for each year. This approach benefits the understanding and the impact of different economic conditions, market dynamics, and investor sentiment across different years on the post-IPO performance segment. According to Ritter (1991), economic conditions at the time of the IPO significantly influence long-term IPO performance. Additionally, Loughran and Ritter (2004) highlight how varying market conditions and investor sentiment over different years impact IPO underpricing and subsequent performance. Ljungqvist, Nanda, and Singh (2006) further emphasize the role of hot markets and investor sentiment in determining IPO pricing and performance.

Table 7: Three Year Based Hypotheses for Post-IPO Performances

Year	Hypothesis	Null Hypothesis (H_0)	Alternative Hypothesis (H_1)
2010	Hypothesis for 2010	No significant difference in post-IPO performance between 2010 and 2021.	Significant difference in post-IPO performance between 2010 and 2021.
2011	Hypothesis for 2011	No significant difference in post-IPO performance between 2011 and 2021.	Significant difference in post-IPO performance between 2011 and 2021.
2012	Hypothesis for 2012	No significant difference in post-IPO performance between 2012 and 2021.	Significant difference in post-IPO performance between 2012 and 2021.
2013	Hypothesis for 2013	No significant difference in post-IPO performance between 2013 and 2021.	Significant difference in post-IPO performance between 2013 and 2021.
2014	Hypothesis for 2014	No significant difference in post-IPO performance between 2014 and 2021.	Significant difference in post-IPO performance between 2014 and 2021.
2015	Hypothesis for 2015	No significant difference in post-IPO performance between 2015 and 2021.	Significant difference in post-IPO performance between 2015 and 2021.
2016	Hypothesis for 2016	No significant difference in post-IPO performance between 2016 and 2021.	Significant difference in post-IPO performance between 2016 and 2021.
2017	Hypothesis for 2017	No significant difference in post-IPO performance between 2017 and 2021.	Significant difference in post-IPO performance between 2017 and 2021.
2018	Hypothesis for 2018	No significant difference in post-IPO performance between 2018 and 2021.	Significant difference in post-IPO performance between 2018 and 2021.
2019	Hypothesis for 2019	No significant difference in post-IPO performance between 2019 and 2021.	Significant difference in post-IPO performance between 2019 and 2021.
2020	Hypothesis for 2020	No significant difference in post-IPO performance between 2020 and 2021.	Significant difference in post-IPO performance between 2020 and 2021.

5.5.3. Sector Based Specific Analysis

This section details the methodology used to investigate whether the Fama and French five-factor model, augmented with age as a control variable, can explain post-IPO performance across various sectors in the Scandinavian market. Given the diverse economic conditions and market dynamics specific to each industry, it is essential to determine if sector-specific factors significantly influence post-IPO performance. To achieve this, sector-specific dummy variables are included in the regression model, with the 'Other' sector serving as the baseline due to its higher number of IPOs, providing a comprehensive reference point.

This analysis aims to reveal differences in post-IPO performance across sectors, offering insights into how industry-specific characteristics impact IPO outcomes. Understanding these distinctions is valuable for investors, policymakers, and firms contemplating going public, underscoring the importance of industry context in the IPO process.

5.5.3.1. Sector Based Model and Description

An OLS panel regression model is employed to assess how the five factors of the Fama and French, along with age and sector-specific effects, influence post-IPO performance. The model is specified as follows:

$$ER_{it} = \beta_0 + \beta_1 MRP_{it} + \beta_2 SMB_{it} + \beta_3 HML_{it} + \beta_4 RMW_{it} + \beta_5 CMA_{it} + \beta_6 AGE_{it} + \sum_j \beta_j SECTOR_j + \varepsilon_{it}$$

- Dependent variable (ER_{it}) = Post IPO Excess Return
- Independent variables

    $\beta 1$ MRP_{it} = Market risk premium for firm i at time t.

    $\beta 2$ SMB_{it} = Size premium

    $\beta 3$ HML_{it} = Value premium

    $\beta 4$ RMW_{it} = Profitability factor

    $\beta 5$ CMA_{it} = Investment factor

- Control variable - $\beta 6$ AGE_{it} = Age of the firm
- Dummy Variables = SECTOR dummies with OTHER sector as the base year
- $\beta 0$ = Intercept
- ε it = Error term.

5.5.3.2. Sector-Based Hypothesis

This section examines whether sector-specific factors significantly influence post-IPO performance in Scandinavian countries. Dummy variables for each sector are included to test the hypothesis that industry-specific characteristics impact IPO performance. This approach provides insights into how different economic conditions, market dynamics, and investor sentiment across sectors affect post-IPO outcomes. According to research by Boulton, Smart, and Zutter (2010), industry-specific trends such as technological advancements and regulatory environments play crucial roles in determining the performance of IPOs within various sectors.

Table 8: Sector Based Hypotheses for Post-IPO Performances

Sector	Hypothesis	Null Hypothesis (H_0)	Alternative Hypothesis (H_1)
NoDur	Hypothesis for NoDur	No significant difference between NoDur and Other sector.	Significant difference between NoDur and Other sector.
Durbl	Hypothesis for Durbl	No significant difference between Durbl and Other sector.	Significant difference between Durbl and Other sector.
Manuf	Hypothesis for Manuf	No significant difference between Manuf and Other sector.	Significant difference between Manuf and Other sector.
Enrgy	Hypothesis for Enrgy	No significant difference between Enrgy and Other sector.	Significant difference between Enrgy and Other sector.
BusEq	Hypothesis for BusEq	No significant difference between BusEq and Other sector.	Significant difference between BusEq and Other sector.
Telcm	Hypothesis for Telcm	No significant difference between Telcm and Other sector.	Significant difference between Telcm and Other sector.
Shops	Hypothesis for Shops	No significant difference between Shops and Other sector.	Significant difference between Shops and Other sector.
Hlth	Hypothesis for Hlth	No significant difference between Hlth and Other sector.	Significant difference between Hlth and Other sector.
Money	Hypothesis for Money	No significant difference between Money and Other sector.	Significant difference between Money and Other sector.

NoDur = Consumer Nondurable, Durbl = Consumer Durable, Manuf = Manufacturing, Enrgy = Energy,
BusEq = Business Equipment, Telcm = Telecom, Shops = Shops, Hlth = Healthcare, Money = Money, Other = Other sectors

5.6. OLS Assumptions

To ensure consistent and unbiased estimates, our project needs to meet several theoretical assumptions. The next chapter outlines the key assumptions of our linear regression model and the methods for testing them. Different sources list between five and eight assumptions, some of which are testable, while others are complex and challenging to test meaningfully.

5.6.1. Normality

Assessing the normality of residuals is crucial for validating linear regression results. Normal residuals indicate that the differences between predicted and actual values are symmetrically distributed around zero and follow a Gaussian distribution. However, with financial data, non-normal residual distributions are common due to inherent volatility and clustering effects, leading to inefficiencies in estimation and inaccuracies in inference (Charles & Darné, 2019; Hambuckers & Heuchenne, 2017). Despite this, the Central Limit Theorem often justifies the normality assumption by stating that the distribution of the sum of a large number of independent, identically distributed random variables tends to be normal, even if the original variable distributions are not. This thesis uses the Jarque-Bera test and Q-Q plots to check residual normality.

5.6.2. Heteroscedasticity

Heteroscedasticity occurs when the variability of residuals in a regression model is inconsistent across all levels of the independent variables. This means that as the values of the independent variables change, the residuals' variance also changes. This violation of the homoscedasticity assumption can significantly impact the reliability of the linear regression model. In a well-constructed model, we expect the residuals' variability to be constant across all levels of the independent variables, indicating homoscedasticity. However, it is common to observe heteroscedasticity, particularly in financial data.

Identifying heteroscedastic residuals is crucial because it can lead to inefficient results, such as biased standard errors. This, in turn, affects the accuracy of hypothesis testing and confidence intervals. Heteroscedasticity is one of the assumptions that can be tested, and we will conduct such a test later in this thesis. There are several methods to test for heteroscedasticity. Initially, a scatterplot of the residuals provides an excellent visual indication of their distribution. For a more formal test, the White test, Goldfeld-Quandt Test, Harvey-Collier Test, and Breusch-Pagan test are used. This thesis uses the Breusch-Pagan test for heteroscedasticity. In this test, the p-value indicates the significance of the test. If the p-value is below a certain threshold (commonly 0.05), it suggests significant heteroscedasticity in the residuals.

5.6.3. Autocorrelation

Autocorrelation occurs when the error term in a regression model depends on its previous values. In other words, information about a past shock helps to explain a current shock. Autocorrelation, or "serial correlation," refers to the degree of similarity between a time series and its lagged version over consecutive time intervals. Specifically, autocorrelation measures this degree of similarity, indicating how past values influence current values in the series (Krämer & Donninger, 1987).

Several methods are used to test for autocorrelation in time series data, including the Ljung-Box test, the Breusch-Godfrey test, the Durbin-Watson test, and visual inspections. For our analysis, we employed the Breusch-Godfrey test. The Breusch-Godfrey test yields a chi-square statistic; a higher p-value (closer to 1) suggests no autocorrelation, while a lower p-value (closer to 0) indicates the presence of autocorrelation.

5.6.4. Linearity

The connection between the independent and dependent variables must be linear. This implies that the anticipated value of the conditional variable is a linear combination of the independent variables (Burnett, N.J, & Scyoc, L. J. V. 2023). The OLS assumption concerning linearity pertains to fitting a linear model to data that may not have a linear relationship. If the relationship is linear, the model becomes effective. To assess linearity, we will use the residuals versus fitted plot in R. This plot illustrates the variability of the residuals against the predictor variables. A more linear relationship enhances the model's predictive accuracy, meeting the OLS assumptions (Stock & Watson, 2019). Linearity can be tested through visual inspections using scatter plots or residual plots, and this thesis uses the Rainbow test to check the linearity; in this test, a significant p-value (typically < 0.05) indicates a departure from linearity.

6. Analysis and Results

This chapter comprehensively analyzes the study's findings, building on the methodology and theories discussed in previous chapters. As outlined in the introduction, the thesis is divided into two main sections: the results of pre-IPO financial performance indicators and the analysis of post-IPO performance using the Fama-French five-factor model.

In the first section (6.1), we examine whether companies' financial performance indicators prior to their IPOs influence their offer prices. In the second section (6.2), we explore how the Fama-French five-factor model explains post-IPO performance.

The analysis begins with removing outliers, ensuring that extreme values do not skew the results. This is followed by descriptive statistics, which summarize the data. Next, we detect multicollinearity, which checks for high correlations between independent variables that could affect the regression results. Finally, we conduct regression analysis and diagnostic testing to validate the findings. This process is applied to both the pre-IPO and post-IPO performance sections.

6.1. Pre-IPO Financial Performance Indicators Results

6.1.1. Pre-IPO Descriptive Statistics

The first step in any statistical investigation is obtaining descriptive statistics for the data. Descriptive statistics summarize a dataset, highlighting key characteristics of the sample. As detailed in the data collection chapter, 131 companies were included in the pre-IPO analysis, resulting in 393 observations, as three years of financial data per company prior to listing are included in the panel regression. Table 9 given below presents the descriptive statistics for the independent, control, and dependent variables before removing outliers.

Table 9: Descriptive statistics of pre-IPO variables before removing outliers

	Observations	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis
PE	393	-1150.00	3790.85	21.56	254.90	8.21	126.34
PB	393	-201.69	324.86	10.48	35.71	3.48	33.94
ROE	393	-1430.61	539.75	-9.60	102.20	-7.02	100.66
NIA	393	-3.27	1.17	-0.07	0.44	-2.85	19.01
MKS	393	-0.22	0.28	0.04	0.08	-0.13	3.53
OFS	393	0.66	580.49	31.29	64.69	6.09	46.80
AGE	393	0.33	123.00	17.89	23.88	2.84	11.16
OFP	393	0.39	23.00	5.27	3.85	1.85	8.02

PE= Price to Earning, PB = Price to Book, ROE = Return on Equity, NIA = Net Income to Assets, MKS = Market Sentiment

OFS = Size of the Offer (Number of shares), AGE = Years from Incorporation to IPO, OFP = IPO Offer

6.1.2. Pre-IPO Outliers

The Pre-IPO analysis consisted of 393 observations. Descriptive statistical analyses reveal the presence of extreme outliers, which is expected given the size of the data sample. The high skewness and kurtosis values in the descriptive statistics indicate a higher number of outliers. To identify these outliers, the thesis employs the z-score method. Specifically, any data points with z-scores below -3 or above +3 were considered extreme outliers and excluded from the analysis. The outliers identified and excluded through this method are detailed in Table 10 under the updated statistical description section. This trimming process reduces the number of observations in the pre-IPO analysis from 393 to 345.

Table 10: Updated Descriptive Statistics of Pre-IPO Variables After Outlier Removal

	Observations	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis
PE	345	-623.29	769.75	17.18	131.28	0.93	16.11
PB	345	-89.45	103.67	7.29	14.94	1.75	22.10
ROE	345	-303.91	219.89	-4.33	54.25	-1.60	9.20
NIA	345	-1.37	1.17	-0.03	0.30	-0.77	8.03
MKS	345	-0.16	0.28	0.04	0.08	0.05	3.17
OFS	345	0.66	220.00	24.78	31.09	2.95	15.86
AGE	345	0.33	77.00	14.28	14.96	2.22	7.81
OFP	345	0.39	16.73	5.11	3.32	1.14	4.62

PE= Price to Earning, PB = Price to Book, ROE = Return on Equity, NIA = Net Income to Assets, MKS = Market Sentiment
OFS = Size of the Offer (Number of shares), AGE = Years from Incorporation to IPO, OFP = IPO Offer

Table 10 above illustrates key statistics for pre-IPO variables after outlier removal using a Z-score threshold 3. The average OFP is 5.11, with a moderate range between the minimum (0.39) and maximum (16.73) values. The PE ratio varies significantly, from -623.29 to 769.75, with an average of 17.18. The PB ratio averages 7.29, ranging from -89.45 to 103.67.

Both ROE and NIA have negative average values, at -4.33 and -0.03, respectively. NIA's standard deviation is relatively low at 0.30, while ROE's is higher at 54.25, indicating greater variability. MKS has a small range from -0.16 to 0.28, with an average of 0.04 and the lowest standard deviation of 0.08, suggesting a uniform distribution.

The OFS shows significant variability, with an average of 24.78 and a standard deviation of 31.09, ranging from 0.66 to 220.00. Finally, the average number of years from incorporation to AGE is 14.28, with a standard deviation of 14.96, spanning from 0.33 to 77.00 years. These statistics highlight substantial PE, PB, ROE, and OFS variability, while NIA and MKS exhibit lower variability. After removing outliers using a Z-score threshold of 3, we observed a significant improvement in the skewness and kurtosis values. However, it is important to note that the PE, PB, and OFS ratios still exhibit distributions with considerable skewness and kurtosis. This suggests the presence of heavy tails and potential outliers even after the initial outlier removal process.

6.1.3. Initial Correlation Matrix

Before conducting the primary analysis central to this empirical study, this thesis examines the data used in the models. A correlation matrix summarizing the coefficients for all variables in this study has been created. Generating correlation coefficient tables for various sets of variables within the context of linear regression analysis provides an initial indication of the relationships between variables. The following Table 11 offers a detailed analysis of the correlations between all variables.

Table 11: Pre-IPO factors' initial correlation matrix

	PE	PB	ROE	NIA	MKS	OFS	AGE	OFP
PE	1.000							
PB	0.153**	1.000						
ROE	0.135*	0.031	1.000					
NIA	0.147**	-0.016	**0.844****	1.000				
MKS	-0.017	0.015	0.049**	0.055**	1.000			
OFS	0.006	-0.076	0.107**	0.103**	0.078	1.000		
AGE	-0.067	-0.019	0.181**	0.308**	0.038	0.102	1.000	
OFP	0.142**	-0.034	0.256**	0.273**	-0.114*	-0.075	0.068**	1.000

** Correlation is significant at the 0.01 level. * Correlation is significant at the 0.05 level.

PE= Price to Earning, PB = Price to Book, ROE = Return on Equity, NIA = Net Income to Assets, MKS = Market Sentiment
OFS = Size of the Offer (Number of shares), AGE = Years from incorporation to IPO date, OFP = IPO Offer

The correlation matrix indicates a high correlation between the ROE and NIA variables. From a financial perspective, this is expected since both ratios evaluate returns on equity and assets, respectively. However, the correlation between these two figures is exceptionally high at 0.844, with a p-value below 0.01, indicating statistical significance. The Variance Inflation Factor (VIF) was calculated to investigate this further. The following Table 12 presents the VIF values for all independent and control variables.

Table 12: Initial VIF values for Pre-IPO Analysis

	Variance Inflation Factor (VIF)
PE	1.064
PB	1.040
ROE	**3.598**
NIA	**3.873**
MKS	1.010
OFS	1.031
AGE	1.156

Variance Inflation Factor (VIF) measures the degree to which the variance of a regression coefficient is inflated due to collinearity with other predictors. A VIF of 1 indicates no correlation between a predictor and any other predictors. Generally, a VIF above ten is considered high and suggests significant multicollinearity, though some scholars use a threshold of 5 (O'Brien, 2007).

Notably, the VIF values for ROE and NIA are relatively high at 3.598 and 3.873, respectively. This is consistent with the high correlation (0.844) between these coefficients in the correlation matrix. However, based on the VIF output values, we will proceed with the initial OLS Panel Regression, including all the variables as the initial step.

6.1.4. Initial Regression Results

Before conducting the final regression analysis, an initial OLS Panel Regression was performed to evaluate the variables' behavior and significance. Table 13 below summarizes the regression results.

Table 13: Pre IPO-Analysis - Results of Initial Regression

Explanatory Variables	Coefficients (Beta)	t-Statistics	Significance (p-Value)
(Constant)	5.676	18.693	0.0000***
PE	0.003	2.083	0.0380**
PB	-0.013	-1.081	0.2807
ROE	0.006	1.072	0.2844
NIA	2.007	1.798	0.0731*
MKS	-5.097	-2.313	0.0214**
OFS	-0.011	-1.952	0.0518*
AGE	0.003	0.258	0.7968

Note: Dependent variable is Offer Price, R = 0.340, R^2 = 0.116, F-Value = 6.311

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

PE = Price to Earning, PB = Price to Book, ROE = Return on Equity, NIA = Net Income to Assets, MKS = Market Sentiment OFS = Size of the Offer (Number of shares), AGE = Years from incorporation to IPO date, OFP = IPO Offer Price

This preliminary regression reveals several interesting findings. First, we see that only PE and MKS, i.e., Price to Earnings and Market Sentiments, are significant at the 5% level, while NIA and OFS, i.e., Net Income to Assets and Size of the Offer (number of shares), are significant at the 10% level. This implies that PB, ROE, and AGE, i.e., Price to Book, Return on Equity, and Age of the firm, are irrelevant.

The coefficient estimates for PE indicate a positive relationship between this factor and the IPO offer price; specifically, a one-unit increase in PE results in a 0.003 unit increase in the IPO offer price. This suggests that PE has a very marginal positive influence on the IPO offer price.

Most interestingly, MKS, the market sentiments of the respective stock market, have a negative relationship with the IPO offer price. A one-unit increase in MKS would reduce the IPO offer price by 5.097. This is worth further investigation, as it suggests that market sentiments negatively affect the IPO offer price. Furthermore, the p-value of 0.0214 indicates that this coefficient is statistically significant, suggesting that the relationship is not due to random chance.

It is worth noting that NIA and OFS, i.e., Net Income to Assets and Size of the Offer in terms of the number of shares, have positive and negative relationships with the IPO offer price, respectively, with coefficients of 2.007 and -0.011, both significant at the 10% level. The R-squared value stood at 0.116, indicating that the model explains 11.6% of the variance in the IPO offer price. The F-value of 6.311, combined with a very low p-value, confirms that the relationships identified by the model are statistically significant and not due to random chance.

6.1.5. Management of Multicollinearity

Multicollinearity arises when two or more independent variables in a multiple regression model exhibit high correlation. In such cases, the coefficients are estimated with less precision, necessitating adjustments to the regression model (Stock & Watson, 2019). Generally, a correlation coefficient above 0.8 suggests the presence of multicollinearity. As evidenced in the earlier correlation matrix, the correlation between ROE and NIA is 0.844. In this section of the thesis, this issue will be addressed. Although the VIF values for both ROE and NIA are below the critical threshold, the high correlation of 0.844 necessitates resolving this issue.

The first step in addressing this issue is determining which independent variable, ROE or NIA, should be removed. Regarding VIF values, ROE and NIA recorded values of 3.598 and 3.873, respectively, implying that ROE contributes less to multicollinearity. However, upon closer examination, it is evident that ROE has a higher p-value than NIA, with values of 0.2844 and 0.0731, respectively. Based on this fact, ROE has been removed from the list of independent variables to minimize multicollinearity. Frost (2024) suggests that removing highly correlated variables can reduce multicollinearity and enhance model stability. Similarly, Bobbitt (2024) highlights that this method is effective when the variables do not add substantial unique information to the model. The correlation matrix after removing the ROE is given in Table 14.

Table 14: Pre-IPO factors' final Correlation Matrix

	PE	PB	NIA	MKS	OFS	AGE	OFP
PE	1.000						
PB	0.153**	1.000					
NIA	0.147**	-0.016	1.000				
MKS	-0.017	0.015	0.055**	1.000			
OFS	0.006	-0.076	0.103**	0.078	1.000		
AGE	-0.067	-0.019	0.308**	0.038	0.102	1.000	
OFP	0.142**	-0.034	0.273**	-0.114*	-0.075	0.068**	1.000

** Correlation is significant at the 0.01 level. * Correlation is significant at the 0.05 level.

PE = Price to Earning, PB = Price to Book, ROE = Return on Equity, NIA = Net Income to Assets, MKS = Market Sentiment
OFS = Size of the Offer (Number of shares), AGE = Years from incorporation to IPO date, OFP = IPO Offer Price

The recalculated correlation matrix confirms that none of the variables exhibit a correlation exceeding 0.8. The highest observed correlation is now 0.308 between NIA and AGE, within acceptable limits. To further ensure the minimization of multicollinearity, the VIF values have been recalculated and are presented in Table 15 below.

Table 15: Final VIF values for Pre-IPO Analysis

	Variance Inflation Factor (VIF)
PE	1.064
PB	1.032
NIA	1.150
MKS	1.010
OFS	1.027
AGE	1.128

The VIF test results from the entire data sample, calculated after removing the ROE variable, indicate a low multicollinearity among the remaining variables. The VIF values range from 1.010 to 1.150, with a mean value significantly below the critical threshold of 10 and even below the more conservative threshold of 5. These results strongly suggest that multicollinearity is minimal, confirming the presence of low correlation between the variables in this analysis.

6.1.5.1. Regression Results and Analysis (Multicollinearity Adjusted)

In the revised data set without multicollinearity, the final regression is implemented following the methodology outlined in this thesis. Specifically, an OLS Panel Regression is employed, and three regression models are Model 1, Model 2, and Model 3. They are constructed for broader evaluation. All three models are tested using the filtered data set to eliminate the effects of multicollinearity, which means that ROE is excluded from these analyses.

6.1.6. Pre-IPO Panel Regression - Model 1

In Model 1, the independent variables are PE, PE, NIA, and MKS, while the OFS (Offer Size) is included as the control variable. Table 16 given below presents the coefficients of the independent variables and their relationship to the conditional variable, the OFP (IPO Offer Price).

Table 16: Pre IPO - Results of final Regression - Model 1

Explanatory Variables	Coefficients (Beta)	t-Statistics	Significance (p-Value)
(Constant)	5.711	22.766	0.0000***
PE	0.003	2.079	0.0384**
PB	-0.011	-0.993	0.3213
NIA	3.028	5.248	0.0000***
MKS	-5.088	-2.312	0.0214**
OFS	-0.010	-1.895	0.0589*

Note: Dependent variable is Offer Price, R = 0.3359, R^2 = 0.1128, F-Value = 8.6251

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

PE = Price to Earning, PB = Price to Book, NIA = Net Income to Assets

MKS = Market Sentiment, OFS = Size of the Offer (Number of shares)

The results from the OLS Panel Regression for Model 1 indicate that several factors influence the OFP (IPO Offer Price). Specifically, the OFP shows a positive relationship with PE and NIA, suggesting that higher values of PE and NIA are associated with higher IPO offer prices. Conversely, the OFP exhibits a negative relationship with PB, MKS, and OFS, with OFS being the control variable, indicating that higher values of these variables correspond to lower IPO offer prices.

Model 1 explains 11.28% of the variance in OFP, which suggests that while these variables impact the offer price, other factors not captured by this model also play significant roles.

The statistical significance of the coefficient estimates further underscores the relationships identified. The NIA (3.028) coefficient is highly significant, with a p-value less than 0.001, indicating a robust and reliable influence on the OFP. Similarly, the PE (0.003) and MKS (-5.088) coefficients are statistically significant, with p-values less than 0.05, reinforcing their respective positive and negative impacts on the offer price.

It is particularly noteworthy that the coefficient for MKS is -5.088, implying that for each 1% increase in market sentiment, the IPO offer price decreases by 5.088 units. This finding contrasts with some previous literature. For instance, Bradley and Jordan (2002) observed that IPO offer prices tend to under-adjust to public information, including positive market returns, leading to greater underpricing. Their study suggests that firms set lower offer prices when market sentiments are positive, but these prices must be higher to reflect the favorable market conditions fully.

This discrepancy highlights the complex dynamics of IPO pricing. Further research is needed to reconcile these differences and better understand the influence of market conditions on IPO offer prices.

Overall, Model 1's results provide valuable insights into the determinants of IPO offer prices, highlighting the importance of financial metrics such as PE and NIA, as well as market conditions represented by MKS and OFS. PB was the only coefficient with an insignificant p-value.

6.1.7. Pre-IPO Panel Regression - Model 2

In Model 2, the independent variables are PE, PE, NIA, and MKS, while the AGE (Years from incorporation to IPO date) is included as the control variable. Table 17 given below presents the coefficients of the independent variables and their relationship to the conditional variable, the OFP (IPO Offer Price).

Table 17: Pre IPO - Results of final Regression - Model 2

Explanatory Variables	Coefficients (Beta)	t-Statistics	Significance (p-Value)
(Constant)	5.457	19.718	0.0000**
PE	0.003	2.039	0.0422**
PB	-0.010	-0.848	0.3972
NIA	2.932	4.811	0.0000***
MKS	-5.394	-2.444	0.0150**
AGE	-0.001	-0.048	0.9614

Note: Dependent variable is Offer Price, R = 0.3217, R^2 = 0.10346, F-Value = 7.8244

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

PE = Price to Earning, PB = Price to Book, NIA = Net Income to Assets

MKS = Market Sentiment, AGE = Years from incorporation to IPO date

The results from the OLS Panel Regression for Model 2 align with those from Model 1, indicating that several factors influence the OFP (IPO Offer Price). Specifically, the OFP shows a positive relationship with PE and NIA, suggesting that higher values of PE and NIA are associated with higher IPO offer prices. Conversely, the OFP exhibits a negative relationship with PB and MKS, indicating that higher values of these variables correspond to lower IPO offer prices.

Model 2 explains 10.35% of the variance in OFP, slightly lower than the R-squared recorded in Model 1. This suggests that while these variables impact the offer price, other factors not captured by this model also play significant roles.

The coefficient estimates in Model 2 share similarities with Model 1 in terms of statistical significance. The NIA (2.931) coefficient is highly significant, with a p-value less than 0.001, indicating a robust and reliable influence on OFP. Similarly, the PE (0.003) and MKS (-5.394) coefficients are statistically significant, with p-values less than 0.05, reinforcing their respective positive and negative impacts on the offer price.

Overall, the results of Model 2 provide valuable insights into the determinants of IPO offer prices, highlighting the importance of financial metrics such as PE and NIA, as well as market conditions represented by MKS. Model 2 also suggests that the coefficient of PB is negative (-0.010) and insignificant. This finding aligns with Model 1 but contrasts with previous literature. For instance, Hove et al. (2020) suggests that a higher PB ratio can positively influence the IPO offer price. Their study demonstrates that financial performance indicators, including the PB ratio, significantly predict IPO offer prices. This implies that companies with a higher PB ratio may experience an inflated IPO offer price due to the perceived higher asset valuation and financial health conveyed to potential investors.

6.1.8. Pre-IPO Panel Regression - Model 3

In Model 3, the independent variables are PE, PB, NIA, and MKS. At the same time, the OFS (Size of the Offer in number of shares) and AGE (Years from incorporation to IPO date) are included as the control variables. Table 18 given below presents the coefficients of the independent variables and their relationship to the dependent variable, which is the OFP (IPO Offer Price).

Table 18: Pre IPO - Results of final Regression - Model 3

Explanatory Variables	Coefficients (Beta)	t-Statistics	Significance (p-Value)
(Constant)	5.696	18.785	0.0000***
PE	0.003	2.072	0.0391**
PB	-0.011	-0.993	0.3217
NIA	3.011	4.947	0.0000***
MKS	-5.091	-2.309	0.0215**
OFS	-0.011	-1.894	0.0591*
AGE	0.001	0.090	0.9286

Note: Dependent variable is Offer Price, R = 0.3360, R^2 = 0.1128, F-Value = 7.1679

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

PE = Price to Earning, PB = Price to Book, NIA = Net Income to Assets, MKS = Market Sentiment

OFS = Size of the Offer (Number of shares), AGE = Years from incorporation to IPO date

The results from the OLS Panel Regression for Model 3 are consistent with those from Model 1 and Model 2, indicating that several factors influence the IPO Offer Price (OFP). Specifically, the OFP shows a positive relationship with PE and NIA, suggesting that higher values of these variables are associated with higher IPO offer prices. Conversely, the OFP exhibits a negative relationship with PB and MKS, indicating that higher values of these variables correspond to lower IPO offer prices.

Model 3 explains 11.28% of the variance in OFP, which is slightly higher than the R-squared value recorded in Model 2 but in line with Model 1. This suggests that while these variables impact the offer price, other factors not captured by this model also play significant roles.

Regarding statistical significance, the coefficient estimates in Model 3 also share similarities with Model 1 and Model 2. The NIA (3.011) coefficient is highly significant, with a p-value less than 0.001, indicating a robust and reliable influence on OFP. Similarly, the PE (0.003) and MKS (-5.091) coefficients are statistically significant, with p-values less than 0.05, reinforcing their respective positive and negative impacts on the offer price.

Overall, the results of Model 3 align with Model 1 and Model 2, providing valuable insights into the determinants of IPO offer prices. These results highlight the importance of financial metrics such as PE and NIA and MKS's market conditions. Model 3 also suggests that the coefficient for PB is negative (-0.011) and insignificant. This finding aligns with both Model 1 and Model 2. However, it contrasts with previous literature, such as the findings by Hove et al. (2020), which suggest that a higher PB ratio can positively influence the IPO offer price. Additionally, the coefficient for MKS is -5.091, implying that for each 1% improvement in market sentiments, the IPO offer price decreases by 5.091 units. This also contrasts with some previous literature, as explained in the findings of Model 1.

6.1.9. Diagnostic Testing

In this section, we will test the Ordinary Least Squares (OLS) assumptions, as explained in the methodology section of this thesis. These assumptions are important for ensuring the validity and reliability of our regression results. Adherence to these assumptions ensures that our model provides unbiased and efficient estimates.

6.1.9.1. Heteroscedasticity

The test for heteroscedasticity is conducted using the Breusch-Pagan test. Recalling from the methodology chapter, we require the regression residuals to have the same variability at all levels of the independent variables, i.e., homoscedasticity.

The Breusch-Pagan test is used to assess whether the residuals (errors) variance from a regression model is constant, i.e., to test for homoscedasticity. The null hypothesis of the Breusch-Pagan test is that the residuals have constant variance (homoscedasticity), while the alternative hypothesis is that the residual variance is not constant (heteroscedasticity). The hypothesis for heteroscedasticity can be presented below.

H_0 = The regression model residuals have constant variance (homoscedasticity).

H_1 = The residuals of the regression model do not have constant variance (heteroscedasticity).

The table.19 given below, presents the Breusch-Pagan test results for all three models.

Table 19: Test for Heteroscedasticity

Model	**Breusch-Pagan test**	**P-Value**
Model 1	9.1660	0.1026
Model 2	3.1987	0.6694
Model 3	9.7928	0.1337

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

Based on the results of the studentized Breusch-Pagan test for all three models (BP = 9.166, BP = 3.1987, BP = 9.7928), we fail to reject the null hypothesis (H_0) of homoscedasticity at the 0.05 significance level, as the p-values are all above 0.05. This indicates that the residuals of all three regression models exhibit constant variance. Consequently, the assumption of homoscedasticity is satisfied, which is necessary for the validity and reliability of our regression analysis.

6.1.9.2. Normality

To assess the Normality of the residuals, we employed the Jarque-Bera test. This statistical test is specifically designed to evaluate whether the residuals from a regression model follow a normal distribution. The hypothesis for Normality can be presented as follows.

H_0 = The residuals of the regression model are normally distributed.

H_1 = The residuals of the regression model are not normally distributed.

Table 20 given below presents the Jarque-Bera Test results for all three models.

Table 20: Jarque-Bera Test for Normality

Model	**X-squared**	**P-value**
Model 1	123.7400	2.20E-16***
Model 2	140.0100	2.20E-16***
Model 3	124.0500	2.20E-16***

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

Based on the findings of the Jarque-Bera test (X-squared = 123.7400, 140.0100, 124.0500; p-value = 2.20E-16 for all models), we reject the null hypothesis (H_0) that the residuals are normally distributed at the 0.05 significance level. This indicates that the residuals of all three regression models do not follow a normal distribution. The non-normality of residuals suggests potential issues with the model specification, such as the presence of outliers, skewness, or other underlying factors that may need further investigation and corrective measures. However, in many practical applications, especially with large sample sizes, the violation of normality in residuals can be less problematic due to the central limit theorem.

The Central Limit Theorem (CLT) implies that as the sample size increases, the distribution of the sample mean will approximate a normal distribution regardless of the original distribution of the data. This robustness allows for reliable inferences even with non-normal residuals in large samples. According to Pek et al. (2017), the CLT ensures that the sampling distribution of the estimates converges toward a normal distribution as the sample size increases, making the normality assumption less critical in large samples.

6.1.9.3. Autocorrelation

To estimate the presence of autocorrelation in the residuals, we employed the Breusch-Godfrey test. This statistical test is specifically designed to evaluate whether the residuals from a regression model are autocorrelated. The hypothesis for autocorrelation can be presented as follows.

H_0: The residuals of the regression model have no autocorrelation.

H_1: The residuals of the regression model have autocorrelation.

Table 21 given below presents the Breusch-Godfrey test results for all three models.

Table 21: Breusch-Godfrey test for Autocorrelation

Model	**LM Test**	**P-value**
Model 1	154.04	2.2E-16***
Model 2	160.37	2.2E-16***
Model 3	154.67	2.2E-16***

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

Based on the results of the Breusch-Godfrey test (LM Test = 154.04, 160.37, 154.67; p-value = 2.20E-16 for all models), we reject the null hypothesis (H_0) that there is no autocorrelation in the residuals at the 0.05 significance level. This indicates that the residuals of all three regression models exhibit significant autocorrelation. The presence of autocorrelation suggests potential issues with the model specification, requiring further investigation and corrective measures to ensure the validity of the regression analysis.

Given that we employed Ordinary Least Squares (OLS) in our panel data analysis, autocorrelation is not unexpected. Panel data, which consists of multiple observations over time for the same entities, often exhibits serial correlation within entities. This is because the residuals from one period may be correlated with those from another for the same entity. Although addressing this issue in depth is beyond the scope of this thesis, it is an important consideration for ensuring the robustness of our findings and warrants further investigation in future research.

6.1.9.4. Linearity

This thesis has employed the Rainbow test to evaluate the linearity of the regression models. This statistical test is designed to evaluate whether the linearity assumption holds for a regression model. The hypotheses for the Rainbow test can be presented as follows:

H_0: The regression model is linear.

H_1: The regression model is not linear.

Table 22 given below presents the Rainbow test results for all three models.

Table 22: Rainbow test for Linearity

Model	**Rain**	**P-value**
Model 1	0.6611	0.9964
Model 2	0.6634	0.9961
Model 3	0.6572	0.9967

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

Based on the results of the Rainbow test (Rain = 0.6611, 0.6634, 0.6572; p-value = 0.9964, 0.9961, 0.9967 for all models), we fail to reject the null hypothesis (H_0) that the regression model is linear at the 0.05 significance level. This indicates no evidence of non-linearity in the residuals of any of the three regression models. The high p-values suggest that the models meet the linearity assumption, confirming the appropriateness of the linear regression specification for these models.

6.1.10. Summary of Pre-IPO Hypothesis

The empirical analysis of pre-IPO financial metrics, as summarized in Table 23, reveals mixed impacts on IPO pricing.

Firstly, the analysis indicates a marginal yet statistically significant positive relationship between the Price to Earnings ratio and the IPO Offer Price (coefficient = 0.0028, p-value = 0.0391). This suggests that companies with higher earnings relative to their share price tend to have higher IPO offer prices, although the effect size is small.

In contrast, the Price to Book ratio shows a non-significant negative impact on the IPO Offer Price (coefficient = -0.0115, p-value = 0.3217). This implies that the book value of a company's assets relative to its share price does not significantly influence IPO pricing in the expected positive direction.

Moreover, a robust positive correlation is observed between Net Income to Assets and the IPO Offer Price (coefficient = 3.0113, p-value = 0.0000). This highlights the strong predictive value of profitability relative to assets in determining IPO pricing, indicating that more profitable companies tend to achieve higher IPO prices.

Surprisingly, the analysis identifies a significant negative relationship between Market Sentiments and the IPO Offer Price (coefficient = -5.0908, p-value = 0.0215). This challenges the expected positive impact and suggests that higher market sentiment might lead to lower IPO offer prices. This finding requires further research as it is not in line with previous literature.

These findings suggest that while certain financial metrics, like Price to Earnings and Net Income to Assets, can effectively predict IPO pricing, others, such as the Price to Book ratio and Market Sentiments, do not align with the anticipated patterns. This underscores the complexity of factors influencing IPO pricing and the need for a nuanced understanding of pre-IPO financial indicators.

Table 23: Pre - IPO, Overview of Empirical Findings (Based on Model 3)

Hypothesis	Coefficient	P-Value	Explanation
H1 - There is a significant positive relationship between Price to Earnings ratio and IPO Offer Price	0.0028	0.0391	There is a small but statistically significant positive relationship, as indicated by the coefficient and p-value just below 0.05. (H0 is rejected)
H2 - There is a significant positive relationship between Price to Book ratio and IPO Offer Price	-0.0115	0.3217	The relationship is negative and not statistically significant, contradicting the expected positive relationship. (H0 is not rejected)
H4 - There is a significant positive relationship between Net Income to Assets and IPO Offer Price	3.0113	0.0000	There is a strong and statistically significant positive relationship, supported by a very low p-value. (H0 is rejected)
H5 - There is a significant positive relationship between Market Sentiment and IPO Offer Price	-5.0908	0.0215	There is a significant negative relationship, opposite to the hypothesized positive direction. (H0 is rejected)

Note: The H3 hypothesis concerning the relationship between ROE and OFP has not been tested due to the exclusion of ROE, which was necessary to avoid issues of multicollinearity.

6.2. Post-IPO Performance Results

In the following section, this thesis examines whether the Fama-French five-factor model explains the post-IPO performances. The analysis begins with removing outliers, ensuring that extreme values do not skew the results. Next, we detect multicollinearity, which checks for high correlations between independent variables that could affect the regression results. This is followed by initial OLS Panel regression statistics, which summarize the data. Finally, we perform four OLS Panel Regressions: The Fama-French five-factor model with AGE as a control variable, and with dummy variables for country, year of listing, and industry, followed by diagnostic testing to validate the findings.

6.2.1. Post-IPO Descriptive Statistics

The first step in any statistical investigation is obtaining descriptive statistics. These summaries provide an overview of the data, highlighting the characteristics of the entire sample. Table 24 presents the descriptive statistics of the independent, control, and dependent variables before removing the outliers.

Table 24: Descriptive statistics of Post-IPO Fama-French variables before removing outliers

	Observations	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis
MRP	97,478	-12.000	8.540	0.005	1.163	-0.364	5.853
SMB	97,478	-3.330	3.250	-0.007	0.420	-0.077	2.741
HML	97,478	-3.040	4.380	0.016	0.607	0.120	2.703
RMW	97,478	-1.960	2.670	0.011	0.342	-0.207	3.108
CMA	97,478	-1.730	1.310	0.010	0.350	0.036	1.609
ER	97,478	-65.344	250.698	-0.009	3.824	5.586	255.472
AGE	97,478	0.000	172.000	16.739	24.637	3.335	12.782

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak
CMA = Conservative Minus Aggressive, ER = Excess Return, AGE = Years from incorporation to IPO date

6.2.2. Post-IPO Outliers

The regression analysis of post-IPO performances identifies the presence of some outliers, which is anticipated due to the large data sample size. To handle this, the thesis adopts a trimming approach. Table 25 details the outliers identified and excluded by this method in the updated statistical description section. Specifically, the z-score method is used for outlier removal, excluding any data points with z-scores less than -3 or more excellent than +3. As a result of this trimming process, the number of observations in the post-IPO analysis was reduced from 97,478 to 88,817.

Table 25: Descriptive statistics of Post-IPO Fama-French variables after removing outliers

	Observations	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis
MRP	88,817	-3.470	3.370	0.005	0.972	-0.214	0.767
SMB	88,817	-1.260	1.250	-0.003	0.373	-0.014	0.430
HML	88,817	-1.740	1.800	0.024	0.526	0.246	0.566
RMW	88,817	-1.010	0.980	0.011	0.306	-0.140	0.473
CMA	88,817	-1.030	1.060	0.013	0.311	0.202	0.348
ER	88,817	-11.478	11.448	-0.108	2.828	0.104	2.041
AGE	88,817	0.000	88.000	13.372	15.357	2.548	7.146

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak
CMA = Conservative Minus Aggressive, ER = Excess Return, AGE = Years from incorporation to IPO date

Table 25 presents the descriptive statistics for post-IPO performance metrics after outlier removal. The analysis reveals that the average ER is -0.108, with values ranging narrowly between -11.478 and 11.448, indicating a relatively uniform distribution. The MRP spans from -3.470 to 3.370, averaging 0.005, with a standard deviation of 0.972.

For the Fama-French factors, the SMB factor shows an average of -0.003 and varies between -1.260 and 1.250. The HML factor averages 0.024, ranging from -1.740 to 1.800. The RMW factor averages 0.011, ranging from -1.010 to 0.980. Lastly, the CMA factor ranges from -1.030 to 1.060, with an average of 0.013.

These statistics highlight the relative stability and uniform distribution across the independent variables. The skewness and kurtosis values indicate minimal deviations from normality, suggesting that the data is well-behaved after outlier removal. However, despite the overall stability, the ER still displays considerable variability, as evidenced by its higher standard deviation.

6.2.3. Correlation Matrix and Management of Multicollinearity

Before delving into the core empirical analysis of post-IPO performances, this thesis examines the dataset utilized in the models. A correlation matrix summarizing the coefficients for all variables has been generated to provide an initial insight into their relationships. Constructing these correlation coefficient tables within the OLS Panel Regression analysis framework helps to identify the interdependencies among the variables preliminarily. Table 26 comprehensively analyzes the correlations between the Fama-French factors (independent variables) and the Excess Return (dependent variable).

Table 26: Post-IPO performances correlation matrix

	MRP	**SMB**	**HML**	**RMW**	**CMA**	**AGE**
MRP	1.0000					
SMB	-0.4050**	1.0000				
HML	0.0474**	-0.1135**	1.0000			
RMW	-0.0126**	0.0549**	-0.7154**	1.0000		
CMA	-0.2328**	-0.1042**	0.6802**	-0.5088**	1.0000	
AGE	0.0039	0.0014	-0.0030	0.0007	0.0011	1.0000

** Correlation is significant at the 0.01 level. * Correlation is significant at the 0.05 level.

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak

CMA = Conservative Minus Aggressive, AGE = Years from incorporation to IPO date

The correlation matrix reveals a moderately high negative correlation between the HML and RMW variables (-0.7154) and a moderately high positive correlation between the HML and CMA variables (0.6802). Although these correlations are notable, they remain below the threshold of 0.8, indicating that extreme multicollinearity is absent. The Variance Inflation Factor (VIF) was calculated to further investigate the potential effects of multicollinearity. Table 27 presents the VIF values for all independent variables.

Table 27. Post IPO Performance Variance Inflation Factor

	Variance Inflation Factor (VIF)
MRP	1.4517
SMB	1.2742
HML	2.9584
RMW	2.0710
CMA	2.2584
AGE	1.0001

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak

CMA = Conservative Minus Aggressive, AGE = Years from incorporation to IPO date

The VIF measures the degree to which the variance of a regression coefficient is inflated due to collinearity with other predictors. A VIF of 1 indicates no correlation between a predictor and any other predictors. Generally, a VIF above 10 suggests significant multicollinearity, although some scholars use a threshold of 5. Notably, the VIF values for HML and CMA are slightly elevated at 2.9584 and 2.2584, respectively, consistent with the moderately high correlation (0.6802) observed between these variables. Given the VIF values and that none of the variables exhibit correlations above 0.8, this study will proceed with the OLS Panel Regression analysis using the current dataset.

6.2.4. Initial Regression Results

6.2.4.1. Fama-French Model - Post-IPO Performance: Impact of Control Variable (AGE)

With the purified data, this thesis has now conducted the OLS Panel Regression to evaluate whether the aftermarket IPO performances are explained by the Fama-French five-factor model with AGE as the control variable. The regression results are given in the following table 28.

Table 28: Post IPO - Results of the Regression

Explanatory Variables	Coefficients (Beta)	t-Statistics	Significance (p-Value)
(Intercept)	-0.121	-9.656	0.000***
MRP	0.273	23.323	0.000***
SMB	0.377	13.194	0.000***
HML	-0.152	-4.942	0.000***
RMW	-0.280	-6.307	0.000***
CMA	-0.443	-9.729	0.000***
AGE	0.002	3.106	0.002***

Note: Dependent variable is Excess Return, R = 0.1171, R^2 = 0.0137, F-Value = 205.731
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

The results from the OLS Panel Regression on the Fama-French five-factor model highlight that Excess Return (ER) is significantly influenced by all factors in the model. The Market Risk Premium (MRP) and the Small Minus Big (SMB) factors show a positive relationship with ER, with coefficients of 0.273 and 0.377, respectively. This suggests that higher values of MRP and SMB are associated with higher ER. Conversely, the High Minus Low (HML), Robust Minus Weak (RMW), and Conservative Minus Aggressive (CMA) factors exhibit a negative relationship with ER, with coefficients of -0.152, -0.280, and -0.443, respectively. This indicates that higher values of these variables correspond to lower ER. Additionally, the AGE variable shows a positive relationship with ER, with a coefficient of 0.002.

The overall model explains only 1.37% of the variance in ER, suggesting that while these factors have a statistically significant impact, their influence is relatively modest. This implies that other factors not captured by this model also play significant roles in determining ER. This finding is consistent with other studies that have noted the limitations of the Fama-French model in capturing the full spectrum of influences on stock returns (Fama & French, 1993; Harvey et al., 2016).

Notably, all the factors are significant, with p-values less than 0.01, reinforcing their respective positive and negative relationships with ER. These results align with prior research, which has demonstrated the significance of these factors in explaining variations in stock returns (Fama & French, 2015; Hou et al., 2015).

6.2.4.2. Fama-French Model - Post-IPO Performance: Country-Based Analysis (Sweden)

This thesis presents a country-based analysis of post-IPO performance to understand the market differences across Scandinavian countries. Despite their geographical proximity and some economic similarities, these countries have distinct financial markets, regulatory environments, and economic conditions, all of which can significantly impact the performance of companies after they go public. By conducting this country-specific analysis, we can isolate and understand the influence of these factors on post-IPO performance. Dummy variables were used in the panel regression to account for the different countries in this analysis. As detailed in the methodology section, Sweden was chosen as the base country for this analysis due to its highest number of IPO listings. Table 29 provides a summary of the regression results.

Table 29: Post IPO - Country based results of the regression

Explanatory Variables	Coefficients (Beta)	t-Statistics	Significance (p-Value)
(Intercept)	-0.112	-7.857	0.000***
MRP	0.273	23.323	0.000***
SMB	0.377	13.195	0.000***
HML	-0.151	-4.913	0.000***
RMW	-0.278	-6.278	0.000***
CMA	-0.443	-9.730	0.000***
AGE	0.002	3.305	0.001***
Denmark	-0.100	-3.103	0.002***
Norway	-0.013	-0.570	0.569
Finland	0.025	0.640	0.522

Note: Dependent variable is Excess Return, R = 0.1176, R^2 = 0.0138, F-Value = 138.347

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak

CMA = Conservative Minus Aggressive, ER = Excess Return, AGE = Years from incorporation to IPO date

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

Based on the regression results, the coefficient for Denmark is -0.100, which is significant at the 0.01 level (p = 0.002). This indicates that, while other factors are constant, post-IPO performance in Denmark is significantly lower than in Sweden by approximately 0.100 units. Additionally, the coefficient for Norway is -0.013, which is not statistically significant (p = 0.569). This suggests no significant difference in post-IPO performance between Norway and Sweden. Finally, the coefficient for Finland is 0.025, which is also not statistically significant (p = 0.522), indicating no significant difference in post-IPO performance between Finland and Sweden. Overall, these results highlight that post-IPO performance varies significantly between Denmark and Sweden, while there are no significant differences between Sweden and the other Scandinavian countries, Norway and Finland.

6.2.4.3. Fama-French Model - Post-IPO Performance: Year-Based Analysis (2021)

This thesis has conducted a year-based analysis of post-IPO performances with the primary intention of understanding the impact of different years on the performance of companies after they go public. The economic conditions, market sentiment, and regulatory environments can vary significantly from year to year, influencing the performance of IPOs. By conducting a year-based analysis, we can isolate and understand the influence of these year-specific factors on post-IPO performance. In this analysis, dummy variables were used in the panel regression to account for the different years. As explained in the methodology section, the year 2021 has been selected as the base year since the highest number of listings were reported in the calendar year 2021. The following table 30 provides a summary of the regression results.

Table 30: Post IPO - Year based results of the regression

Explanatory Variables	Coefficients (Beta)	t-Statistics	Significance (p-Value)
(Intercept)	-0.225	-11.936	0.000***
MRP	0.267	22.834	0.000***
SMB	0.361	12.631	0.000***
HML	-0.131	-4.251	0.000***
RMW	-0.260	-5.867	0.000***
CMA	-0.437	-9.602	0.000***
AGE	0.002	2.348	0.019**
2010	0.173	3.864	0.000***
2011	0.142	2.736	0.006***
2012	0.125	0.950	0.342
2013	0.068	1.351	0.177
2014	0.194	5.714	0.000***
2015	0.222	6.716	0.000***
2016	0.174	4.858	0.000***
2017	0.237	5.985	0.000***
2018	0.115	1.851	0.064*
2019	0.283	5.760	0.000***
2020	0.003	0.083	0.934

Note: Dependent variable is Excess Return, R = 0.1224, R^2 = 0.0150, F-Value = 79.402

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak

CMA = Conservative Minus Aggressive, ER = Excess Return, AGE = Years from incorporation to IPO date

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

Based on the regression results, the coefficients for several years show significant differences compared to the base year 2021. For instance, the coefficient for 2010 is 0.173, significant at the 0.001 level (p = p < 0.001), indicating that post-IPO performance in 2010 was significantly higher than in 2021 by approximately 0.173 units. Similarly, significant positive coefficients were observed for 2011, 2014, 2015, 2016, 2017, and 2019. Conversely, the coefficients for 2012, 2013, 2018, and 2020 are not statistically significant, suggesting no significant difference in post-IPO performance compared to 2021.

These findings are consistent with prior research. For example, Ritter (1991) identified considerable variations in IPO performance across different years, linking these variations to prevailing market conditions and economic cycles. Ibbotson and Jaffe (1975) introduced the concept of "hot" and "cold" IPO markets, demonstrating that market conditions heavily influence IPO performance at the time of issuance. Additionally, Affleck-Graves, Hegde, and Miller (1996) found that IPO aftermarket performance is conditional on the market conditions at the time of the IPO.

6.2.4.4. Fama-French Model - Post-IPO Performance: Sector-Based Analysis (Other Sector)

This section examines whether sector-specific factors significantly influence post-IPO performance in Scandinavian countries. Dummy variables for each sector are included to test the hypothesis that industry-specific characteristics impact IPO performance. As explained in the methodology section, all 196 IPOs were reclassified into 10 sectors, with the "Other" sector identified as the base sector since most of the IPOs were categorized there. This approach provides insights into how different economic conditions, market dynamics, and investor sentiment across sectors affect post-IPO outcomes.

By isolating and analyzing industry-specific factors, the sector-based analysis aims to understand the impact of various industries on post-IPO performance in the Scandinavian market. Differences in economic conditions, market sentiment, and regulatory environments across sectors can significantly influence IPO performance. This study seeks to provide a clearer understanding of these influences on post-IPO outcomes. Table 31 below summarizes the regression results.

Table 31: Post IPO - Sector based results of the regression

Explanatory Variables	Coefficients (Beta)	t-Statistics	Significance (p-Value)
(Intercept)	-0.031	-1.353	0.176
MRP	0.273	23.320	0.000***
SMB	0.377	13.199	0.000***
HML	-0.151	-4.919	0.000***
RMW	-0.279	-6.287	0.000***
CMA	-0.443	-9.729	0.000***
AGE	0.002	2.725	0.006***
NoDur	-0.142	-3.303	0.001***
Durbl	-0.064	-1.662	0.096*
Manuf	-0.113	-2.714	0.007***
Enrgy	-0.094	-2.201	0.028**
BusEq	-0.156	-4.872	0.000***
Telcm	-0.335	-6.266	0.000***
Shops	-0.071	-2.224	0.026**
Hlth	-0.059	-1.699	0.089*
Money	-0.088	-1.822	0.069*

Note: Dependent variable is Excess Return, R = 0.1197, R^2 = 0.0143, F-Value = 88.030

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak

CMA = Conservative Minus Aggressive, ER = Excess Return, AGE = Years from incorporation to IPO date

NoDur = Consumer Nondurable, Durbl = Consumer Durable, Manuf = Manufacturing, Enrgy = Energy

BusEq = Business Equipment, Telcm = Telecom, Shops = Shops, Hlth = Healthcare, Money = Money, Other = Other sectors

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

Based on the regression results, the coefficients for several sectors show significant differences compared to the base sector 'Other.' For instance, the coefficient for NoDur (Non-Durables) is -0.142, which is significant at the 0.01 level (p = 0.001). This indicates that holding other factors constant, post-IPO performance in the NoDur sector is significantly lower than in the 'Other' sector by approximately 0.142 units. Significant negative coefficients were also observed for the Manuf (Manufacturing), Enrgy (Energy), BusEq (Business Equipment), Telcm (Telecommunications), and Shops (Retail). Specifically, the coefficients for Manuf, Enrgy, BusEq, Telcm and Shops are -0.113 (p = 0.007), -0.094 (p = 0.028), -0.156 (p < 0.001), -0.335 (p = 1 p < 0.001) and -0.071 (p = 0.026) respectively. These results suggest that these sectors experience significantly lower post-IPO performance than the 'Other' sector.

Conversely, the coefficients for the Durbl (Durables), Hlth (Healthcare) and Money (Financial Services) sectors are not statistically significant, indicating no significant difference in post-IPO performance compared to the 'Other' sector. The coefficient for Durbl is -0.064 ($p = 0.096$), Hlth is -0.059 ($p = 0.089$) and for Money it is -0.088 ($p = 0.069$). These findings highlight that while several sectors exhibit notably lower post-IPO performance, the Durbl, Hlth and Money sectors do not show a statistically significant deviation from the 'Other' sector. This analysis underscores the importance of considering sector-specific dynamics when evaluating post-IPO performance, as industry-specific factors play a crucial role in the Scandinavian market.

6.2.5. Diagnostic Testing

This section of the thesis tests for Ordinary Least Squares (OLS) assumptions, as explained in the methodology section, in relation to section 5.2, which covers post-IPO performance. As mentioned in the pre-IPO analysis section, these assumptions are necessary to ensure the validity and reliability of the regression output. In this thesis, all OLS assumptions are tested for all four models discussed above: the Fama-French five-factor model with Age as a control variable, the Fama-French five-factor model with country-based analysis, the year-based analysis, and the sector-based analysis.

6.2.5.1. Heteroscedasticity

The test for heteroscedasticity is conducted using the Breusch-Pagan test. Recalling from the methodology chapter, we require the regression residuals to have the same variability at all levels of the independent variables, i.e., homoscedasticity.

The Breusch-Pagan test is used to assess whether the residuals (errors) variance from a regression model is constant, i.e., to test for homoscedasticity. The null hypothesis of the Breusch-Pagan test is that the residuals have constant variance (homoscedasticity), while the alternative hypothesis is that the residual variance is not constant (heteroscedasticity). The hypotheses for heteroscedasticity are presented below:

H_0 = The regression model residuals have constant variance (homoscedasticity).

H_1 = The residuals of the regression model do not have constant variance (heteroscedasticity).

The table below (Table 32) presents the Breusch-Pagan test results for all three models in the post-IPO analysis.

Table 32: Post-IPO Breusch-Pagan test for Heteroscedasticity

Model	Test Statistic (BP)	P-value
FF Model - Control Variable (AGE)	262.82	0.000***
FF Model - Country based (Sweden)	436.00	0.000***
FF Model - Year based (2021)	1,765.90	0.000***
FF Model - Sector based (Other sector)	1,126.20	0.000***

FF Model = Fama French Five Factor Model, *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10
AGE = Years from incorporation to IPO date

Based on the studentized Breusch-Pagan test results for the updated models, we reject the null hypothesis (H_0) of homoscedasticity at the 0.05 significance level, as the p-values for all tests are below 0.05. This indicates that the residuals of the regression models do not exhibit constant variance. Consequently, the assumption of homoscedasticity is violated, which could affect the validity and reliability of our regression analysis.

These results suggest that the models suffer from heteroscedasticity, and therefore, corrective measures such as robust standard errors or other heteroscedasticity-consistent methods should be considered to ensure reliable inference.

6.2.5.2. Normality

To assess the normality of the residuals, we employed the Jarque-Bera test. This statistical test is specifically designed to evaluate whether the residuals from a regression model follow a normal distribution. The hypotheses for normality can be presented as follows:

H_0 = The residuals of the regression model are normally distributed.

H_1 = The residuals of the regression model are not normally distributed.

The table below (Table 33) presents the Jarque-Bera Test results for all four models.

Table 33: Post IPO Jarque-Bera Test for Normality

Model	X-squared	P-value
FF Model - Control Variable (AGE)	16,304.00	0.000***
FF Model - Country based (Sweden)	16,327.00	0.000***
FF Model - Year based (2021)	16,544.00	0.000***
FF Model - Sector based (Other sector)	16,372.00	0.000***

FF Model = Fama French Five Factor Model, *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10
AGE = Years from incorporation to IPO date

Based on the results of the Jarque-Bera test (X-squared values ranging from 16,304.00 to 16,544.00; p-value < 0.001 for all models), we reject the null hypothesis (H_0) that the residuals are normally distributed at the 0.05 significance level. This indicates that the residuals of all four regression models do not follow a normal distribution. The non-normality of residuals suggests potential issues with the model specification, such as the presence of outliers, skewness, or other underlying factors that may need further investigation and corrective measures.

6.2.5.3. Autocorrelation

To evaluate the existence of autocorrelation in the residuals, we employed the Breusch-Godfrey test. This statistical test is specifically designed to evaluate whether the residuals from a regression model are autocorrelated. The hypotheses for autocorrelation can be presented as follows:

H_0: The residuals of the regression model have no autocorrelation.

H_1: The residuals of the regression model have autocorrelation.

The table below (Table 34) presents the Breusch-Godfrey test results for all four models.

Table 34: Post IPO Breusch-Godfrey test for Autocorrelation

Model	LM Test	P-value
FF Model - Control Variable (AGE)	316.68	0.000***
FF Model - Country based (Sweden)	317.98	0.000***
FF Model - Year based (2021)	330.41	0.000***
FF Model - Sector based (Other sector)	323.56	0.000***

FF Model = Fama French Five Factor Model, *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10
AGE = Years from incorporation to IPO date

Based on the results of the Breusch-Godfrey test (LM Test values ranging from 316.68 to 330.41; p-value < 0.001 for all models), we reject the null hypothesis (H_0) that there is no autocorrelation in the residuals at the 0.05 significance level. This indicates that the residuals of all four regression models exhibit significant autocorrelation. The presence of autocorrelation suggests potential issues with the model specification, requiring further investigation and corrective measures to confirm the validity of the regression analysis.

6.2.5.4. Linearity

This thesis has employed the Rainbow test to evaluate the linearity of the regression models. This statistical test evaluates whether the linearity assumption holds for a regression model. The hypotheses for the Rainbow test can be presented as follows:

H_0: The regression model is linear.

H_1: The regression model is not linear.

The table below (Table 35) presents the Rainbow test results for all four models.

Table 35: Rainbow test for Linearity

Model	Rain	P-value
FF Model - Control Variable (AGE)	0.916	1.000
FF Model - Country based (Sweden)	0.916	1.000
FF Model - Year based (2021)	0.916	1.000
FF Model - Sector based (Other sector)	0.917	1.000

FF Model = Fama French Five Factor Model, *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10
AGE = Years from incorporation to IPO date

Based on the Rainbow test results (Rain values ranging from 0.916 to 0.917; p-value < 1.000 for all models), we fail to reject the null hypothesis (H_0) that the regression model is linear at the 0.05 significance level. This indicates no evidence of non-linearity in the residuals of any of the four regression models. The high p-values suggest that the models meet the linearity assumption, confirming the appropriateness of the linear regression specification for these models.

6.2.6. Post-IPO Performance Hypotheses Based on Refined Results

The regression analysis identified several issues through diagnostic testing. The Breusch-Pagan test indicated heteroscedasticity with significant p-values, while the Breusch-Godfrey test revealed the presence of autocorrelation in the residuals. Additionally, the Jarque-Bera test showed that the residuals were not normally distributed. However, the Rainbow test for linearity did not indicate any issues, confirming that the models meet the linearity assumption.

These findings necessitated corrective measures to improve the model's reliability and ensure that the regression analysis assumptions were met. The following corrective measures were applied to address the identified issues:

Table 36: Summary of Diagnostic Issues and Corrective Measures

Issue	Solution	Description
Heteroscedasticity	Robust Standard Errors	Robust standard errors were used
Heteroscedasticity and Autocorrelation	Newey-West Standard Errors	Newey-West standard errors were implemented.
Non-normality	Log Transformation	Dependent variable was log-transformed.

6.2.6.1. Post-IPO Performance Refined Results - Impact of Control Variable (AGE)

The initial diagnostic tests revealed several issues with the regression model. Specifically, the Breusch-Pagan test indicated heteroscedasticity, the Breusch-Godfrey test showed autocorrelation, and the Jarque-Bera test revealed non-normality in the residuals. However, the Rainbow test confirmed that the models met the linearity assumption. Corrective Measures Applied:

1. Robust Standard Errors: To address heteroscedasticity, robust standard errors were used. This adjustment is crucial as the Breusch-Pagan test for heteroscedasticity was highly significant across all models ($p\text{-value} < 2.2e\text{-}16$).

2. Newey-West Standard Errors: To correct for both heteroscedasticity and autocorrelation, Newey-West standard errors were implemented. The Breusch-Godfrey test indicated significant autocorrelation in the residuals (p-value < 2.2e-16).

Initially, a log transformation of the dependent variable was considered to address non-normality. However, this transformation resulted in coefficients that were excessively small, making them impractical for interpretation. Thus, it was decided to prioritize the use of robust standard errors and Newey-West standard errors, which directly address the primary issues of heteroscedasticity and autocorrelation, while maintaining the interpretability of the coefficients. The updated results summary in table 37 and hypothesis results in table 38 are summarized below.

Table 37: Post IPO - Results of the Regression (Refined Results)

Explanatory Variables	**Coefficients (Beta)**	**t-Statistics**	**Significance (p-Value)**
(Intercept)	-0.1211	-10.4985	0.0000***
MRP	0.2726	21.0607	0.0000***
SMB	0.3767	12.8689	0.0000***
HML	-0.1522	-4.6358	0.0000***
RMW	-0.2797	-5.9582	0.0000***
CMA	-0.4426	-9.4047	0.0000***
AGE	0.0019	4.0453	0.0001***

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak
CMA = Conservative Minus Aggressive, AGE = Years from incorporation to IPO date
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

The refined results from the Fama-French Five-Factor Model, incorporating age as a control variable, provided significant insights into post-IPO performance. All variables in the model, including the market risk premium (MRP), size factor (SMB), value factor (HML), profitability (RMW), investment (CMA), and age (AGE), were found to have significant effects. Notably, AGE had a positive coefficient (0.0014) with a p-value of 0.0001, indicating that older companies tend to perform better after going public. This result underscores the importance of considering a company's age in predicting its post-IPO performance. As a summary, we reject the H0 (null hypothesis) for all the variables. (Summary of hypothesis is given in table 38).

Table 38: Fama French Five Factor Model Hypothesis Results

Variable	Hypothesis	Coefficient	P-value	Conclusion
(Intercept)	H0: No effect H1: Significant effect	-0.1211	0.0000	H0: Rejected H1: Accepted
MRP	H0: No effect H1: Significant effect	0.2726	0.0000	H0: Rejected H1: Accepted
SMB	H0: No effect H1: Significant effect	0.3767	0.0000	H0: Rejected H1: Accepted
HML	H0: No effect H1: Significant effect	-0.1522	0.0000	H0: Rejected H1: Accepted
RMW	H0: No effect H1: Significant effect	-0.2797	0.0000	H0: Rejected H1: Accepted
CMA	H0: No effect H1: Significant effect	-0.4426	0.0000	H0: Rejected H1: Accepted
AGE	H0: No effect H1: Significant effect	0.0014	0.0001	H0: Rejected H1: Accepted

6.2.6.2. Post-IPO Performance Refined Results: Country-Based Analysis (Sweden)

This thesis has reevaluated the country-based coefficients, p-values, and other statistics, comparing the performance of IPOs in Denmark, Norway, and Finland against Sweden as the base country after applying the corrected measures. We recalculated the coefficients, p-values, and other statistics for the additional variables using robust standard errors and Newey-West standard errors to address heteroscedasticity and autocorrelation. The decision not to apply the log transformation, due to the reasons previously mentioned, ensures the interpretability of the results.

Upon recalculation, the results showed some differences in the p-values, indicating slight changes in the statistical significance of certain variables. In comparing IPO performances relative to Sweden, Denmark shows a statistically significant negative difference, with IPO performance averaging 10.0% lower, a finding underscored by a decreasing p-value from 0.0040 to 0.0015.

Conversely, Norway's IPO performance is also lower by 1.35% but lacks statistical significance, as reflected by a p-value that slightly improved from 0.5689 to 0.5569. Finland presents a positive difference of 2.50% higher than Sweden's IPO performance, although this is not statistically significant, with the p-value decreasing from 0.5222 to 0.4219. The refined results are elaborated below in Table 39, and the updated hypothesis is provided in table 40.

Table 39: Post IPO - Country based results of the regression (Refined results)

Explanatory Variables	Coefficients (Beta)	t-Statistics	Significance (p-Value)
(Intercept)	-0.1117	-8.5875	0.0000***
MRP	0.2726	21.0553	0.0000***
SMB	0.3767	12.8729	0.0000***
HML	-0.1513	-4.6092	0.0000***
RMW	-0.2784	-5.9314	0.0000***
CMA	-0.4427	-9.4069	0.0000***
AGE	0.0020	4.2622	0.0000***
Denmark	-0.1000	-3.1733	0.0015***
Norway	-0.0135	-0.5875	0.5569
Finland	0.0250	0.8031	0.4219

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak
CMA = Conservative Minus Aggressive, ER = Excess Return, AGE = Years from incorporation to IPO date
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

The country-based analysis compared IPO performances across Denmark, Norway, and Finland, using Sweden as the reference point. The findings revealed that Denmark's IPOs significantly underperformed relative to Sweden, with a coefficient of -0.1000 and a p-value of 0.0015, leading to the rejection of the null hypothesis. In contrast, IPOs in Norway and Finland did not show significant differences compared to Sweden, with coefficients of -0.0135 (p-value: 0.5569) and 0.0250 (p-value: 0.4219), respectively. In summary, we reject the H_0 for Denmark, while we do not reject the H_0 for Norway and Finland. (The summary of the hypothesis is given in table 40).

Table 40: Post-IPO, Country-based hypotheses results (Compared to Base Country 'Sweden')

Country	Hypothesis	Coefficient	p-value	Conclusion
Denmark	H0: No significant difference between Sweden and Denmark H1: Significant difference between Sweden and Denmark	-0.1000	0.0015	H0: Rejected H1: Accepted
Norway	H0: No significant difference between Sweden and Norway H1: Significant difference between Sweden and Norway	-0.0135	0.5569	H0: Not Rejected H1: Rejected
Finland	H0: No significant difference between Sweden and Finland H1: Significant difference between Sweden and Finland	0.0250	0.4219	H0: Not Rejected H1: Rejected

6.2.6.3. Post-IPO Performance Refined Results: Year-Based Analysis (2021)

This thesis has revisited the year-based coefficients, p-values, and other statistics, comparing the performance of IPOs from different years against the base year 2021 after applying the corrected measures (robust standard errors and Newey-West standard errors). The recalculated results show differences in the p-values, indicating slight changes in the statistical significance of specific years. These changes are highlighted below.

Analysis of IPO performance from 2010 to 2020 compared to 2021 reveals distinct trends. The IPO performances in 2010, 2011, 2014, 2015, 2016, 2017, and 2019 were significantly higher, ranging from 14.2% to 28.3% compared to 2021, all with statistically significant differences. In contrast, 2012, 2013, 2018 and 2020 showed higher performances of 12.5%, 6.8%, 11.5% and 0.3%, respectively, but these were not statistically significant. Remarkably, 2020's performance was nearly unchanged at only 0.03% higher than 2021 and had no statistical significance. This data illustrates a generally more robust IPO market in earlier years than 2021, except for 2012, 2013, 2018, and 2020, where the differences were minimal or insignificant. The overall refined results summary based on year is explained in Table 41 below, and the hypothesis summary updated according to the refined results is given in Table 42 in the following pages.

Table 41: Post IPO - Year based results of the regression (Refined results)

Explanatory Variables	Coefficients (Beta)	t-Statistics	Significance (p-Value)
(Intercept)	-0.225	-11.617	0.000***
MRP	0.267	20.608	0.000***
SMB	0.361	12.328	0.000***
HML	-0.131	-3.990	0.000***
RMW	-0.260	-5.544	0.000***
CMA	-0.437	-9.268	0.000***
AGE	0.002	2.959	0.003***
2010	0.173	3.916	0.000***
2011	0.142	2.957	0.003***
2012	0.125	1.740	0.082*
2013	0.068	1.714	0.087*
2014	0.194	6.441	0.000***
2015	0.222	7.812	0.000***
2016	0.174	5.372	0.000***
2017	0.237	6.862	0.000***
2018	0.115	1.895	0.058*
2019	0.283	6.131	0.000***
2020	0.003	0.081	0.935

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

The year-based analysis assessed IPO performance from 2010 to 2020 against the base year 2021. The results indicated that IPOs in the years 2010, 2011, 2014, 2015, 2016, 2017, and 2019 significantly outperformed those in 2021, with coefficients ranging from 0.142 to 0.283 and p-values below 0.05, leading to the rejection of the null hypothesis for these years. However, the years

2012, 2013, 2018, and 2020 did not show statistically significant differences, with the 2020 performance almost unchanged (coefficient: 0.003, p-value: 0.935). In summary, we reject the H_0 for the years 2010, 2011, 2014, 2015, 2016, 2017, and 2019, while we do not reject the H_0 for the years 2012, 2013, 2018, and 2020. (A summary of the hypothesis is given in Table 42).

Table 42: Post-IPO, Year-Based Hypothesis Results (Compared to Base Year 2021)

Year	Hypothesis (Compared to 2021)	Coefficient	P-value	Conclusion
2010	H0: No performance difference H1: Significant performance difference	0.173	0.000	H0: Rejected H1: Accepted
2011	H0: No performance difference H1: Significant performance difference	0.142	0.003	H0: Rejected H1: Accepted
2012	H0: No performance difference H1: Significant performance difference	0.125	0.082	H0: Not Rejected H1: Rejected
2013	H0: No performance difference H1: Significant performance difference	0.068	0.087	H0: Not Rejected H1: Rejected
2014	H0: No performance difference H1: Significant performance difference	0.194	0.000	H0: Rejected H1: Accepted
2015	H0: No performance difference H1: Significant performance difference	0.222	0.000	H0: Rejected H1: Accepted
2016	H0: No performance difference H1: Significant performance difference	0.174	0.000	H0: Rejected H1: Accepted
2017	H0: No performance difference H1: Significant performance difference	0.237	0.000	H0: Rejected H1: Accepted
2018	H0: No performance difference H1: Significant performance difference	0.115	0.058	H0: Not Rejected H1: Rejected
2019	H0: No performance difference H1: Significant performance difference	0.283	0.000	H0: Rejected H1: Accepted
2020	H0: No performance difference H1: Significant performance difference	0.003	0.935	H0: Not Rejected H1: Rejected

6.2.6.4. Post-IPO Performance Refined Results: Sector-Based Analysis (Other Sector)

This thesis has reanalyzed the sector-based coefficients, p-values, and other statistics, comparing the performance of IPOs across different sectors with the base sector 'Other' after applying the corrected measures (robust standard errors and Newey-West standard errors). The recalculated results revealed some differences in the p-values, which led to changes in the statistical significance of specific sectors. They are explained below.

The performance comparisons across various sectors relative to the 'Other' sector reveal significant variations in their average performances. The non-durable goods sector (NoDur), manufacturing sector (Manuf), energy sector (Enrgy), business equipment sector (BusEq), telecommunications sector (Telcm), retail sector (Shops), and finance sector (Money) all show statistically significant lower performances, with reductions ranging from 7.1% to 33.5%. The telecommunications and business equipment sectors are particularly notable, underperforming by 33.5% and 15.6%, respectively. Notably, the finance sector (Money), which previously had a p-value of 0.069, now shows a p-value of 0.036 after applying the corrective measures, making its underperformance statistically significant.

Conversely, the durable goods sector (Durbl) and health sector (Hlth), with differences of -6.4% and -5.9%, respectively, do not exhibit statistically significant differences from the 'Other' sector. These findings highlight a generally lower performance in these specified sectors than others, with variances in the degree of significance and magnitude of underperformance. The overall refined results summary is given in Table 43 below, and the hypothesis summary has been prepared according to the refined results in Table 44 in the following pages.

Table 43: Post IPO - Sector based results of the regression (Refined results)

Explanatory Variables	Coefficients (Beta)	t-Statistics	Significance (p-Value)
(Intercept)	0.031	-1.683	0.092*
MRP	0.273	21.045	0.000***
SMB	0.377	12.871	0.000***
HML	-0.151	-4.614	0.000***
RMW	-0.279	-5.942	0.000***
CMA	-0.443	-9.405	0.000***
AGE	0.002	-3.546	0.000***
NoDur	-0.142	-3.553	0.000***
Durbl	-0.064	-1.846	0.065*
Manuf	-0.113	-3.051	0.002***
Enrgy	-0.094	-2.353	0.019**
BusEq	-0.156	-5.031	0.000***
Telcm	-0.335	-6.206	0.000***
Shops	-0.071	-2.651	0.008***
Hlth	-0.059	-1.864	0.062*
Money	-0.088	-2.096	0.036**

MRP = Market risk premium. SMB = Small minus Big, HML = High Minus Low, RMW = Robust Minus Weak
CMA = Conservative Minus Aggressive, ER = Excess Return, AGE = Years from incorporation to IPO date
NoDur = Consumer Nondurable, Durbl = Consumer Durable, Manuf = Manufacturing, Enrgy = Energy
BusEq = Business Equipment, Telcm = Telecom, Shops = Shops, Hlth = Healthcare, Money = Money, Other = Other sectors
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10

The sector-based analysis compared IPO performances across various sectors with the 'Other' sector as the baseline. Significant underperformance was found in the non-durable goods, manufacturing, energy, business equipment, telecommunications, retail, and finance sectors, with coefficients ranging from -0.071 to -0.335 and p-values below 0.05. The telecommunications and business equipment sectors, in particular, showed the most substantial negative differences. Conversely, the durable goods and healthcare sectors did not exhibit statistically significant differences, with p-values of 0.065 and 0.062, respectively. As a summary, we reject the H_0 for the sectors non-durable goods, manufacturing, energy, business equipment, telecommunications, retail, and finance, while we do not reject the H_0 for the sectors durable goods and healthcare. (Summary of the hypothesis is given in table 44).

Table 44: Post-IPO, Sector-based hypotheses results (Compared to Base Sector 'Other')

Sector	Hypothesis (Compared to 'Other')	Coefficient	P-value	Conclusion
NoDur	H0: No performance difference H1: Significant performance difference	-0.142	0.000	H0: Rejected H1: Accepted
Durbl	H0: No performance difference H1: Significant performance difference	-0.064	0.065	H0: Not Rejected H1: Rejected
Manuf	H0: No performance difference H1: Significant performance difference	-0.113	0.002	H0: Rejected H1: Accepted
Enrgy	H0: No performance difference H1: Significant performance difference	-0.094	0.019	H0: Rejected H1: Accepted
BusEq	H0: No performance difference H1: Significant performance difference	-0.156	0.000	H0: Rejected H1: Accepted
Telcm	H0: No performance difference H1: Significant performance difference	-0.335	0.000	H0: Rejected H1: Accepted
Shops	H0: No performance difference H1: Significant performance difference	-0.071	0.008	H0: Rejected H1: Accepted
Hlth	H0: No performance difference H1: Significant performance difference	-0.059	0.062	H0: Not Rejected H1: Rejected
Money	H0: No performance difference H1: Significant performance difference	-0.088	0.036	H0: Rejected H1: Accepted

NoDur = Consumer Nondurable, Durbl = Consumer Durable, Manuf = Manufacturing, Enrgy = Energy,
BusEq = Business Equipment, Telcm = Telecom, Shops = Shops, Hlth = Healthcare, Money = Money, Other = Other sectors

7. Discussion

In the concluding section of the thesis, we critically evaluate our findings, focusing on the significant values derived from our regression analyses. This evaluation will consider how our results align or diverge from existing literature in pre- and post-IPO contexts. We will also explore further research avenues that could refine or augment our findings. This approach will validate the robustness of our analyses and highlight areas for future investigation that may enhance our understanding of IPO performance metrics.

7.1. Pre-IPO Analysis Discussion

In the pre-IPO analysis section, this thesis intends to study whether the company's financial performances influence the company's IPO offer price. This thesis studied the relationship with three models prepared with control variables. The results are evaluated based on Model 3, which is more comprehensive and has two control variables: offer size and the firm's age.

Firstly, the results imply a significant positive relationship between the Price-to-Earnings (PE) ratio and IPO offer price, substantiated by empirical evidence, suggesting a p-value of less than 0.05. This finding aligns with the research by Shenoy and Kannan (2018), who analyzed a sample of BSE-listed IPOs and found that financial information, including PE ratios, positively influences IPO stock pricing. Furthermore, Sahoo and Rajib (2012) demonstrated that the offering price-to-earnings ratio of an IPO significantly influences its pricing, establishing a direct link between PE ratios and IPO pricing strategies. These studies collectively support the critical role of PE ratios in evaluating and determining IPO offer prices.

Secondly, the study revealed a weak, though statistically insignificant, positive relationship between the Price-to-Book (PB) ratio and the Initial Public Offering (IPO) offer prices, evidenced by a p-value greater than 0.1. Consequently, this finding lacks statistical significance to substantiate previous claims in the literature. Thus, it does not corroborate the earlier assertions. Notably, Chang (2010) identified a significant positive correlation between the PB ratios of previously public companies and the IPO offer prices of subsequent firms within the same industry. Furthermore, Chambers and Dimson (2009) expanded this discussion by tracing long-term trends in IPO underpricing, illustrating how financial ratios, including the PB ratio, historically influenced IPO pricing. The recent study's inability to confirm significant influences suggests variability in how these metrics may affect IPO evaluations over different periods or market conditions.

Thirdly, the pre-IPO study revealed a significant positive relationship between the Net Income to Assets (NIA) ratio and IPO offer price ($p < 0.01$), implying that a higher ratio reported three years before listing increases the IPO offer price. These results further affirm previous literature by Willenborg et al. (2015), who investigated how pre-IPO financial performance, including the Net Income to Assets ratio, influences IPO pricing decisions in their study. They found that higher values of these financial indicators are generally associated with higher IPO offer prices.

Fourthly, in this thesis, the analysis of pre-IPO financial indicators reveals that market sentiments significantly ($p < 0.05$) influence IPO offer prices. Specifically, market sentiments in the 91 days before listing positively and negatively impact these prices, suggesting that firms command lower offer prices when market sentiment is favorable. This finding does not align with existing scholarships on the subject. Batnini and Hammami (2015) noted that favorable past market returns increase the number of IPOs and positively affect their pricing. Similarly, Lowry and Schwert (2001; 2003) documented that positive market returns during the registration period led to adjustments in IPO offer prices, allowing firms to set higher prices in favorable market conditions and lower ones when market returns are negative.

7.2. Post-IPO Analysis Discussion

The second section of this thesis analyzed the ability of the Fama and French five-factor model to capture the post-IPO performance of new public companies in the Scandinavian market. Key insights reveal the influence of market risk premium, firm size, book-to-market value, profitability, and investment patterns on excess returns. Additionally, country, year, and sector-specific analyses highlight performance differences across various contexts. Results are discussed in four sections.

7.2.1. Fama-French Five-Factor Model Analysis

This section of analysis investigates whether post-IPO performance in the Scandinavian market can be elucidated using the Fama-French five-factor model alongside control variables such as the firm's age. The findings align closely with existing literature, demonstrating that all five factors that are Market Risk Premium (MRP), Small Minus Big (SMB), High Minus Low (HML), Robust Minus Weak (RMW), and Conservative Minus Aggressive (CMA) significantly account for the excess returns of IPO stocks. Notably, the results indicate a positive association between the MRP and SMB factors and excess returns, whereas the HML, RMW, and CMA factors negatively correlate with these returns.

Support for these findings is robust within the scope of extant research. The positive relationships identified for the Market Risk Premium (MRP) and Small Minus Big (SMB) factors corroborate Fama and French's (2015) documentation that these elements generally contribute positively to returns. This reflects the overall market risk and the tendency of smaller firms to outperform larger ones. Additionally, Kuo and Huang (2022) observed that the High Minus Low (HML) factor may exhibit a negative coefficient under conditions characterized by high investor sentiment and low interest rates, where value stocks underperform relative to growth stocks.

Concurrently, studies such as those by Racicot et al. (2019) indicate that the negative Robust Minus Weak (RMW) coefficient may arise in markets where high profitability does not translate into higher returns, possibly due to market saturation or competitive pressures. Their research further supports a negative coefficient for the Conservative Minus Aggressive (CMA) factor, suggesting that firms with aggressive investment strategies have, since 2013, outperformed those adopting more conservative approaches. Together, these studies provide a comprehensive understanding of how different factors influence market returns under varying conditions.

7.2.2. Country-Specific Analysis of Post-IPO Performance

This thesis extends its analysis to country-specific IPO returns within Scandinavia, highlighting Sweden due to its high IPO activity during the study period. The analysis reveals that Denmark exhibits significantly lower post-IPO excess returns than Sweden. Conversely, comparisons between Sweden and Finland and Sweden and Norway did not yield statistically significant differences in post IPO performance from 2010 to 2021.

These country-specific outcomes are reinforced by prior research, such as the study by Bask and Läck Nätter (2021), which found that Swedish IPOs tend to achieve higher long-term returns than Danish IPOs. This disparity may be attributed to more favorable market conditions and greater investor interest in Sweden. Furthermore, the Swedish stock market structure, featuring multiple exchanges catering to a diverse array of companies, likely contributes to a more vibrant IPO landscape.

7.2.3. Year-Specific and Sector-Specific Analysis of Post IPO Performance

This study focuses on IPO aftermarket returns, using 2021 as the base year due to its record number of IPO listings. The analysis reveals a generally stronger IPO market in the years preceding 2021, except for 2012, 2013, 2018, and 2020, where differences were minimal or insignificant. This trend may be attributed to negative market sentiments following the COVID-19 outbreak despite a surge in tech-related IPOs.

As Lowry et al. (2010) noted, the volatility of IPO returns can significantly vary based on market conditions and the characteristics of firms going public in different years. This variability underscores the findings of this thesis, which shows higher returns for IPOs listed in years prior to 2021. Such variations underscore the impact of broader economic factors and market sentiment, particularly in the Scandinavian market, where earlier years exhibited higher returns.

In sector-specific analysis, the 'Other' sector served as the baseline due to its predominance among listed IPOs. The results indicate that, except for the Durable (Durbl) and Health (Hlth) sectors, which showed insignificant p-values, all other sectors underperformed relative to the 'Other' sector, even though the performance differences were still negative.

8. Further Research

Overall, the pre-and post-IPO performance investigation in Denmark, Sweden, Norway, and Finland has pointed to various opportunities for further research. These opportunities involve filling the identified gaps and adding a layer of complexity that could increase the predictability of IPO pricing and post-IPO performance of companies. Thus, developing more robust forecasting models and making contributions useful for investors, policymakers, and the academic community may be possible.

In particular, further analysis of financial ratios may be helpful. First, future studies may consider additional ratios such as cash flow ratios or earnings volatility. That may help to obtain a more comprehensive picture of the company's financial health and its impact on the success of an IPO. In turn, such analysis may help to understand which financial ratios are more critical for IPO pricing and final success. It may also be beneficial to conduct a longitudinal study of IPOs, tracking them for more time after the listing. This would help to understand whether there are any delayed effects of pre-IPO financial ratios and broader market conditions, as well as to evaluate the trends and stability of IPO success or failure. Finally, future research may also benefit from conducting a comparative analysis with IPO markets of other regions. This would help to understand whether the identified patterns are exclusive to the Nordic market or are similarly applicable in other regions and countries with different economic and regulatory environments in Asia, North America, or other parts of Europe.

One area of future work could be exploring how broader macroeconomic factors and market sentiment impact IPO pricing and performance. This could be achieved by analyzing economic cycles, interest rates, and geopolitical events during the IPO. The objective of such an exploration would be to understand the interactions between IPO outcomes and conditions in the market. Another topic that could serve as a focus of research is analysis by sector and the investigation of performance in technology or healthcare IPOs, where the pace of development is rapid. By applying advanced econometric models and machine learning techniques, it would be possible to improve the depth of the analysis and its robustness.

Additionally, the combination of random forests or neural networks might enable handling complexity and nonlinearity and lead to more accurate predictive models. Another area of future work could be the study of anomalies and outliers identified in the present paper. The analysis could be structured as a case study investigating exceptional outliers in more detail. Understanding the underlying reasons and why they differ from the standard patterns would be possible. As a result, conclusions could be reached to explain the inaccuracies of the models. A further area of work could be the study of the impact of regulatory changes on IPO performances. Considering that regulations are the cornerstone of financial markets, it is worthwhile to analyze the levels of influence that policy changes have and how they affect the market dynamics. These research areas could make a valuable contribution to the analysis of IPO performance.

9. Conclusion

This thesis critically examines the performance of initial public offerings (IPOs) in the Nordic region, specifically Denmark, Sweden, Norway, and Finland, from 2010 to 2021. The findings are derived from a meticulous analysis of pre-IPO and post-IPO metrics and their implications for IPO performances.

In the pre-IPO phase, the analysis focused on the influence of financial performance indicators on the IPO offer price. It is established that the Price-to-Earnings (PE) ratio exerts a significant positive effect on the IPO offer prices; higher PE ratios before listing indicate inflated initial offer prices. Additionally, the Net Income to Asset (NIA) ratio positively correlates with IPO offer prices, suggesting that superior financial health before listing can command higher market prices. Furthermore, this study observes that IPO offer prices are susceptible to external economic factors. Specifically, the market sentiments in the 91 days preceding the IPOs show a negative relationship with the IPO prices, indicating that lower market sentiments can lead to elevated offer prices. While statistically significant, this conclusion deviates from previous research, highlighting an area for further investigation.

The post-IPO analysis reveals that the excess returns of stocks listed in the Scandinavian market can be effectively modeled using the Fama-French five-factor framework. The market portfolio (MKT) and small minus big (SMB) factors show a positive correlation with the excess returns (ER) of IPOs, while high minus low (HML), robust minus weak (RMW), and conservative minus aggressive (CMA) factors are inversely related to the ER. This suggests that certain market factors are conducive to higher returns while others may hinder performance during the initial two years of trading.

Further distinctions are observed at the country level. Swedish IPOs consistently outperformed those in Denmark, while differences in Norway and Finland were not statistically significant from 2011 to 2021. This highlights that Denmark's IPOs performed significantly worse than Sweden's, whereas Norway and Finland's performances did not significantly differ from Sweden. Interestingly, IPOs initiated in 2021 demonstrated lower returns than those launched between 2011 and 2020, except for the years 2012, 2013, 2018, and 2020 where no significant performance differences were observed. This indicates temporal variations in IPO success. Sector-based analysis within this period further indicates that stocks listed under the 'other' sector category yielded higher returns than those in traditional sectors such as Non-Durables, Manufacturing, Energy, Business Equipment, Telecommunications, Retail, and Finance, while Durables and Health sectors showed no significant performance differences.

In conclusion, this thesis comprehensively evaluates IPO performance dynamics in the Nordic countries, uncovering the nuanced influence of financial indicators and market conditions on IPO pricing and subsequent market performance. The evidence suggests a complex interplay of internal and external factors that potential investors and policymakers should consider. Future research may explore the deviations and anomalies observed in this study to offer deeper insights into the mechanics of IPO success in various economic climates.

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11. Appendix

Appendix 1: Main sectors

Fama-French Industry Portfolios	Sub Sections
NoDur - Consumer Nondurables	Food, Tobacco, Textiles, Apparel, Leather, Toys
Durbl - Consumer Durables	Cars, TVs, Furniture, Household Appliances
Manuf - Manufacturing	Machinery, Trucks, Planes, Off Furn, Paper, Com Printing
Enrgy - Enrgy	Oil, Gas, and Coal Extraction and Products
Chems - Chemicals	Chemicals and Allied Products
BusEq - Business Equipment	Computers, Software, and Electronic Equipment
Telcm - Telecom	Telephone and Television Transmission
Utils - Utilities	Utilities
Shops - Shops	Wholesale, Retail, and Some Services (Laundries, Repair Shops)
Hlth - Health	Healthcare, Medical Equipment, and Drugs
Money - Money	Finance
Other - Other	Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment

Appendix 2:

Stocks included under sectors

NoDur	Durbl	Manuf	Enrgy	BusEq
ACAD-SE	ACUVI-SE	ARPL-SE	ALNG-NO	ALBERT-SE
ALEFRM-DK	ALIG-SE	BWE-NO	ARISE-SE	AUTO-NO
BAKKA-NO	BMAX-SE	CADLR-NO	BULTEN-SE	B3-SE
BFISH-NO	CTEK-SE	EKOBOT-SE	GRNG-SE	BFG-SE
HBC-NO	DOM-SE	ELO-NO	HANZA-SE	BRILL-SE
HUMBLE-SE	GARO-SE	EMBELL-SE	MAHA.A-SE	CLAV-SE
RVRC-SE	HTRO-SE	FMM.B-SE	MINEST-SE	CRAYN-NO
SATS-NO	LEDIBOND-DK	GREENH-DK	NTI-NO	DATA-DK
SBOK-SE	NCAB-SE	HOVE-DK	ODL-NO	DWF-FI
SCST-SE	PLT-NO	HUSCO-DK	OKEA-NO	EAM-NO
SPINN-FI	PRFO-SE	HYDRCT-DK	PEN-NO	ELABS-NO
STG-DK	SMOP-NO	LIFCO.B-SE	SCATC-NO	EVO-SE
	TCM-DK	MTRS-SE	TROAX-SE	FRAG-SE
	THULE-SE	NORSE-NO		FSPORT-SE
	TOBII-SE	NPAPER-SE		IMPERO-DK
	USWE-SE			LINK-NO
	VOLCAR.B-SE			NEPA-SE
				NEXCOM-DK
				NEXT-NO
				NNIT-DK

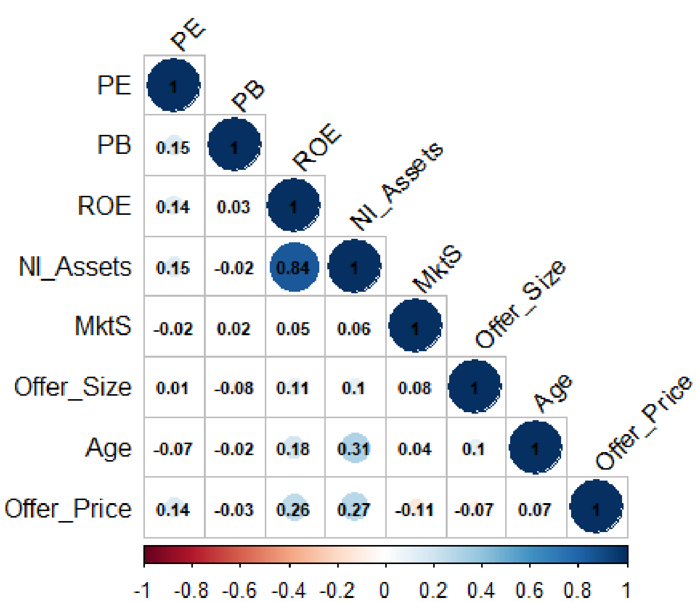
				PDX-SE
				PEXIP-NO
				PLEX-SE
				REMEDY-FI
				SMCRT-NO
				SPIFF-SE
				TRUE.B-SE
				TWIIK-SE
				VINCIT-FI
				ZWIPE-NO

Telcm	Shops	Hlth	Money	Other
MONSO-DK	AINO-SE	ATORX-SE	CPAC.SPAC-SE	AGLX-NO
NAPA-NO	B2I-NO	ATT-SE	DAB-DK	AGROUP-SE
PIERCE-SE	BETCO-SE	BACTI.B-SE	FLAT.B-SE	AJA.B-SE
READ-SE	BETOLAR-FI	BGBIO-NO	IDUN.B-SE	BALCO-SE
TH1NG-SE	BOOZT-SE	BIOA.B-SE	LINC-SE	BESQ-SE
VERK-FI	BUFAB-SE	BOUL-SE	NAIG.B-SE	BOAT-SE
WAYS-SE	CEDER-SE	CAMX-SE	NORTH-NO	BRAV-SE
	CHARGE-SE	DEAR-SE	RESURS-SE	BRG-NO
	CINT-SE	DVYSR-SE	SPOL-NO	DONKEY-DK
	COOR-SE	INDEX-SE	YIELD-SE	ELTEL-SE
	DUST-SE	MAGLE-SE		ENTRA-NO
	EPR-NO	MCOV.B-SE		FG-SE
	ESENSE-FI	MOB-SE		GPG-SE
	EWIND-NO	MODTX-SE		HEM-SE
	FNM-SE	NANOFH-FI		INWI-SE
	FRNT.B-SE	ONCO-SE		JOMA-SE
	GJF-NO	PHAL-SE		K2A.B-SE
	HOFI-SE	SECARE-SE		KFAST.B-SE
	HUM-SE	SIMRIS.B-SE		KLARA.B-SE
	HYPRO-NO	TELLUS-SE		MIPS-SE
	ISS-DK	TITA.B-SE		MODEL.B-SE
	KAR-SE	VOW-NO		MULTI-NO
	KID-NO	ZEAL-DK		NETEL-SE
	MATAS-DK			NIVI.B-SE
	PNDORA-DK			NORB.B-SE
	RELAIS-FI			NORVA-SE
	SFL-SE			NP3-SE
	SYNSAM-SE			OVARO-FI

	WMA-DK			OX2-SE
	XXL-NO			PENG.B-SE
	ZAL-NO			PLAZ.B-SE
				PNDX.B-SE
				SBO-NO
				SFAST-SE
				SHOT-SE
				SOLWERS-FI
				TOIVO-FI
				WBGR.B-SE

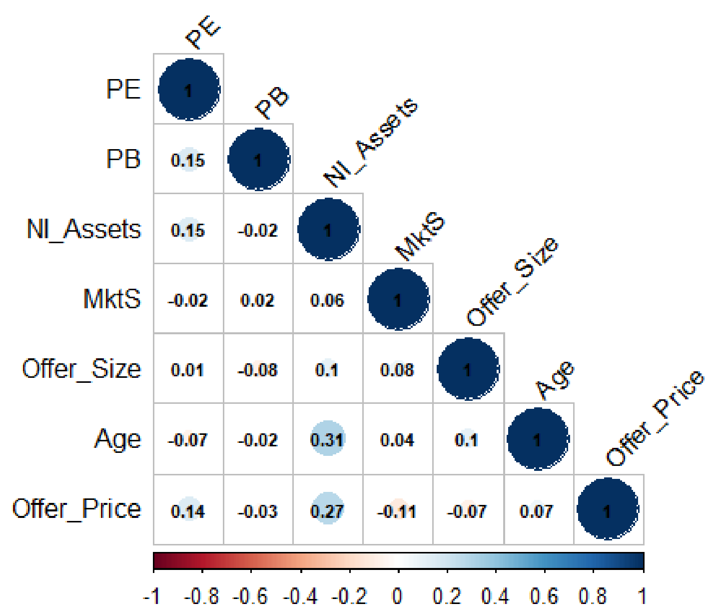
Appendix 3.

Correction matrix before removing outliers

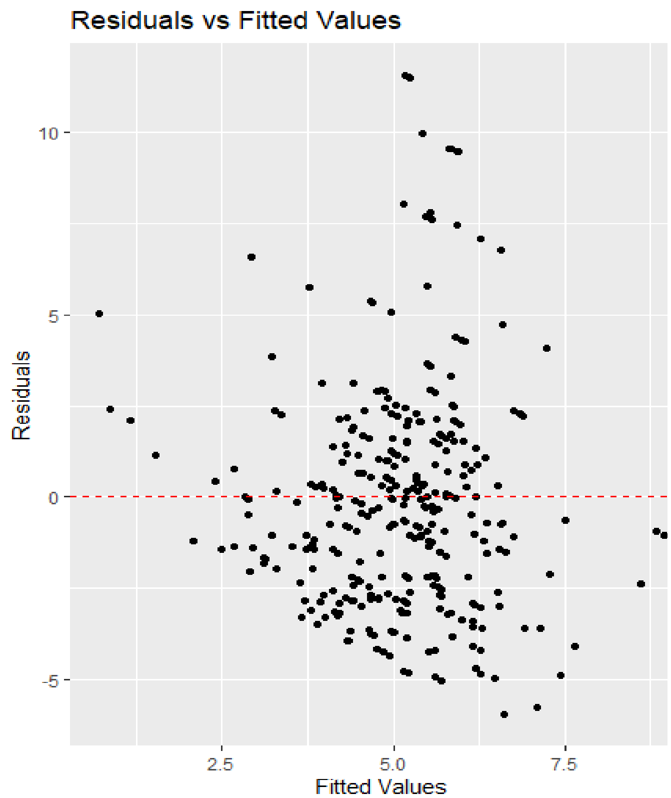


Appendix 4.

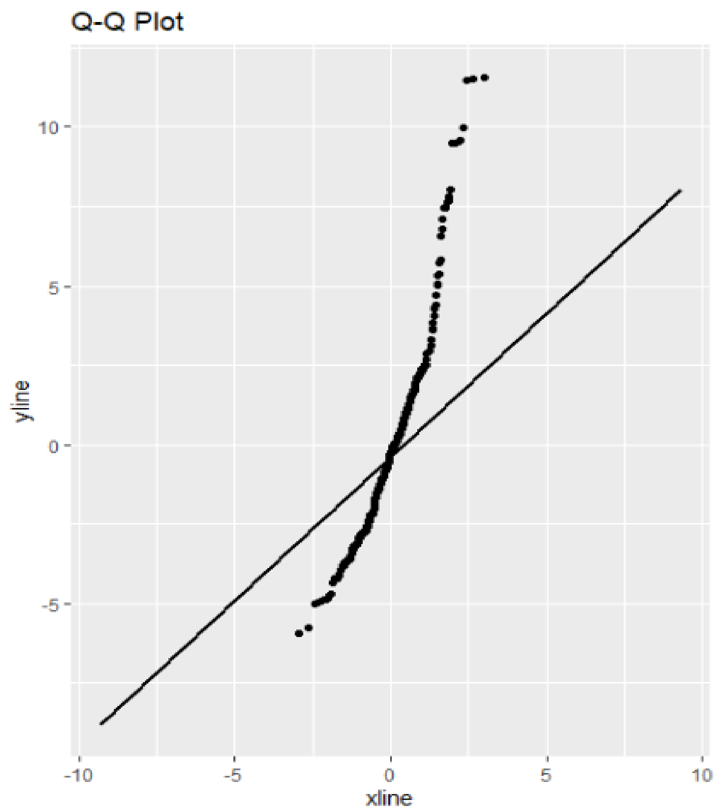
Correlation matrix After removing outliers.



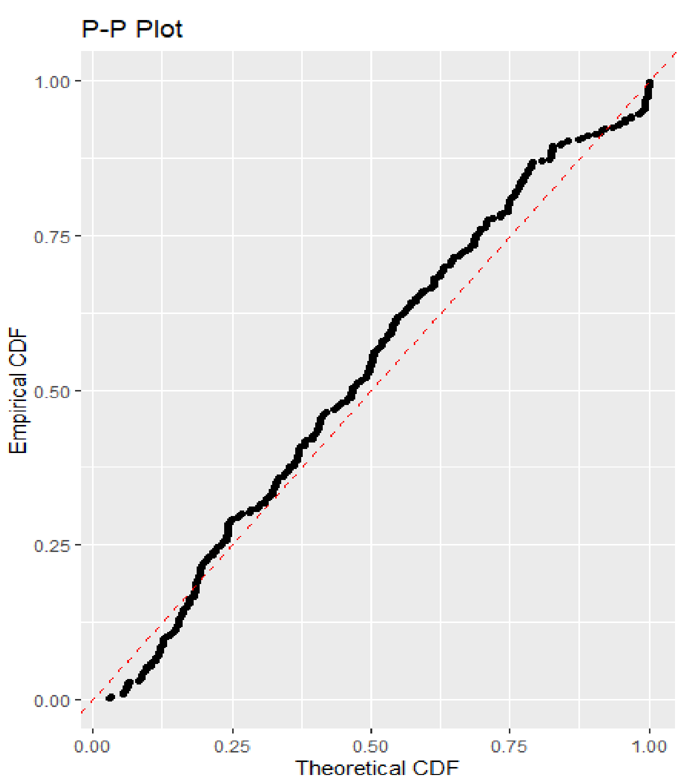
Appendix 5: Pre-IPO Analysis (Model 3)



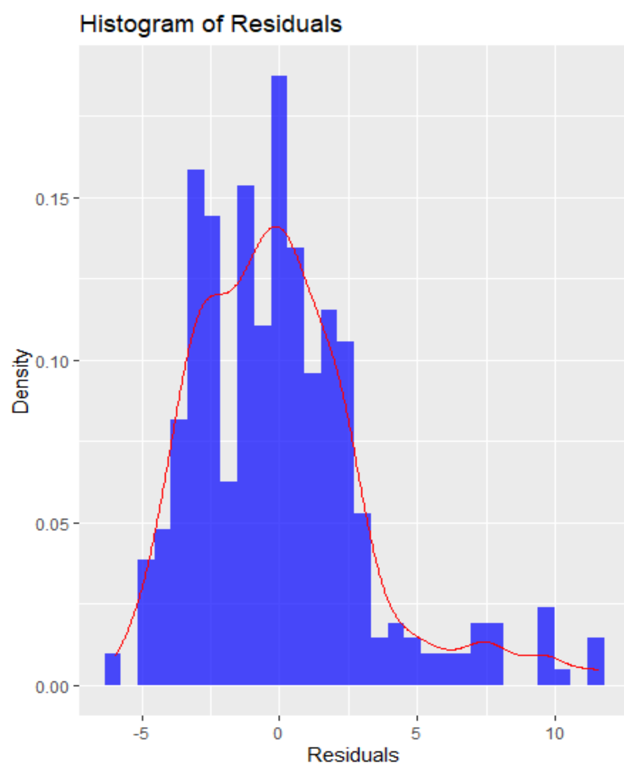
Appendix 6: Pre -IPO Analysis (Model 3)



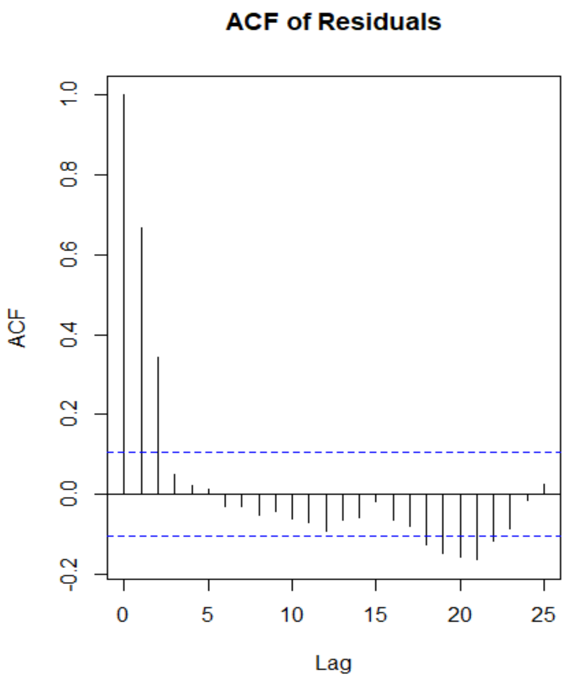
Appendix 7: Pre-IPO Analysis (Model 3)



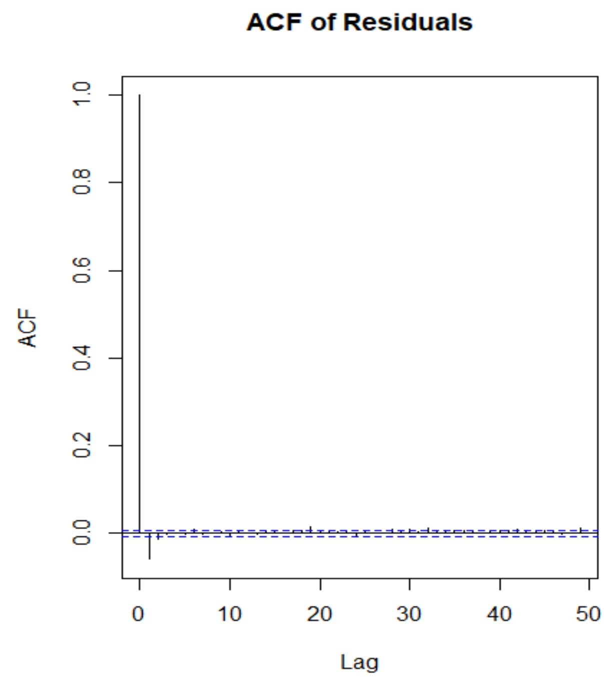
Appendix 8: Pre-IPO Analysis (Model 3)



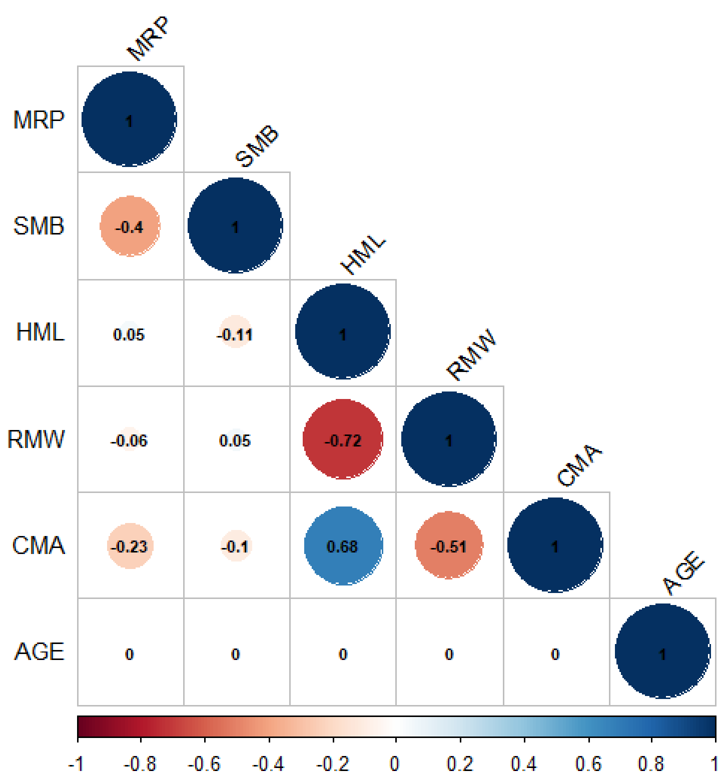
Appendix 9: Pre-IPO Analysis (Model 3)



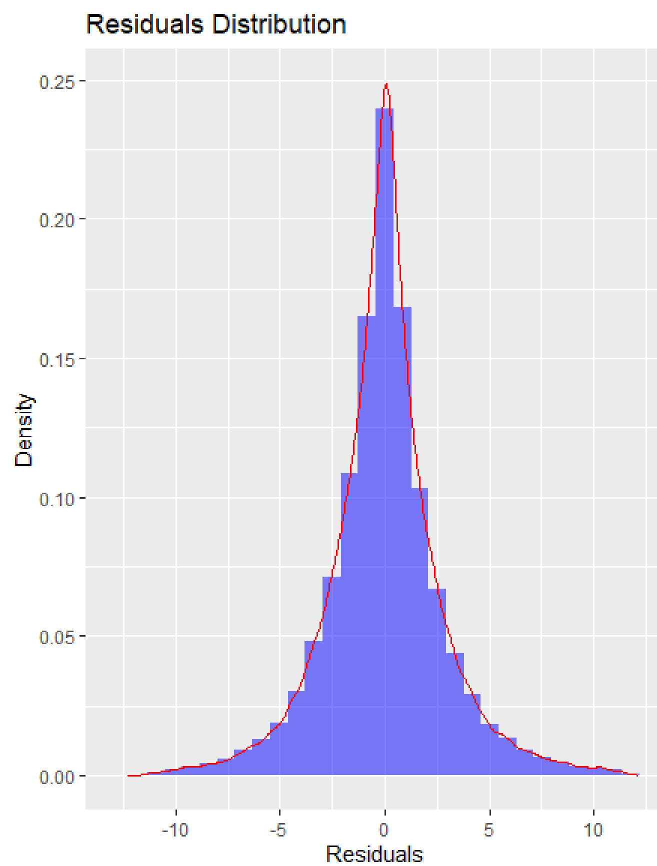
Appendix 10: Post-IPO Analysis (Fama F.)



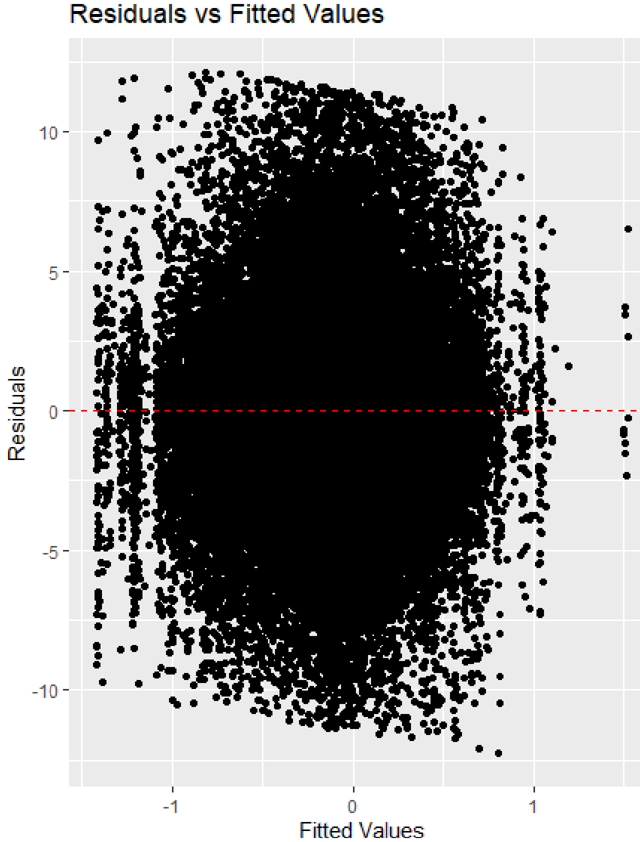
Appendix 11: Post IPO Correlation matrix (Fama F.)



Appendix 12: Post IPO Analysis (Fama F.)



Appendix 13: Post IPO Analysis (Fama F.)



Appendix 14: Post IPO Analysis (Fama F.)