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IFRS 16 impact on equity analysts' forecast accuracy

Have estimates become less accurate after the mandatory adoption of IFRS16?

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Abstract

This study analyzes the impact that IFRS 16 has had on the accuracy of equity analysts' forecasts in Scandinavia, with a particular focus on potential sector variations. The primary objectives of this research are (1) to examine whether the mandatory implementation of IFRS 16 led to decreased accuracy in equity analysts' forecasts, and (2) to assess whether changes in accuracy vary by sector.

We employed multivariate regressions to test for statistical significance in changes in forecast accuracy measured by the Median Absolute Forecast Error (MAPE). Additionally, a survey was conducted involving equity analysts from a variety of investment banks in Oslo to supplement the quantitative data.

We found no statistical evidence to support the hypothesis that the implementation of IFRS 16 led to an increase in forecast errors. This suggests that either the forecast accuracy did not change significantly post-implementation or that the time frame since implementation has been insufficient to observe its full effects. While the immediate impact of IFRS 16 on forecast accuracy was not evident, this study serves as a foundation for further research on the topic.

Keywords – IFRS 16, Equity Analysts, Forecast Accuracy, Lease Capitalization, MAPE

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1 Introduction

We investigate whether the mandatory adoption of IFRS 16 has impacted sell-side analysts' forecast properties negatively for publicly traded companies in the Scandinavian countries. While there is a significant amount of literature about the sell-side analysts' role in the capital markets and factors affecting their ability to forecast accurately, there is less literature about the relationship between analysts' forecast accuracy and changes in accounting standards. At the time of writing, more than 150 countries require publicly listed companies to use IFRS standards when preparing their financial statements. Although proponents assert that the adoption of IFRS enhances the functioning of capital markets, the genuine ramifications can only be discerned post-adoption. Previous literature, such as Jiao et al. (2012), finds that the analyst forecast error has decreased post-adoption of IFRS. However, that research assesses the entire framework, while this thesis investigates a significantly more narrow area of the framework.

We examine previous literature about the role of the sell-side analyst in order to create an understanding of how a change in accounting standards affects their daily job, and ultimately performances. This element is of interest to accounting standard makers (i.e. IASB), publicly listed companies, investors, and ultimately also analysts in order to better understand the effects that changes in standards have on securities. The literature widely accepts that financial statement information should primarily facilitate contracting and investing decision-making. Consequently, financial statement information and detailed explanation of underlying assumptions are of higher quality when it is more useful to those undertaking investment decisions. This paper focuses on a group of users with particular importance for investment decisions: namely sell-side analysts. Analysts are widely considered sophisticated users of financial statements (Schipper, 1991), and they are dependent on financial statements as the basis for input in their models to produce earnings estimates, with the purpose of deriving a value and recommendation on whether investors should buy, hold or sell the equity. Previous literature finds that market participants undertake investment decisions on the basis of analysts' recommendations as their reports are highly informative and impact security pricing (Frankel et al., 2006).

Close to every financial valuation model relies on the financial statement, directly or indirectly through analyst forecasts (Hutira, 2016). Consequently, the financial statement is an important source of information, serving as one of the key inputs that sell-side analysts rely upon when they produce their recommendations. In light of this, it is of interest to study whether the adoption of new accounting standards affects the properties of analysts' forecasts, giving its implication potential for securities. Market participants rely on the income statement for multiple valuations (implied DCF valuation), and changes in the forecast properties on the back of the new accounting standards have the potential to change the output from this methodology. Moreover, introducing new accounting standards could change analysts' cash-flow forecast properties as cash-flow forecasts are usually modeled as a derivative of the income statement.

We hypothesize that IFRS 16 has resulted in increased analyst forecast error due to the increased complexity of modeling that follows from the capitalization of operating leases, particularly in the case of companies that provide limited information about the methods and assumptions behind the derivation of IFRS 16 items. We regress the analyst forecast error, measured by the EBIT-margin on the independent variables MarketCap, Standard Deviation of ROE, Number of Analysts, GICS Sector Names, and a Post IFRS 16 dummy to conclude whether mandatory adoption of IFRS 16 has increased sell-side analysts' forecast error.

We add value to the literature by examining how a mandatory change in financial standards affects the reporting of companies, and consequently also the properties of sell-side analysts' forecast properties. This distinguishes from previous literature, which has only investigated the effect that the full IFRS framework has had on analyst accuracy [1]. Moreover, our methodology differentiates itself from methodologies in previous literature as we measure the effect from adoption of IFRS 16 on EBIT-margin forecasting accuracy, while previous research has focused on its impact on earnings. Consequently, we provide more nuance by assessing the change in accounting standards' effect on various industries.

From our findings, comparing forecast error pre and post the mandatory adoption of IFRS 16 in Scandinavia, we find that analysts' EBIT-margin forecasts instead have become more accurate after the adoption of IFRS 16. The mean forecasting error prior to the IFRS 16 implementation was approximately 0.036 compared to the mean error after of 0.034. This indicates a slight decrease

[1] Mandatory IFRS Adoption and its Impact on Analysts' Forecasts by Jiao, Koning, Mertens, and Roosenboom (2012).

in forecast error post-implementation and hence an increase in forecast accuracy. However, the slight numerical decrease was not statistically significant. The outcomes derived from the regression analysis provide empirical support for the proposition that IFRS 16 has led to a reduction in forecast errors. Notably, the Post IFRS 16 dummy variable, which serves as an indicator for the period after the implementation of IFRS 16, demonstrated statistical significance. This suggests that the adoption of IFRS 16 did not adversely impact forecast accuracy. The output from our sector-based regressions suggests that the sectors of Consumer Discretionary, Consumer Staples, and Utilities all experienced higher forecast errors following the adoption of IFRS 16. All coefficients were found to have statistical significance.

2 Hypothesis development and background

2.1 Standards and definitions

2.1.1 International Financial Reporting Standards

The following subsection provides an introduction to the International Financial Reporting Standards (IFRS) and its objectives. In addition, the section provides a detailed explanation of the conceptual framework of IFRS 16 and its predecessor IAS 17. Building on this introduction, it explains the rationale behind the implementation of IFRS 16, and how adoption has impacted financial statements and ratios.

2.1.2 Background and objectives

The predecessor of IFRS, the International Accounting Standards Committee (IASC) was established in 1973 (IFRS Foundation, 2023) and was agreed to be adopted for international listings by the professional accounting bodies of Australia, Canada, France, Germany, Holland, Japan, Mexico, UK and the US. Consequently, the Committee began publishing International Accounting Standards (IAS) for each item in the financial statement. In 2000, IASC was restructured into a full-time International Accounting Standards Board (IASB) to be overseen by independent Trustees to improve governance and as a prerequisite for approval by the European Union (IFRS Foundation, 2016). From 2005, publicly listed companies in the European Union, including non-member countries such as Switzerland and Norway, replaced national accounting standards with IFRS standards (IFRS Foundation, 2016). As of December 2022, IFRS is required or permitted in 153 of the 166 assessed jurisdictions.

The IFRS Foundation aims to develop high-quality and globally accepted financial reporting standards that serve the public interest (IFRS Foundation, 2023). These standards are based on clear principles, seeking to enhance transparency, accountability, and efficiency in financial markets. Transparency means making financial information more comparable across different countries. Accountability means providing more information to hold management responsible and reduce information gaps for stakeholders. Efficiency means enabling investors to identify risks and opportunities around the world.

2.1.3 IAS 17

IAS 17 was the international accounting standard for leases until January 1, 2019 (IFRS Foundation, 2016). A lease is a contract where one party (the lessor) gives the right to use an asset to another party (the lessee) for a certain period and some payments. IAS 17 classified leases as either finance or operating leases depending on who bears the risks and benefits of owning the asset (IFRS, 2019). A finance lease transfers most of the risks and benefits to the lessee, who recognizes the asset and the liability on the balance sheet. An operating lease does not transfer the risks and benefits to the lessee, who records the lease as a rental expense on the income statement. For both lessors and lessees, IAS 17 also requires particular disclosures regarding the amount and nature of lease payments (IFRS Foundation, 2016). The IAS 17 also provides guidance on how to account for sale and leaseback transactions, when an entity sells an asset and leases it back from the buyer. IFRS 16 replaced IAS 17, which became effective on January 1, 2019.

2.1.4 IFRS 16

IFRS 16 is the international accounting standard for leases that came into effect on January 1, 2019. It provides guidelines for accounting for leases for lessors and lessees. Like IAS 17, it classifies leases as finance or operating leases, but with different criteria. Under IFRS 16, lessees have to recognize most leases on their balance sheets as assets and liabilities, except for short-term or low-value leases. The asset reflects the right to use the leased asset, and the liability reflects the obligation to pay for it. The purpose of IFRS 16 is to make lease transactions more transparent and comparable for financial statement users across different industries (IFRS Foundation, 2016).

2.2 Rationale behind the implementation of IFRS 16

2.2.1 Increasing transparency

The IASB initiated a project on lease accounting in 2009 and issued IFRS 16 ‘Leases’ in 2016 (IFRS Foundation, 2016). This standard replaced IAS 17 and became effective on January 1, 2019, for most companies that report under IFRS. The main purpose of IFRS 16 was to make lease accounting more transparent and comparable between different industries by requiring lessees to capitalize and recognize leases as assets and liabilities on the balance sheet.

IAS 17 categorizes leases as operating or finance leases at the inception of the lease, based on whether the lessee assumes substantially all the risks and rewards of ownership (IFRS Foundation, 2016). In contrast to operating leases, finance leases were recognized on the balance sheet. Using operating leases to keep lease obligations off-balance-sheet created inconsistencies and made financial reporting difficult to compare.

2.2.2 IAS 17 prone to subjectivity

Some companies took advantage of the operating lease classification to keep leases off-balance sheet, allowing them to present favorable financial positions as the lease liabilities were not reflected on the balance sheet (Petersen et al., 2017). The authors found that the practice was more prevalent in industries where leasing is common, such as retail, airlines, and shipping. The lack of transparency in lease accounting caused concern for regulators in terms of lessees being able to alter negotiations with lessors to classify financial leases as operating, thus understating their true liabilities by keeping the lease off-balance sheet. Moreover, investors and analysts could benefit from the change when comparing companies across sectors as the change would require fewer adjustments to financial figures. To address these issues, IFRS 2016 required all leases to be recognized on the balance sheet, with the exception of leases of low-value assets and short-term leases (i.e. leases of tables and PCs, small items of office furniture and telephones). Consequently, companies must recognize lease liabilities and right-of-use assets on their balance sheet, with the goal of providing a more accurate reflection of their financial position.

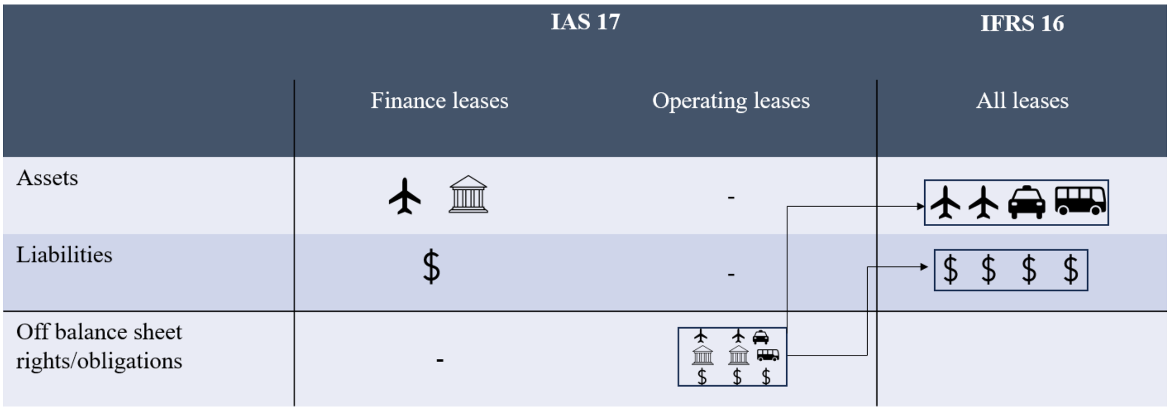
2.3 Impact on financial statements

This subsection provides an explanation of the changes that have followed from the adoption of IFRS 16 on financial statements, as well as challenges related to implementation from the perspective of the lessee's lessors and other stakeholders.

2.3.1 Initial impact post adoption

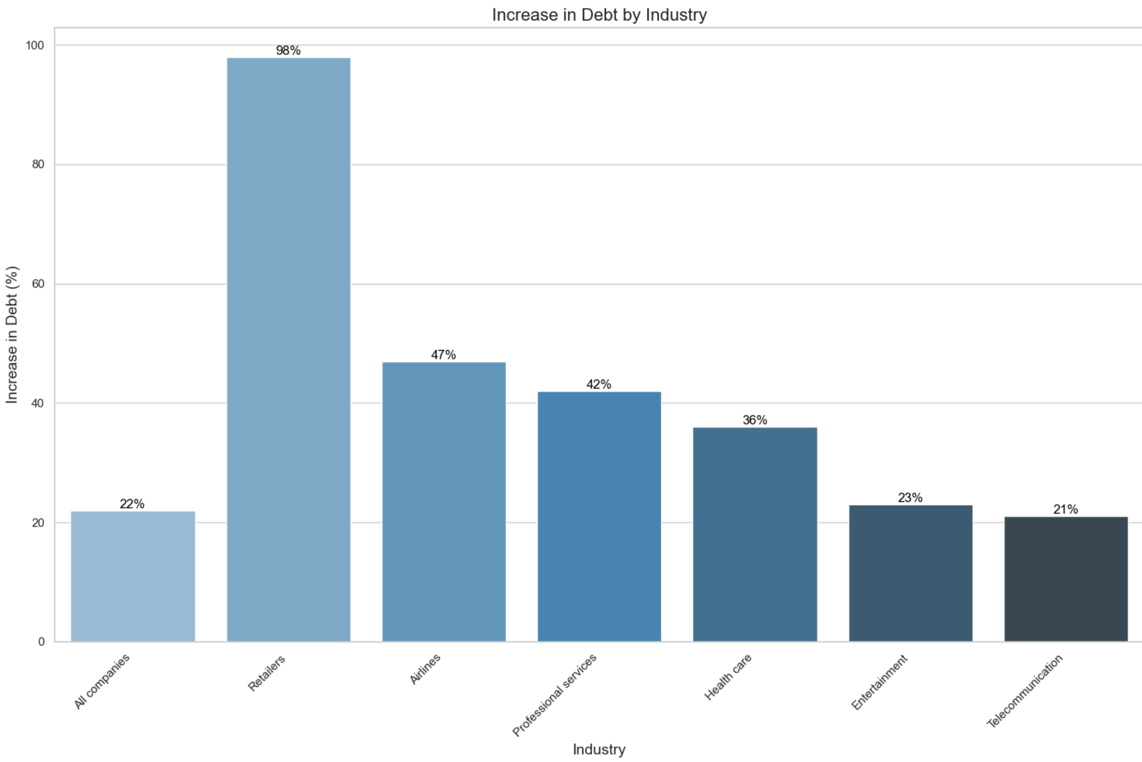
The adoption of the standard had a significant impact on financial reporting, as illustrated by a study conducted by PwC (2021) which indicated that the average increase in total assets was 12% for companies that adopted IFRS 16, while the average increase in total liabilities was 12.5%. Retail, airlines, and manufacturing sectors were the most affected by the new standard, according to this study. Financial ratios and performance metrics were also affected as debt-to-equity ratios for companies increased after the adoption of IFRS 16, as lease obligations were recognized on the balance sheet, and therefore total liabilities were increased (IFRS Foundation, 2016).

Figure 2.1: This figure illustrates the differences between IAS 17 and IFRS 16 with regard to balance sheet items and capitalization of leases. Capitalization of leases in IFRS 16 notably increases assets and liabilities



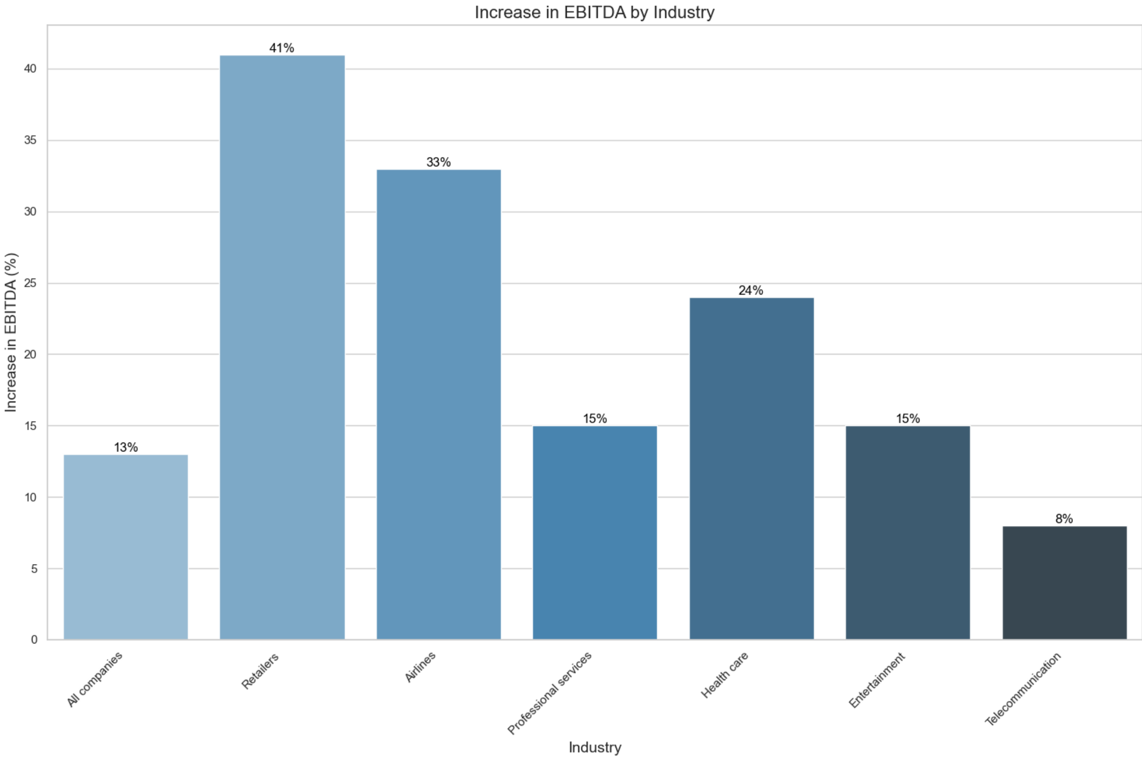
Source: IFRS Foundation (2016)

Figure 2.2: This figure illustrates the median increase in debt for various industries. The bars represent the median percentage increase in debt for each industry. Retailers show the highest increase, whereas telecommunication has the least.



Source: PwC (2021)

Figure 2.3: This figure shows the median increase in EBITDA for different industries. Each bar signifies the median percentage increase in EBITDA for the respective industry. Retailers demonstrate the most substantial increase, while telecommunication exhibits the smallest increase.



Source: PwC (2021)

2.3.2 Impact on the income statement

Although the most obvious impact following the implementation of IFRS 16 is on the balance sheet through the above-mentioned increase in assets and liabilities, its presence is also significant on the income statement. Following the capitalization of leases, IFRS 16 primarily impacts EBITDA as operating lease expenses are reclassified from operating expenses to the depreciation of the right-of-use asset and interest expense from the lease liabilities (IFRS Foundation, 2016). A depreciation charge for the leased asset replaces the operating expense, while the interest expense is determined based on an estimated cost of debt, which will be reduced over time as the amortization of the debt (i.e. lease payments) decreases the lease liabilities. Total recognition of expenses will decline as the lease matures, contrary to the previous recognition of leasing, which had a straight-line cash cost profile. Thus, net profit will be lower in the initial phase of a lease under the new standard. As the lease matures, it will gradually increase in line with decreasing interest costs related to the lease liability. Consequently, IFRS 16 makes EBITDA margins and profitability measures such as return on capital employed more comparable across different industries due to the capitalization of leases (IFRS Foundation, 2016).

Figure 2.4: This figure shows the difference between IAS 17 and IFRS 16 with regard to the impact on the P&L statement. EBITDA and EBIT increase, all else equal, as the cost of leasing is capitalized.
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	IAS 17		IFRS 16
	Finance leases	Operating leases	All leases
Revenue	x	x	x
Operating costs	-	Single expense	-
EBITDA			↑↑
Depreciation & amortization	Depreciation		Depreciation
EBIT			↑
Finance costs	Interest		Interest
Pre-tax profit			↑/↓

Source: IFRS Foundation (2016)

2.3.3 Challenges related to the determination of lease discount- and borrowing rate

When entering into an operating lease agreement, the lessee and the lessor face a challenge when determining the discount rate of right-of-use assets and the borrowing rate on lease liabilities (KPMG, 2021). In accordance with IFRS 16, the discount rate is not always easily determinable. For the lessee, the discount rate for the lease is the implicit rate attached to the lease, unless that rate cannot be easily determined. If so, the lessee is required to apply its incremental borrowing rate, while for the lessor, the discount rate for the lease is always the rate implicit in the lease. An additional challenge arises when the lease stems from a third party as the rate implicit in the lease tends to be not readily determinable as the lessee in general rarely has direct insight into the lessor's assumptions such as investment tax credit, initial direct costs or estimated residual value of the right-of-use asset (KPMG, 2021). Thus, lessees that lease from third parties frequently have to use a different discount rate. The incremental borrowing rate is another option for lessees to determine their discount rate, as it is the rate of interest a lessee else would have to pay to borrow on a collateral basis over a similar term in an amount equal to the lease payments in a similar economic environment. To reach this determination, lessees have several options; i) evaluate existing debt, ii) draw comparisons to similar entities, iii) solicit lender quotes or iv) estimate their IBS through the use of adjusted yield curves (KPMG, 2021). However, all these methods can obviously bring difficulties for a lessee.

2.4 Sell-side analysts

The following subsection is providing a discussion and examination of the sell-side analyst's role in the financial markets, including the implications of potential biases that could emerge from working in the sell-side industry and other factors that might have an effect on their forecasting ability.

2.4.1 Equity analysts role in capital markets

The overall task of a sell-side analyst is to provide participants in the capital markets with an analysis of industries and markets and structure this into firm-specific information. The latter includes developing forecasts of the future financial performance of companies in order to derive an estimated fair value and recommendation to investors on whether to buy, hold or sell the individual equities in their coverage universe. In the industry, analysts are considered sophisticated users of financial statements (Schipper, 1989) as nearly all financial valuation models are directly or indirectly based on earnings forecasts, underpinning the importance of financial statements (Hutira, 2016). In the extension of this, equity research works as marketing for corporations' equities and contributes to increased liquidity (Krigman et al., 2001) as investors use the research to make investment decisions (Groysberg et al., 2011). The findings of Frankel et al (2006) show that market participants act upon the recommendations provided by analysts as their reports are significantly informative (i.e., impact the pricing of securities). The sell-side analysts are thus crucial for providing the market with important information, offsetting asymmetric information, and contributing to more efficient markets.

2.4.2 Equity analysts' position in the sell-side industry

"Sell-side" refers to investment banks and intermediaries whose business is based on brokering securities, providing corporate finance advisory services to companies, and underwriting new security issues (i.e. equity and bond issues). Investment banks have traditionally been divided into three departments based on the nature of their services and clientele, namely brokerage, research, and investment banking. The two former departments work closely together and cater to investors, while the latter department caters to corporations. Although the brokerage and research departments are motivated by providing their clients with the best trading advice and most precise research, this motive can be conflicted with the investment banking department's incentive to maximize their own mandates and transactions. Potential conflicts of interest may as such present themselves when analysts are engaged to contribute with research and marketing of a transaction, and in the extension of that have to follow these companies post transaction. As such, the business model of an investment bank creates structural incentives for analysts to be optimistic about companies in which the firm has acted as an advisor in a corporate finance transaction.

McKnight and Todd (2013) found that analysts are more optimistic when they work for an investment bank that has business with the company they cover. By mid-2000, the percentage of buy recommendations had reached 74% of total recommendations outstanding, while the percentage of sell-recommendations had fallen to 2% (Barber et al., 2007). Unsurprisingly, the main reason behind this unequal distribution was that optimistic analyst recommendations could earn their employers significant fees from corporate finance mandates. The study by Barber et al. (2007) also showed that buy recommendations from independent research firms (i.e. firms providing equity research without having a corporate finance department) outperformed those issued by investment banks by 3.1 basis points, while the hold/sell recommendations of the investment banks outperformed those of the independent research firms by 1.8 basis points. Analysts hence face the challenge of being able to keep their investment banking clients (and colleagues in the investment banking department) satisfied, while simultaneously producing honest estimates and recommendations in the best interest of investors. Similar previous literature also concludes that forecasts on companies where the investment bank has executed corporate finance mandates are overly optimistic relative to forecasts provided by analysts in brokerage firms that have not catered investment banking services (Dugar and Nathan, 1995). These types of findings might suggest that analysts, in general, tend to prioritize keeping investment banking clients happy over making recommendations that are in the best interest of investors. Buy-and-hold strategies based on recommendations on IPOs from underwriter analysts, underperform the buy recommendations issued on IPOs from non-mandated brokerage firms.

It is intuitive that firms planning to go public assign high value to the quality of the investment bank's equity research department when deciding which investment bank will conduct their IPO. This is done in order to maximize the firm's value and market themselves to investors. Findings from surveys conducted in the 1990s (Krigman et al., 1999), showed that approximately 75% of decision makers in firms planning to go public assign high value to the quality of the investment bank's equity research department. Furthermore, the reputation of the potential underwriter's security analyst (in this case equity analyst) carries high importance when deciding upon potential underwriters (Krigman et al., 2001).

Another potential factor that could impact bias among analysts is the impact of compensation on motivation. In the industry, compensation is rarely related to forecast accuracy. If the opposite were the case, analysts would have less incentive to produce overly positive estimates and recommendations. This is supported by the findings of Groysberg et al. (2011), who found no evidence linking the accuracy of the estimate to compensation in a major investment bank. Instead, the study found that compensation was related to recognition among institutional investors, ranking within Wall Street Journal's top stock picker ranking, the size of their portfolio following, and their contribution to investment banking mandates (Groysberg et al., 2011). The study found that underwriting fees from companies covered by the analyst would increase analyst compensation by 7% for every USDm in fees, further underpinning the idea that analysts are broadly overly optimistic on behalf of every company they cover due to the potential for future investment banking business.

One aspect that is often overlooked in the literature is the reluctance of analysts to issue negative recommendations, especially after initiating coverage with a favorable recommendation. This can result in selection bias. As such, one contributing factor to the persistent optimistic bias in analyst forecasts and recommendations may be that we rarely observe analysts' negative views (Bradshaw, 2011).

2.4.3 Additional factors affecting analysts' optimism

Among the research on sell-side analysts, the most pervasive understanding is that the analyst forecasts are systematically overly optimistic (Bradshaw, 2011). In addition to structural reasons stemming from the sell-side industry, past literature points to analysts' desire to maintain positive relationships with management as the second most common explanation. Regardless of the decisive factor, a vast amount of literature documents that analysts are indeed routinely overly optimistic. In 2010, McKinsey & Company (2010) showcased how analysts have been overly optimistic in their earnings forecasts for American companies over the past 25 years. While earnings for companies included in the S&P 500 grew by around 6% over the same period, analysts consistently forecasted earnings growth of 10-12%. At the higher end of the forecasted earnings range, analyst forecasts were found to be 100% above the actual reported figure. This includes all firms and does not distinguish between analysts working for banks with investment banking interests. McKinsey & Company (2010) also found that analysts are slow to revise their forecasts to reflect new economic conditions. During periods of economic growth, forecast errors were reduced while they increased during downturns. This is consistent with the findings of Chopra (1998) and, Clayman and Schwartz (1994), who document that analysts' forecasts are more accurate during periods of strong and constant economic growth. These findings align with our perception of how equity sell-side analysts conduct forecasting. Most analysts disregard macroeconomic analysis for forecasts made far into the future, as such events are difficult to predict, even for experienced macro analysts. Forecasts are usually made to reflect a firm's financial performance given a steady growth state in the overall economy. Stale forecasts included in such analysis further exacerbate this phenomenon.

2.4.4 Accuracy among sell-side analysts in Scandinavia

While there is no research dedicated to the Scandinavian capital markets on a stand-alone basis, the research of Røstberg et al. (2001) found that Norwegian analysts are less accurate than their peers in the US and Japan, in addition to its neighbor Sweden. A random walk model, utilizing the EPS (earnings per share) for the preceding period to forecast the EPS in the following period, showcased how the Norwegian market is more challenging to predict. The estimated error was calculated using MAPE. When comparing the results across the three markets, findings showed that the random walk model yielded the highest MAPE for Norway, suggesting that the business climate is more volatile than in the US, Japan, and Sweden. Other research by Jiao, Koning, Mertens, and Roosenboom (2012) and, Lang and Lundholm (1993) attributes the power of explanation to factors such as lower market capitalization and less analyst coverage, which is not discussed by Røstberg et al. (2001).

Moreover, Oslo Stock Exchange has a relatively high concentration of companies that process raw materials such as oil & gas, seafood, and other asset-heavy industries such as shipping. Hence, the financial performance of companies listed on the Oslo Stock Exchange is more dependent on the development of commodities and raw materials that in nature are prone to exogenous shocks, affecting their prices. These types of companies are more capital-intensive, causing larger movements in the balance sheet due to investment requirements, fair value adjustments, and impairments. Thus, the forecast accuracy on EBIT and net income are impacted. Merkley et al. (2017) find that the number of analysts per industry is more important than the number of analysts per company for determining the quality and informativeness of equity reports. The paper studies companies in 41 countries from 1994-2009 on a global basis, and the findings suggest that a larger sell-side analyst industry drives competition, increasing the research quality by reducing bias and error in forecasts as they compete for reputation and attention. However, Norway had a lower forecast error and dispersion than Finland and Sweden, despite having fewer analysts per industry. This is consistent with the findings of Clement (1999), who found that the average forecast error for analysts in Norway is higher than in Denmark but lower than in Sweden and Finland, which is contrary to Røstberg (2001), who found that Swedish analysts on average were more accurate than their Norwegian peers. Moreover, all Scandinavian countries bar Finland had a lower average forecast error than the overall average of 12 European countries that were assessed in the study.

2.4.5 Time horizon and accuracy

The MAPE for Norwegian analysts decreased the closer the estimate was published to the actual date of reporting (Røstberg et al., 2001). The same has been found true in similar studies in other markets (Clement, 1999), which implies that analysts process new information and incorporate it into their forecasts. MAPE for EPS forecasts published 15 months prior to the date of reporting was 51.87% vs 26.67% after the fiscal quarter ended, but before the actual results were released (Røstberg et al., 2001).

2.5 Analysts with a large coverage universe are less accurate

One of the factors that affect the accuracy of analysts' forecasts is the complexity of their coverage universe, measured by the number of firms and industries they follow. Previous research suggests that analysts who follow more firms and industries face higher information processing costs and cognitive limitations, which may impair their ability to produce accurate forecasts ((Clement, 1999) (Jacob et al., 1999)). Empirical evidence supports this hypothesis. Clement (1999) finds a negative and significant relationship between the number of firms and industries in an analysts' coverage universe and the forecast accuracy, arguing that analysts who follow more firms and industries have less time and resources to devote to each firm, which could also cause information overload and confusion. Similarly, Jacob et al. (1999) find that analysts who follow more industries have lower forecast accuracy than those following fewer industries. They suggest that industry specialization allows analysts to develop more expertise and better understand the industry dynamics and trends.

2.6 IFRS 16 and modeling from an analysts' perspective

In this subsection, we provide an explanation of how the mandatory adoption of IFRS 16 has caused increased modeling complexity for analysts, particularly for the coverage of companies that do not disclose detailed information about their leases on a quarterly basis.

2.6.1 More moving parts requires more disclosure

As all leases are now recognized on the balance sheet following IFRS 16 adoption, companies with leased assets have to estimate the present value of future lease payments and record them as lease liabilities, while simultaneously recognizing ROU (Right of Use) assets that represent their right to use the leased assets for the term of the lease(s). This requires more complex financial modeling for sell-side analysts as they need to incorporate the companies' assumptions and judgments that lay behind the ROU liabilities and assets, including each individual lease's term, discount rate, lease payments, depreciation, and interest expense. Moreover, lessees must reassess these assumptions and estimates periodically and adjust lease assets and liabilities accordingly, adding more complexity and volatility to their financial statements. Consequently, analysts face a significantly more complex process if they choose to model these items on a stand-alone basis as opposed to under IAS 17, where they could model the item in the OpEx as a percentage of sales, or based on the number of employees.

For companies that disclose the amortization of their leases, the interest element, and the depreciation associated with its ROU assets, analysts are well equipped with sufficient information to model quarterly estimates for ROU assets and liabilities, in addition to associated interest, repayments, and depreciation. This information is usually provided in the annual reports for most companies and to some degree in quarterly reports among companies operating in more capital- and asset-heavy industries. However, asset-light companies tend to be more restrictive in providing this information on a quarterly basis. As such, analysts could struggle to make meaningful estimates and be tempted to roll over the previous period's balance sheet items and lease payments in the cash flow statement. In addition, the interest element and depreciation related to ROE-liabilities and assets could be neglected on a stand-alone basis, and instead modeled on gross interest-bearing debt and property, plant, and equipment, respectively. As such, estimates that follow this approach could over time be prone to understating growth in these elements as a company grows, and require more leases.

2.7 The introduction of IFRS has increased analyst accuracy

The following subsection examines previous research on the mandatory adoption of IFRS' impact on estimate accuracy, and the relationship between stock recommendations by financial analysts, earnings management, and the accuracy of earnings forecasts.

2.7.1 Mandatory IFRS Adoption and its Impact on Analysts' Forecasts

The study by Jiao, Koning, Mertens, and Roosenboom (2012) investigates the effects of mandatory IFRS adoption on the accuracy, dispersion, and optimism of analysts' earnings forecasts. The study specifically investigates the changes in these three characteristics of analysts' forecasts in the European Union (EU) following the mandatory IFRS adoption in 2005. The authors aim to provide a comprehensive understanding of the impact of IFRS on the financial information environment and the role of financial analysis in the capital market.

The study builds upon previous literature that has investigated the effects of IFRS adoption on various aspects of financial reporting, such as the improvement of financial information quality, the increased comparability of financial statements, and the reduction in information asymmetry. Some prior studies have focused on the impact of IFRS adoption on the properties of analysts' forecasts, but the results have been mixed and inconclusive. To conduct their analysis, Jiao, Koning, Mertens, and Roosenboom (2012) utilized a sample of firms from 15 EU countries, comparing the characteristics of analysts' earning forecasts before and after the mandatory IFRS adoption. They employ regression analysis to examine the changes in forecast accuracy, dispersion, and optimism over time, controlling for various firm-specific and country-level factors. The study yields several key findings:

Forecasts Accuracy: The authors find that after the mandatory IFRS adoption, analysts' earnings forecasts have become significantly more accurate. This result supports the notion that IFRS adoption leads to improvements in the financial information environment, allowing analysts to better predict firms' future earnings.

Forecast Dispersion: Jiao, Koning, Mertens, and Roosenboom (2012) report a decrease in the dispersion of analysts' earnings forecasts following the IFRS adoption. This finding suggests that the adoption enhances the comparability of financial statements across firms, reducing the divergence in analysts' opinions and fostering consensus among them.

Forecast Optimism: The authors find no significant change in the optimism of analysts' forecasts after the IFRS adoption. This result indicates that while IFRS adoption may improve the information environment, it does not necessarily lead to more conservative or pessimistic forecasts by analysts.

Overall, the research by Jiao, Koning, Mertens, and Roosenboom (2012) contributes to the literature on IFRS adoption and its implications for financial reporting and capital markets. The authors provide evidence that mandatory IFRS adoption has a positive impact on the accuracy and dispersion of analysts' earnings forecasts, demonstrating the potential benefits of a unified set of accounting standards for the information environment and decision-making processes in capital markets. However, the lack of a significant change in forecast optimism suggests that the adoption of IFRS does not directly influence analysts' sentiments or expectations. We argue that this study has implications for regulators, standard-setters, and market participants, emphasizing the importance of high-quality, comparable financial information for market efficiency and the role of financial analysts in the dissemination and interpretation of this information. It also highlights the need for continued research into the consequences of IFRS adoption, particularly as more countries adopt the standard and as accounting practices continue to evolve.

In conclusion, the article presents valuable insights into the effects of IFRS adoption on the properties of analysts' earnings forecasts in the European Union. These findings underscore the positive impact of IFRS on financial information quality and comparability, while also emphasizing the need for further research to better understand the broader implications of IFRS adoption for financial markets and decision-making processes.

2.7.2 Can Stock Recommendations Predict Earnings Management and Analysts' Earnings Forecast Error?

This study by Jeffery Abarbanell and Reuven Lehavy (2003b) examines the relationship between stock recommendations made by financial analysts, earnings management, and the accuracy of earnings forecasts. To test their hypotheses, they use a sample of 8 716 firm-year observations between 1985 and 1997. They measure earnings management using the modified Jones model, which captures the discretionary accruals component of earnings. The authors control for various factors that may influence buy-, hold-, or sell recommendations and forecast errors. Furthermore, they also include firm size, market-to-book ratio, past stock returns, and past earnings performance. The authors perform a cross-sectional regression analysis to examine the relationship between earnings management and stock recommendations, as well as the accuracy of analysts' earnings forecasts.

The findings raise questions about the role of financial analysts in capital markets and their ability to detect and report earnings management. The results may have implications for regulators and standard setters, who may need to consider the potential impact of earnings management on the credibility of analyst recommendations and the accuracy of earnings forecasts. The study also highlights the importance of further research to understand the factors that drive analysts' decisions to issue favorable recommendations for firms with higher levels of earnings management.

In conclusion, the research by Aberbanell and Lehavy (2003b) contributes to the understanding of the relationship between earnings management, analyst recommendations, and earnings forecast accuracy. The study highlights potential issues with the reliability of analyst recommendations and forecasts in the presence of earnings management. All of these issues have implications for investors, regulators, and standard setters.

2.8 Hypothesis development

Based on the findings in our literature review, which suggests that analysts, in general, are overly optimistic, in combination with increased modeling complexity following IFRS 16, we hypothesize that sell-side analyst forecast accuracy has decreased post-IFRS 16. Based on the fact that the change in accounting standard all-else equal should result in higher depreciation due to capitalization of leases, we suspect that sell-side analysts' EBIT-margin estimates have become less accurate, as increased financial disclosure is required in order to be able to model the items that affect EBIT (i.e. IFRS 16 depreciation), resulting in an increase of the number of analysts that roll over the previous periods' items, causing lower depreciation and lease-payments than what would be the case if these were modeled individually, all else equal. Most of the previous research has been on the adoption of IFRS, which is a significantly broader aspect than IFRS 16 on a stand-alone basis. Moreover, the research is rather old, and we find it interesting to see if the development of IFRS in recent times has had the same effect as previous literature points to. Consequently, we want to find out if the mandatory adoption of IFRS 16, and the increased complexity it has brought with it has negatively impacted analyst forecast properties.

H1a: *Analysts' forecasts have become less accurate after the mandatory implementation of IFRS16 in Scandinavia.*

H1b: *Analysts' forecasts have become less accurate depending on the sector in which companies operate.*

3 Data and Methodology

In this section, we detail our data sourcing, data cleaning and summarize descriptive statistics. Previous literature regarding the accuracy of equity analysts has demonstrated that the most recent forecasts issued prior to the reporting date tend to be the most reliable. As a result, we find mean estimates to be of most relevance for our research and also minimize the effects of exogenous factors not captured by our models to be able to perform the most accurate results from the implementation of IFRS 16. To examine the effect of IFRS 16 implementation on analyst accuracy we include data from all Nordic countries and use multivariate regressions. Including all Nordic countries is beneficial due to the increased sample size and diversification of data.

3.1 Data Sources

Our initial data is retrieved from I/B/E/S through the Eikon Refinitiv database on May 1st, 2023. The data consists of 89,232 single quarterly mean estimates and actual figures for 859 listed companies from Q1 2010 to Q4 2022 on Oslo Børs (Euronext), Nasdaq Helsinki, Stockholm Stock Exchange (STO) and Nasdaq Copenhagen. As described earlier, the analyst forecasts in our data are the latest available estimates ahead of the reporting date. This means that we do not distinguish between forecasts potentially made well ahead and right before publication. Furthermore, we exclude observations for firms that do not impose mandatory IFRS 16 reporting, which primarily results in the exclusion of the majority of the companies listed on Euronext Growth as these are allowed to follow NGAAP accounting rules. The same applies to Nasdaq First North Growth Market and the Nasdaq Transfer Market Segment (both associated with Nasdaq Stockholm). All data is divided into each country and GICS Sector Name. The Number of analysts, MarketCap, and standard deviation of ROE are also retrieved from Eikon Refinitiv. All data has been merged on "Identifier", the assigned code designed to identify each instrument uniquely.

3.1.1 Data quality

The quality of the data used in this paper is important to ensure the reliability and validity of potential findings. The primary data sources for this study are conducted from a highly reliable source, underpinned by its market position in capital markets and academia. The data obtained have undergone rigorous data collection processes. However, it is important to acknowledge that data quality issues may still exist. Missing values, data inconsistencies, outliers, and measurement errors are examples of potential data quality concerns. To mitigate these concerns, we perform a variety of measures. We exclude missing values after considering the number of observations to be sufficient. Moreover, we address data inconsistencies and outliers through careful data cleaning and validation procedures. Additionally, robust statistical techniques such as winsorizing are employed to minimize the impact of extreme values. All of these measures are aimed at improving the overall quality and integrity of the data. This is crucial so that analysis and conclusions are based on reliable information.

Specifically, the forecast error data was winsorized at the 5th and 95th percentiles, meaning that all data points below the 0.05 quantile were replaced with the value at the 0.05 quantile. Also, all data above the 0.95 quantiles were replaced with the value at the 0.95 quantiles. This process effectively limits the range of the data, thereby reducing the influence of extreme values. We argue that winsorizing is a popular method for handling outliers as it retains the structure of our data. As we work with deviations on a percentage level, outliers are inevitable and hence more crucial to handle in a delicate way (Investopedia, 2023). In addition to handling outliers, another vital aspect of the data quality process in our study involves the treatment of missing values and NULL entries in all datasets. Missing values and NULLs can introduce uncertainty and bias in the analysis, as they indicate the absence of information. For the purpose of this study, we remove missing values and nulls from the dataset for EBIT (actual and estimates), Revenue (actual and estimates), stdvROE, MarketCap, Number of Analysts, and GICS Sector Name prior to analysis. However, it is important to recognize that this approach assumes that the data are missing completely at random. We argue that this is the case for our data since missing values and NULLs did not exhibit any systematic pattern, which supports the assumption of randomness. Furthermore, given the size of the data sets used in our study, the loss of information due to removal is considered to have a negligible effect on the statistical power and quality of the results.

3.2 Dependent Variable

3.2.1 Median absolute forecast error (MAPE)

Forecast error in our paper is characterized as the Median Absolute Forecast Error (MAPE), which is essentially the absolute, proportional discrepancy between estimated and actual reported figures. The forecasted figures are determined by the median of all available analyst forecasts for a given company at any time, often referred to as the consensus forecast. By using the median we exclude the impact of potential outliers. Furthermore, when presenting our findings graphically, we apply the median of all forecast error per quarter to prevent the influence of outliers (Abarbanell and Lehavy (2003a)). The forecast error measurement is utilized for EBIT margin and is defined by the following formula:

$$\text{ForecastError}_{t,i} = \frac{\text{Consensus EBIT-margin}_{t,i} - \text{Actual EBIT-margin}_{t,i}}{\text{Actual EBIT-margin}_{t,i}} \tag{3.1}$$

We highlight that the forecast error defined in our paper is computed differently from what analysts and investment banks define as forecast error. By using actual values as the denominator we will obtain high values of MAPE when the reported values are close to zero. Forecast errors are thus likely to be higher for companies that have reported low values, which can be true for companies that barely provide profits or surprisingly report poor results. Furthermore, increased differences in forecast error can occur if forecasted and actual figures have opposing signs. This would not necessarily imply bad forecasting. An EBIT-margin forecast of 20% compared to a reported -10% could in some contexts be classified as accurate forecasting when for example margins are low. Despite that, we would estimate a 300% error. This example highlights the reason for using the median of forecast error as a more accurate way of presenting analysts' forecast properties. As we are using EBIT-margin, figures will normally be smaller since we are further down in the P&L and will consequently lead to more outliers on EBIT compared to for example revenue. If we did not use EBIT-margin and instead use MAPE on revenue or EBIT alone, the forecast errors would be expected to be higher for EBIT compared to revenue, all else equal. We argue that the EBIT margin will work as a good measure since it combines both items higher up and lower down in the income statement. We investigate forecast errors for the EBIT margin since our hypothesis suggests that the EBIT margin has higher relevance than the absolute deviation as it is considered an important measure of a company's profitability. Analysts often refer to EBIT margin as an important determinant for valuation multiples, particularly for asset-light companies (i.e. software, consulting, etc.).

3.3 Regressions

We apply a set of multivariate OLS regressions with industry-fixed effects. We include these dummy variables to account for any unobserved, sector-specific effects that are constant over time. There are 3 models in total, and each model is tested on the error term of EBIT-margin. The regression models in this paper are described as follows:

$$\begin{aligned}\text{MAPE}_{t,i} = \alpha &+ \beta_1 \cdot \text{PostIFRS16}_t + \beta_2 \cdot \ln(\text{Mcap}_{t-1,i}) \\ &+ \beta_3 \cdot \text{StdROE}_{t,i} + \beta_4 \cdot \ln(\text{NAnalysts}_{t,i}) \\ &+ \beta_5 \cdot \text{IndustryDummies}_{t,i} + \beta_6 \cdot \text{QuarterlyDummies}_{t,i} + \epsilon_{t,i} \quad (3.2)\end{aligned}$$

PostIFRS16 is the variable of interest since it captures the changes in financial reporting from the new standards in 2019. This is a dummy variable, which takes on the value 1 after the implementation quarter (Q15) of the respective new accounting standard. Before implementation, the variable takes on the value 0. We purposely leave out the first quarter for all regressions in each year. This method ensures that any effects stemming from the quarter of implementation are not mixed up with the ongoing impacts that follow. We argue that a new accounting standard might be challenging for analysts to cope with initially, but it should be substantially easier to incorporate as soon as a quarter has passed. This could also lead to a one-off miscalculation in the first quarter. Additionally, from our observation, forecasts for the first quarter during an implementation year were typically framed according to the former standard. Finally, a few companies might have issued guidance for the coming quarter, either through an analyst seminar or within the annual reports, usually issued before the final Q1 forecasts are developed. By leaving out the first quarter we do not need to separate between companies disclosing information or the ones that do not. All of these examples above argue in favor of excluding the first quarter in our regressions. The same strategy has been done by Jiao et al. (2012), who excluded the implementation year of IFRS in 2005 in their study.

We include control variables that previous literature has shown to influence analyst forecast properties. Our variables are summarized in Table 1, while the rationale for their inclusion is presented below.

Table 3.1: We summarize the definition of variables used as control variables.

Variable	Definition
ForecastError/MAPE	*ForecastError/MAPE* is the error in analysts' consensus forecasts, calculated as the absolute difference between the median analyst forecast and actual reported figures.
PostIFRS16	*PostIFRS16* is a dummy, which equals 1 after Q1 2019 (represents Q15 in data set) and 0 before Q1 2019.
MktCap	*MktCap* is a firm's market capitalization at the end of year t-1, which controls for the effects of firm size.
NAnalysts	*NAnalysts* is the number of analysts covering the company. This variable controls for the number of analysts covering the stock which also controls for higher competition among these analysts.
StdROE	*StdROE* is the standard deviation of ROE and controls for the volatility of firm performance. It is calculated based on the five quarters before year *t*.
Industry Dummies	This is a set of industry dummies indicating the GICS Sector Name to which the firm belongs.
Country Dummies	This is a set of country dummies that indicate which Scandinavian country the firm is registered in.

Size of the firm (ln(MktCap(t-1)): Lang and Lundholm (1993) show that larger companies tend to disclose more information, which can lead to more accurate forecasts as well as less variation in earnings predictions. A similar influence of a company's market capitalization on forecasting attributes has been documented by Jiao et al. (2012). For our analysis, we apply a firm's market capitalization at the end of the previous quarter, denoted as t-1. This approach aligns with prior studies that also used t-1 data for the preceding year.

Number of analysts (ln(NAnalysts): Lang and Lundholm (1993) also highlighted that analyst following is related to disclosure level and forecast properties. They showed that analyst following increases when disclosure levels improved. Jiao et al. (2012) also found that higher analyst following is positively correlated with forecast accuracy. They argue that a larger analyst following will increase the competition among analysts, hence creating stronger incentives to increase the level of accuracy. Greater analyst following did also, according to Brown (1997), increase marginal information gathering and improved consensus quality. In this paper, we do also expect forecasts to be more accurate as the number of forecasts increase.

Volatility (StdROE): It might be difficult to predict earnings when a firm's performance is volatile. Thus, the accuracy of forecasts for firms with more volatile performance could be lower. We control for this with a standard deviation of ROE as a measure for performance volatility, which is in line with prior research from Jiao et al. (2012). We based our standard deviation of ROE on the five preceding quarters with the purpose of smoothing out events that are not occurring in nature.

Industry (IndustryDummies): Industry dummies are included to control for the non-observable factors associated with the characteristics of different industries that might influence the accuracy. In our models, we implement these dummies based on the GICS Sector Name for each firm. As highlighted in the introduction and literature review, some industries might include a higher degree of leases due to their nature of business, which further might affect forecast accuracy.

Country (CountryDummies): The same applies to countries. The models include country dummies to control for non-observable factors associated with the characteristics of different countries.

3.3.1 Heteroskedasticity and robust standard errors

We observe heteroskedasticity in the residuals for our OLS estimator. To address this issue, robust standard errors are applied to correct for the non-constant variance caused by heteroskedasticity and allow for valid testing. Our approach is the White or HC3 estimator, which adjusts for heteroskedasticity by estimating the covariance matrix of the OLS estimator using a consistent estimator of the error variance. By doing so, the standard error becomes robust to heteroskedasticity. Heteroskedasticity is present when the variance of the error term is across observations varying, and the OLS is no longer BLUE (Wooldridge, 2015). In all of our regressions, heteroskedasticity has been treated by employing robust standard errors.

3.4 Descriptive Statistics

Descriptive statistics are presented in Table 2 for the forecast error sample. This paper's original data set includes 18,096 observations from Q4(22) - Q1(10). In the table below we illustrate the distribution of forecast error across industries in all of Scandinavia. The *Financials* sector accounts for the majority of observations, making up 28% of available forecast error observations, while the *Utilities* sector amounts to the smallest portion of observations at approx. 1.5%. Prior studies on earnings forecast accuracy are on average about 2% of the stock prices (Bae et al., 2008). However, since we are studying accuracy on EBIT-margin which is cited in percentage terms, the errors become larger.

Table 3.2 below gives an overview of this paper's sample selection after winsorizing and removing missing data and inconsistent data.

Table 3.2: Sector distribution. This table shows the forecast error sample by sector with the number of observations, mean, standard deviation, min, and max.

Sector	Count	Mean	Std.	Min	Max
Communication Services	177	0.0783	0.0466	0.0236	0.3688
Consumer Discretionary	188	0.1385	0.1185	0.0491	0.6612
Consumer Staples	318	0.1394	0.0753	0.0362	0.5474
Energy	780	0.2953	0.2121	0.0549	1.4529
Financials	1408	0.1750	0.2026	0.0132	0.9399
Health Care	100	0.2257	0.1917	0.0182	1.0000
Industrials	992	0.1683	0.2067	0.0182	1.4460
Information Technology	417	0.2004	0.1873	0.0168	0.7985
Materials	364	0.1689	0.1121	0.0399	0.9179
Real Estate	205	0.0829	0.1830	0.0183	1.5943
Utilities	79	0.1465	0.0520	0.1074	0.3643

For our research question, we have three multivariate regressions across similar time frames between 2010 and 2022. Table 3.3 presents descriptive statistics for our chosen variables used in the MAPE regressions across the EBIT margin. One notable observation is the difference between the mean and median for MAPE (Error), which is due to a thicker right tale in the distribution of analyst forecast errors.

Table 3.3: Descriptive statistics. The table reports the descriptive statistics of the sample for the accuracy test. We refer to Table 3.1 in section 3.3 for variable definitions.

	Error	IFRS 16	NAnalysts	MktCap	StdvROE
Count	4995	4995	4995	4995	4995
Mean	0.0356	0.3513	1.9550	22.8992	0.0633
Median	0.0191	0.0000	2.0794	23.0756	0.0331
Std. dev.	0.0545	0.4774	0.6406	2.0327	0.1610
Min	0.0014	0.0000	0.0000	15.1513	0.0000
25%	0.0101	0.0000	1.6094	21.4107	0.0122
75%	0.0364	1.0000	2.3978	24.3090	0.0686
Max	0.8486	1.0000	3.5835	27.9471	2.7405

3.5 Correlation matrix

Table 3.4 presents the simple correlations between the variables, both dependent- and independent variables. For the independent variables, NAnalysts (analyst coverage) is positively associated with firm size (Market_Cap) and IFRS16. Furthermore, NAnalysts is negatively associated with volatility measured as the standard deviation of ROE, in our sample. We observe that the correlations are relatively low suggesting that multicollinearity is not likely to be an issue. Moreover, we calculated the Variance Inflation Factors (VIFs) to control for multicollinearity in our regression analysis. VIFs above five indicate severe multicollinearity issues. We find that none of the VIFs are above two, which implies that multicollinearity does not pose a problem to our regression models.

Table 3.4: Correlation matrix between variables for the accuracy test.

	Error	Market_Cap	Stdv_ROE	NAnalysts	IFRS16
Error					
Market_Cap	-0.3581***				
Stdv_ROE	0.0481***	-0.0506***			
NAnalysts	-0.3493***	0.3831***	-0.0535***		
IFRS16	-0.0122	0.0883***	0.0654***	-0.1907***	

**significant at 10%; **significant at 5%; ***significant at 1%, 2-sides.*

In addition, the correlation matrix presents the correlations between the independent- and dependent variable. Table 3.4 reports that forecast error is negatively correlated with the IFRS 16 dummy. This suggests that forecasts are more accurate after the implementation of IFRS 16. Additionally, forecast errors are negatively correlated with firm size and analyst coverage. This is also in line with previous findings that analysts' forecasts are more accurate for larger firms (Lang and Lundholm, 1993). Furthermore, previous research shows that forecasts are more accurate for firms with high analyst following (Lys and Soo, 1995). The fact that the standard deviation of ROE and forecast error are positively correlated, supports the expectation that forecasts are less accurate when performance is more volatile.

3.5.1 Survey

The survey is composed of three questions and statements that provide us with qualitative and quantitative data in the form of open-ended questions and answers. Initially, the survey asks questions with options related to which sector they are covering. This will give us insight into their modeling practices, which can be useful when interpreting the results of the other questions. The reason for this is that an analyst covering a sector that usually is less dependent on leased assets may have different knowledge and understanding of forecasting these. Similarly, an analyst covering more companies with higher portions of lease payments might have more experience in considering and adjusting for lease-related financial items.

The respondents are then asked about how they are modeling lease payments for the next quarter and whether they are considering the interest element in the lease payment. With this question, we aim to determine if and potentially how their modeling approaches are being impacted by the mandatory adoption of IFRS 16. The remaining question is more technical and asks the respondent how exactly they are modeling or considering the depreciation of leased assets. This will also provide the respondent with an opportunity to elaborate on their practices in a more detailed manner.

1. Do you model the entire lease payment for the next quarter, or do you roll over the previous quarters' payment to the next one?

2. If yes, do you model the lease payment by separating the interest element and the amortization?

3. Do you separate depreciation on each individual non-current asset item, or do you model all depreciation on property, plant, and equipment, and roll over other non-current assets such as ROU assets?

4 Analysis

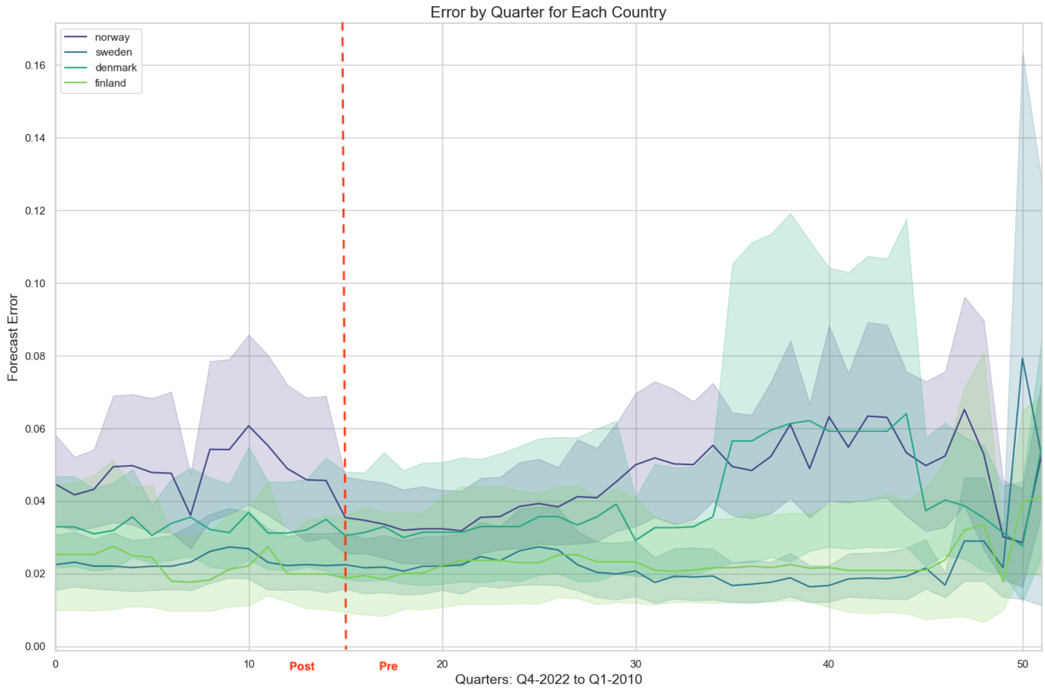
In this section, we test the impact of IFRS 16 implementation on analysts' forecast accuracy. First, we provide several visual presentations and observations within our data. This might give the reader a greater understanding of the issue at hand. Moreover, we provide an overview of the distribution of forecast errors, along with accuracy tests. We examine our chosen control variables using the selected regression models. The primary focus of this analysis will be on the EBIT margin, which serves as the input for the dependent variable of Median Absolute Forecast Error (MAPE) both before and after the implementation of IFRS 16. This approach represents a novel perspective that has not been addressed in previous studies.

4.1 Analysts' accuracy in Scandinavia pre & post IFRS 16 (2019)

4.1.1 MAPE in Scandinavia

Figure 5.1 below provides a graphical representation of the MAPE for each quarter, spanning from Q4-2022 through Q1-2010, with respect to the EBIT margin. Notably, the MAPE for EBIT margin maintains a relatively stable trajectory throughout the period. Across the four countries analyzed, Norway consistently registers the highest error, followed in descending order by Sweden, Denmark, and Finland. The trend in forecast errors is showing some particular eye-catching events. There is a seemingly higher forecast error for all countries when the economic outlook was uncertain and volatile, such as during the corona pandemic (Q8) and the oil price crash (Q32). We can also observe that right after the financial crisis in 2008-2009 (Q51), the forecast error decreases as the economic outlook is stabilizing. These instances likely reflect the challenges in forecasting during volatile and unpredictable economic landscapes, as external shocks can drastically impact financial performance and margins. The sharp decline in forecast errors following the 2008-2009 financial crisis shows that the economic climate began to stabilize, and that forecast accuracy seemingly improved. In summary, the patterns underscore the sensitivity of forecasting to macroeconomic events and the difficulties in achieving accuracy during periods of economic volatility.

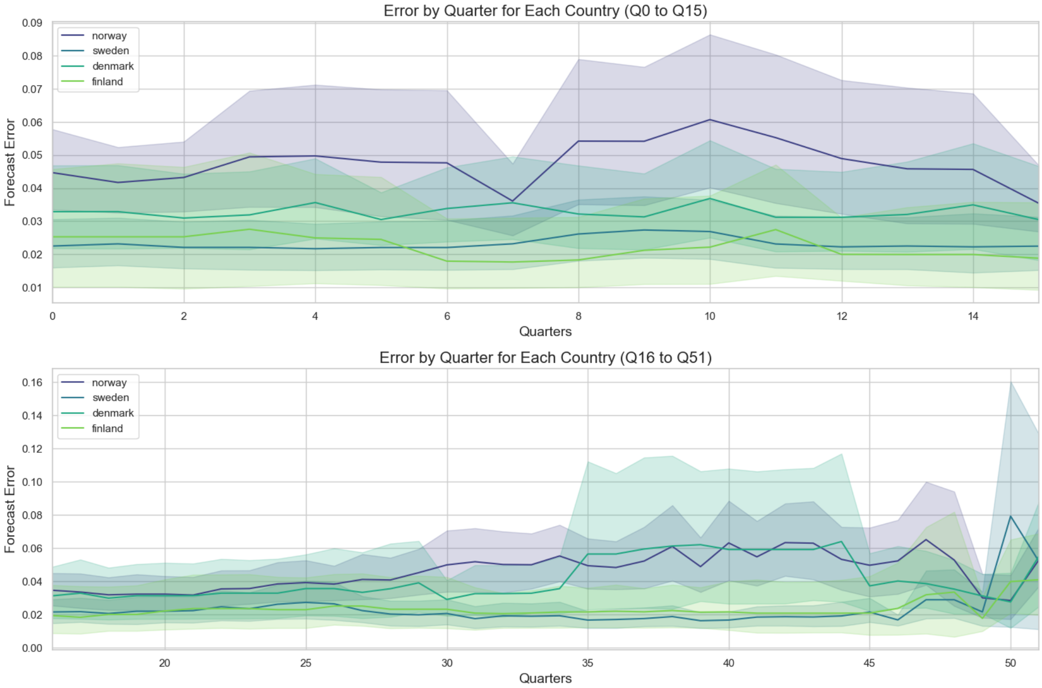
Figure 4.1: The figure shows the forecast error trend measured by MAPE across countries in Scandinavia from Q4/22 to Q1/10.



Note: *The x-axis represents the time from Q4/2022 to Q1/2010.*

In the figure presented below, the forecast error is separated into two distinct periods; pre- and post-implementation of IFRS16. It is essential to closely examine these periods to understand the potential impact of IFRS16. Upon initial observation, it is not immediately apparent that there are significant trends or patterns in forecast error. One might have expected to see a distinct shift due to changes in accounting standards. However, visually, the graph does not exhibit any remarkable deviations post-implementation. It is plausible to reason that the effect of the transition to the new accounting standard is subtle and might not disclose in a visually prominent manner in the graph. The change may not necessarily translate into large-scale shifts in forecasting patterns, especially in the short term. In conclusion, while the graph does not present any clear visual evidence of changes in forecast error, it is reasonable to further investigate this with more refined analytical regressions to fully understand the potential implications of the new accounting standard.

Figure 4.2: Forecast error trend pre and post implementation. The figures show the trend pre and post implementation of IFRS 16. The first figure shows the trend after and the second shows before adoption.



Note: *The x-axis represents the time from Q4/2022 to Q1/2010.*

4.1.2 Paired mean comparison

In order to assess the potential impact of IFRS16 further, we conduct a paired mean comparison. The analysis focuses on comparing the mean forecasting errors before and after the implementation with an equal amount of observations. The mean forecasting error prior to the IFRS 16 implementations is approximately 0.0361, while the mean error after is around 0.0347. The difference between these means, approximately 0.0014, indicates a slight decrease in the forecasting error post-implementation. To determine if this difference is statistically significant, a paired t-test is performed. The t-statistic is calculated to be approximately 0.9552. This value, in combination with a p-value of approximately 0.3414, suggests that the difference in the means is not statistically significant at either 10, 5, or 1 percent. Given the relatively high p-value, we fail to reject the null hypothesis that the mean forecasting error before IFRS 16 is equal to the mean forecasting error after its implementation. This implies that the change in the accounting standard, as captured by IFRS 16, did not have a statistically significant impact on the forecasting errors. In summary, although there is a slight numerical decrease in the mean forecasting errors, the change is not statistically significant. This suggests that the IFRS 16 implementation does not have a substantial impact on the accuracy of forecasting errors within this analysis.

Table 4.1: Paired T-test. The table shows the results of the paired mean comparison between forecast error pre and post-IFRS 16 implementation.

Variable	**Value**
Mean of errors pre IFRS16	0.0361
Mean of errors post IFRS16	0.0347
Diff	0.0014
t-statistic	0.9552
p-value	0.3414
No. of obs pre IFRS16	120
No. of obs post IFRS16	120

4.1.3 Regressions on forecast accuracy pre and post-IFRS16

In Table 5.1.2 below we present the results from the OLS regressions on our quarterly forecast errors after winsorizing. The first table shows that Post_IFRS16, Log_Number_of_Analysts, Log_Market_Cap, and StdvROE are statistically significant in this model. The Post_IFRS16 coefficient indicates that the introduction of IFRS16 standards has resulted in lower forecast errors. This suggests that increased modeling complexity has not had a negative effect on forecast accuracy, although the coefficient is relatively low at -0,0055. Also, Log_NAnalysts implies that as the number of analysts increases, forecast error decreases, in line with the findings from our literature review. More analysts drive competition and in turn forecast accuracy and better research. For Log_Market_Cap, the variable is negative which suggests that larger companies in terms of market cap have lower forecast error, hence increased accuracy. This first model is also statistically significant which is indicated by a high F-statistic and a low p-value.

Table 4.2: Regression results. It reports the results of Eq.(3.2) based on Q4/2022 to Q1/2010 forecast error. This model regresses ForecastError (intercept) on the Post_IFRS16 (dummy), logged number of analysts (Log_NAnalysts), logged market cap (Log_Market_Cap), and standard deviation of ROE (StdvROE).

	Dependent Variable: Error					
	Coef.	Std. Err.	z	P>|z|	[0.025	0.975]
Intercept	0.2040	0.010	20.352	0.000	0.184	0.224
Post_IFRS16***	-0.0055	0.001	-3.976	0.000	-0.008	-0.003
Log_NAnalysts***	-0.0191	0.002	-11.281	0.000	-0.022	-0.016
Log_Market_Cap***	-0.0057	0.000	-13.025	0.000	-0.007	-0..005
StdvROE**	0.0075	0.003	2.494	0.013	0.002	0.013
Sector Dummies		*No*				
Country Dummies		*No*				
R^2		0.190				
Adjusted R^2		0.189				

**significant at 10%; **significant at 5%; ***significant at 1%*

In the second model, most of the variables remain significant, but the significance of StdvROE is lost as sector dummies are added. This could be a result of the Sector Dummies capturing some of the effects that were previously attributed to StdvROE. Some industries are more volatile than others, making it possible that the volatility is captured within these. The restricted time period, which reduces the number of observations, could also be an explanation for lost significance. When we control for sector effects (*Sector Dummies*), the R-squared increases.

Table 4.3: Regression results. It reports the results of Eq.(3.2) based on Q4/2022 to Q1/2010 forecast error. This model regresses ForecastError (intercept) on the Post_IFRS16 (dummy), logged number of analysts (Log_NAnalysts), logged market cap (Log_Market_Cap), and standard deviation of ROE (StdvROE). This model takes *Industry Dummies* as additional control variables.

	Dependent Variable: Error					
	Coef.	Std. Err.	z	P>|z|	[0.025	0.975]
Intercept	0.1647	0.009	17.627	0.000	0.146	0.183
Post_IFRS16***	-0.0040	0.001	-3.164	0.002	-0.006	-0.002
Log_NAnalysts***	-0.0176	0.002	-9.726	0.000	-0.021	-0.014
Log_Market_Cap***	-0.0045	0.000	-10.654	0.000	-0.005	-0.004
StdvROE	0.0017	0.003	0.617	0.537	-0.004	0.007
Sector Dummies		*Yes*				
Country Dummies		*No*				
R^2		0.298				
Adjusted R^2		0.296				

**significant at 10%; **significant at 5%; ***significant at 1%*

We add country dummies to our third model, resulting in continued insignificance from the StdvROE variable. The other variables remain significant, and the R-squared increases further to 0.306. The signs of the control variables are as expected, with firm size and number of analysts still being negatively correlated with MAPE. Performance volatility (StdvROE) continues to be positively associated with the dependent variable.

Table 4.4: Regression results. It reports the results of Eq.(3.2) based on Q4/2022 to Q1/2010 forecast error. This model regresses ForecastError (intercept) on the Post_IFRS16 (dummy), logged number of analysts (Log_NAnalysts), logged market cap (Log_Market_Cap), and standard deviation of ROE (StdvROE). This model takes *Industry Dummies* and *Country Dummies* as additional control variables.

	Dependent Variable: Error					
	Coef.	Std. Err.	z	P>|z|	[0.025	0.975]
Intercept	0.1572	0.011	14.747	0.000	0.136	0.178
Post_IFRS16***	-0.0032	0.001	-2.499	0.012	-0.006	-0.001
Log_NAnalysts***	-0.0172	0.002	-9.104	0.000	-0.021	-0.013
Log_Market_Cap***	-0.0044	0.001	-8.539	0.000	-0.005	-0.003
StdvROE	-0.0017	0.003	-0.592	0.554	-0.007	0.004
Sector Dummies		*Yes*				
Country Dummies		*Yes*				
R^2		0.306				
Adjusted R^2		0.303				

**significant at 10%; **significant at 5%; ***significant at 1%*

Overall, the control variables in models 1 to 3 show that forecast errors are negatively associated with firm size and number of analysts, which is consistent with prior studies discussed earlier. In essence, the models suggest that forecast error is generally lower for companies that are larger, have higher analyst coverage, and are post-IFRS 16. Also, for models 2-3, companies with higher variability in Return on Equity tend to have a slightly higher forecast error. The results from our multivariate analysis suggest that the mandatory adoption of IFRS 16 has increased the accuracy of analysts, and so reduced the forecasting error among equity analysts. In the following section, we look into whether analysts have adopted the new accounting standard by updating their modeling practices. We present a survey on IFRS 16 modeling practices with answers from a variety of analysts across different sectors and present our empirical findings. Moreover, we introduce some examples of how certain companies present items relevant to IFRS 16 modeling from an analyst's perspective.

4.1.4 Emprirical findings from survey

The table below summarizes the answers from our survey on IFRS 16 modeling practices among sell-side analysts in selected Oslo-based investment banks. The survey asked the following three questions:

1. Do you model the entire lease payment for the next quarter, or do you roll over the previous quarters' payment to the next one?

2. If yes, do you model the lease payment by separating the interest element and the amortization?

3. Do you separate depreciation on each individual non-current asset item, or do you model all depreciation on property, plant, and equipment, and roll over other non-current assets such as ROU assets?

The results from the survey indicate that analysts' covering asset-heavy industries such as oil services and shipping tend to model IFRS 16 items more often than analysts covering other sectors. One potential explanation is that the companies in these areas provide more disclosure on the assumptions behind the figures, making modeling significantly less complex for the analyst. For companies that are less dependent on tangible assets to generate return on capital (i.e. offices are the main lease in place), disclosure of underlying assumptions tends to be significantly lower. In addition, asset-light companies with a lower capitalization often provide significantly less information about their assets in place on a quarterly basis. As such, analysts can become prone to understating future depreciation and lease payments, decreasing estimate accuracy.

For example, four out of five publicly listed EMS companies in Scandinavia do not provide, what in our view is sufficient information required to model IFRS 16 items individually on a quarterly basis. Kitron (Norway) and NOTE (Sweden) do not separate the financing part of their cash-flow statement, Hanza combines regular debt amortization with IFRS 16 amortization, and Incap does not provide a cash-flow statement on a quarterly basis. Scanfil is the only company that separates between regular debt amortization and lease amortization. None of the companies separate interest payments, depreciation, or additions on item-level. Apart from operating in the same industry, the other common factor for these companies is that they can be considered as "small-cap" as the highest market cap among them belongs to Kitron at NOK 8.5bn (06.08.2023), and the lowest market cap belongs to Incap, which has a market capitalization of NOK 290.5m (06.08.2023).

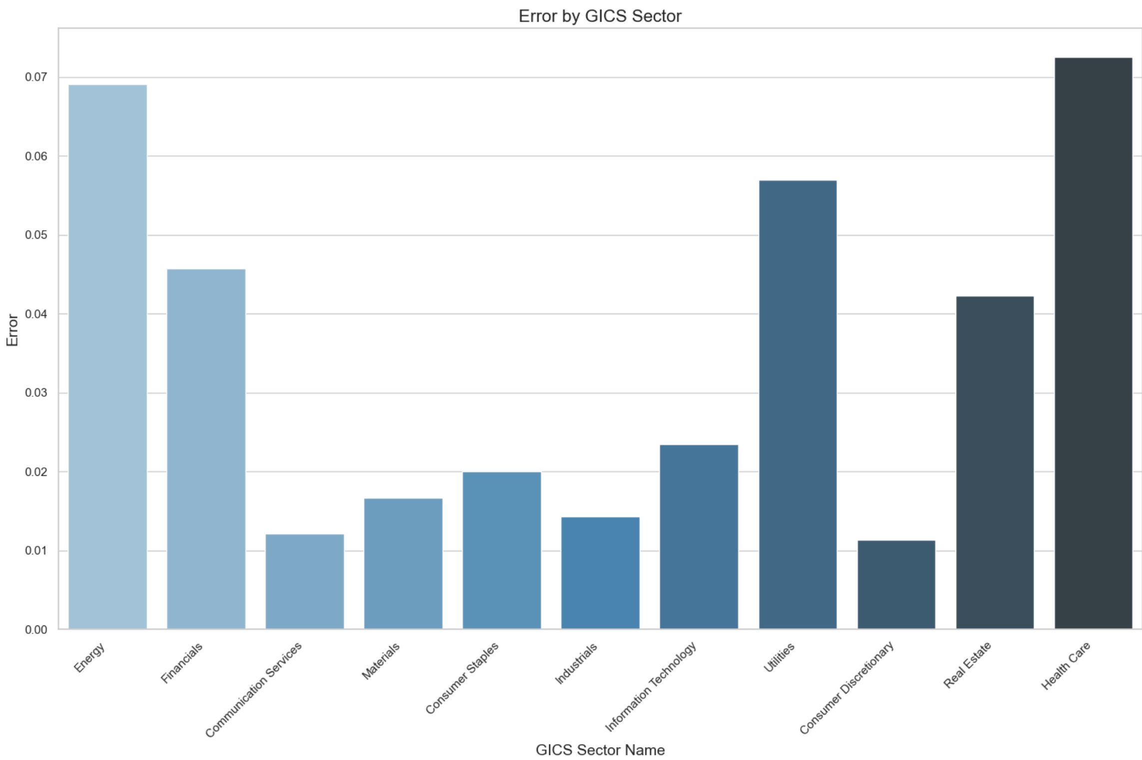
Contrary to the reporting methodology of the above-mentioned companies, the Norwegian, fabless semiconductor company Nordic Semiconductor discloses quarterly lease payments, quarterly FX adjustment effect on ROU assets, and quarterly depreciation of ROU assets. This means that analysts only need to make an assumption about the interest the company is paying on its lease liabilities, which is stated in its annual reports. This is in stark contrast to many other Scandinavian listed Tech, Media, and Telecom (TMT) companies, who are typically closer to the above-mentioned EMS companies than Nordic Semiconductor with regards to disclosure levels on IFRS 16 items. As such, the companies could benefit from more accurate modeling from the analysts that have coverage, making it less prone to deviations from analyst expectations on reporting days as the forecast accuracy on EBIT, and consequently EBIT-margin, which these types of companies profitability is measured on. In the extension of this, companies that regularly miss analyst expectations and/or have lower margins than their competitors tend to achieve lower valuations (Liu et al., 2002).

4.2 A sector-based approach to forecast accuracy

4.2.1 Forecast errors by sectors

To facilitate visual comprehension, we present MAPE across sectors in the form of a bar chart. Figure 5.1 below illustrates the median MAPE by sector from Q1-2010 to Q4-2022 in Scandinavia.

Figure 4.3: Median forecast error by industry. The table shows the distribution of forecast errors within each sector across Scandinavia. We refer to Table 3.2 in section 3.5 for the number of observations per sector.



Unsurprisingly, Energy and Health Care prove to have the highest forecast errors during the time period. The former could be explained by the cyclical nature of energy prices, while the latter could be explained by the complexity that is associated with forecasting sales and the development of binary products. On the other end, Consumer Discretionary and Communication Services have the lowest forecast errors in Scandinavia. The readings from the figure do not indicate that IFRS 16 has caused higher forecast errors due to increased modeling complexity following IFRS 16. Hence, we need to assess the most prone industries in more detail.

To address our second hypothesis (H1b), that the adoption of IFRS 16 has resulted in higher forecast error for companies in certain industries, we assess the regression models on a sector basis. This helps us investigate whether some sectors have experienced higher forecast errors on the EBIT margin post-adoption of IFRS 16. The results are presented in Table 5.5 below.

The figure below presents regressions with the same variables as previously presented. The effect of the implementation of IFRS 16 is captured by the interaction terms between the sector and the forecast error changes in the post-IFRS 16 periods, compared to the pre-IFRS 16 periods. Key findings suggest that the sectors Consumer Discretionary, Consumer Staples, and Utilities all experienced higher forecast errors following the adoption of IFRS 16, with coefficients of 0.0029, 0.0037, and 0.0138, respectively. All coefficients are found to have statistical significance. A possible explanation behind the change can be put in context with the findings from our survey, as the companies that make up the Consumer Discretionary and Staples industries stretch from a variety of industries such as online gambling, retailing, textile manufacturing, software, and EMS-manufacturing, respectively. Regarding utilities, a significant portion of this sector consists of renewable energy producers, a somewhat immature industry with a significant portion of leased assets. As such, analysts could be prone to understating additions of lease assets, and consequently, also lease depreciation if the companies they cover do not provide sufficient information to model these items in a reasonable manner. Consequently, forecast error on EBIT margin could increase. However, we highlight the need for further validation as there could be other factors that have influenced the forecast error in the post-IFRS 16 period, such as cost inflation, and unexpected company-specific events.

Table 4.5: Regression results from the OLS Regression. The independent variables are Post_IFRS 16 (dummy variable) and industry categories based on GICS. Interaction terms between the Post_IFRS16 dummy and the GICS sectors are included to capture the industry-specific effects of the IFRS 16 implementations.

	Dependent Variable: Error			
	Coef.	Std. Err.	z	P>|z|
Intercept	0.0124	0.000	43.167	0.000
Post_IFRS16**	-0.0013	0.001	-2.000	0.045
GICS_Consumer_Discretionary**	-0.0015	0.001	-2.679	0.007
GICS_Consumer_Staples***	0.0068	0.001	8.776	0.000
GICS_Information_Technology***	0.0128	0.002	5.376	0.000
GICS_Energy***	0.0536	0.003	19.151	0.000
GICS_Financials***	0.0330	0.002	21.968	0.000
GICS_Materials***	0.0056	0.002	3.646	0.000
GICS_Industrials***	0.0007	0.001	1.077	0.281
GICS_Utilities***	0.0398	0.003	12.795	0.000
GICS_Real_Estate***	0.0370	0.007	5.103	0.000
GICS_Health_Care***	0.0626	0.015	4.233	0.000
interaction_GICS_Consumer_Discretionary**	0.0029	0.001	2.632	0.008
interaction_GICS_Consumer_Staples**	0.0037	0.001	2.826	0.005
interaction_GICS_Information_Technology	-0.0035	0.003	-1.188	0.235
interaction_GICS_Energy	0.0119	0.009	1.261	0.207
interaction_GICS_Financials	0.0021	0.002	0.914	0.361
interaction_GICS_Materials	-0.0013	0.002	-0.692	0.489
interaction_GICS_Industrials**	0.0046	0.002	2.219	0.026
interaction_GICS_Utilities***	0.0138	0.003	4.170	0.000
interaction_GICS_Real_Estate***	-0.0271	0.007	-3.687	0.000
interaction_GICS_Health_Care	-0.0209	0.022	-0.929	0.353
R^2	0.147			
Adjusted R^2	0.143			

**significant at 10%; **significant at 5%; ***significant at 1%*

5 Robustness

To ensure the robustness of the results, we cover our robustness assessment of the results in section 4.1.3 testing the accuracy of analysts post-implementation of IFRS 16.

5.1 Heteroskedasticity, multicollinearity, and autocorrelation

Heteroskedasticity, multicollinearity, and autocorrelation are well-known econometric issues when performing regressions. In this subsection, we explain the econometric issues while clarifying how they have been addressed in our study.

5.1.1 Multicollinearity

Multicollinearity occurs when two or more explanatory variables in a regression model are highly correlated. Consequently, it becomes difficult to estimate their individual effects on the dependent variable of interest. While multicollinearity does not bias the OLS estimates, it does inflate their standard errors, reducing their precision. Potential solutions to avoid the issue of multicollinearity are dropping variables, ridge regressions, and auxiliary regressions (Wooldridge, 2015). In our case, we experience some correlation between the number of analysts covering a company and the market capitalization of a company. We observe that the correlations are relatively low, suggesting that multicollinearity is not likely to be an issue. In addition, we calculate the Variance Inflation Factors (VIFs) to address the importance of avoiding multicollinearity in our regression analysis. VIFs above five indicate severe multicollinearity problems. We find that none of the VIFs are above two, which implies that multicollinearity does not pose a problem to our regression models. Consequently, we argue that our regression models do not suffer from high multicollinearity on the basis of this test.

5.1.2 Autocorrelation

Autocorrelation refers to the correlation of the residuals which potentially could lead to inefficient and biased parameter estimates. It can be identified visually by examining a plot of the residuals over time. Another test for autocorrelation is the Durbin-Watson test, where a value around 2 suggests that the residuals are not autocorrelated (Wooldridge, 2015). The Durbin-Watson statistic is

Table 5.1: Variance Inflation Factors (VIF) of Model Features. The tables show the VIF for the features in the regression model. None of the VIF values in this model exceed the commonly used threshold of 5, suggesting that multicollinearity is not significantly affecting the estimates of the regression coefficients in this model.

Feature	VIF
Post_IFRS16	1.08
Log_NAnalysts	1.36
Log_Market_Cap	1.32
Stdv_ROE	1.01

close to 2 in all three models, suggesting that there is no autocorrelation in the residuals.

5.2 Excluding the *Financials* sector

We investigate whether the exclusion of the largest industry in our dataset, *Financials*, changes our results. Excluding the Financials sector leads to a reduction of observations by 1378. For Post_IFRS16, the coefficient remains positive and statistically significant after excluding the Financials sector. This indicates that the relationship between Post_IFRS16 and Error is robust to the exclusion of the financial sector. Similar observations can be made for the other coefficients, which are still significant and have not changed dramatically. The R-squared is similar to the original model. This implies that the model is still explaining a similar proportion of the variance in the dependent variable, Error, after the sector is excluded. Furthermore, the F-statistic remains significant in the modified model. When looking at the signs and magnitude of coefficients, we observe that they are relatively stable, which suggests that the relationships are not exclusively driven by the financial sector. In conclusion, the results seem to be fairly robust to the exclusion of the *Financials* sector. The key relationships, as indicated by the sign, significance, and magnitude of coefficients, remain consistent. This suggests that the findings from the original models are not solely driven by the observations in the financial sector. We can therefore conclude that the modified model has passed a meaningful robustness check by showing stability in the results after exclusion. The results are reported in Tables A2.1 and A2.2 in the appendix below.

6 Discussion

While the study provides insights into the immediate aftermath of IFRS 16 implementations, it is essential to recognize its potential limitations. A critical limitation could be the relatively short time period since the adoption of the new standard. It is plausible that the long-term effects are yet to materialize. Therefore, we caution that our study is not intended to give a final assessment of the effects of the new IFRS 16 accounting standards.

In light of these findings, future research is recommended to expand the temporary scope to assess the long-term implications of IFRS 16. Additionally, the analysis could be extended to explore the accuracy of equity analysts' forecasts in relation to operating cash flows, which might provide different insights and capture the modeling complexity in a different manner. In conclusion, while the anticipated increase in forecast errors following the IFRS 16 implementations was not evidenced in this study, it opens the door for further research. It serves as a basis for future studies to explore the nuances of how accounting standards like IFRS 16 can impact equity analysts' forecast accuracy over a more extended period and across different sectors.

6.1 Suggestions for future research

6.1.1 IFRS 16 impact on estimate accuracy through Diff-in-Diff

We continue to find the topic of IFRS 16 and its impact on analyst accuracy highly interesting. Consequently, we would like to investigate whether a different methodology could result in a different result. Applying diff-in-diff on US-listed companies (primarily following US-GAAP) to European-listed companies (IFRS 16) could potentially yield a different conclusion than ours due to the fact that the method compares the changes in outcomes over time between a treatment group (companies that have adopted IFRS 16) and a control group (companies that adopt US-GAAP). Diff-in-Diff could hence be a more useful tool in order to find causality.

6.1.2 The Euronext Growth bubble (2020-2022)

During the initial stages of the pandemic, the sentiment quickly changed from bust to boom on the back of the global ZIRP, and helicopter money being dropped into capital markets. This drove the IPO market, and particularly in

Norway on the Euronext Growth Index, which has lower requirements than the regular list. In the aftermath of this, the majority of companies that were listed have plunged after not meeting street expectations, combined with a higher cost of capital following interest hikes. We hence believe it could be interesting to study whether investment banks were too naive and overly optimistic with regard to future performances when introducing young companies to the public market during these market conditions. In hindsight, expectations proved to be significantly above what turned out to be the reality.

6.1.3 Private Equity-backed IPOs in Norway

In the extension of the suggestion above, we would be interested to see research on Private Equity-backed (PE) IPOs in the Norwegian market. Private to public transactions backed by PE players boomed compared to previous years. In the aftermath of this, we think it would be interesting to study whether these companies underperformed expectations to a higher degree than non-PE-backed IPOs. In addition, we have seen some of these names being acquired back by PE after losing a significant portion of their valuation.

6.1.4 Fewer sale-leaseback transactions post-IFRS 16?

IASB's stated that they expect fewer sale-leaseback agreements following the adoption of IFRS 16 (Deloitte, 2018). We would as such find it interesting to see if this expectation has been fulfilled, and if IFRS 16 in reality has removed the incentive to replace traditional bank debt with sale-leasebacks.

7 Conclusion

We examine how the event of the mandatory adoption of IFRS 16 affects the accuracy of equity analysts' forecasts in Scandinavia. We use OLS regressions to test the change in forecast accuracy, measured by the Median Absolute Forecast Error (MAPE). We find that analysts' accuracy has increased after the mandatory adoption of IFRS 16 and so on reducing the forecast error among analysts. This effect persists after controlling for factors such as the number of analysts, market cap, volatility in performance, and industry and country dummies. In the robustness assessment, we exclude the largest sector in terms of the number of companies, *Financials*, and find that the results from the original models are not solely driven by the observations in the Financials sector. Additionally, we conduct a survey with equity analysts from various investment banks in Oslo to complement our quantitative analysis. The survey results suggest that analysts covering asset-heavy industries such as oil services, real estate, and shipping are more likely to model IFRS 16 items than analysts covering other sectors, due to higher disclosure levels in these companies' financial reports.

We also study the forecast errors by sector. Comparing the analyst forecast error across sectors before and after the adoption of IFRS 16, we find that sectors such as Consumer Discretionary, Consumer Staples, and Utilities all experienced a higher forecast error following the adoption of IFRS 16. All coefficients are statistical significant. Although cost inflation and unexpected company-specific events could influence our results, our findings suggest that the adoption of IFRS 16 has made it more difficult for analysts to model lease-related items, causing higher deviations from sell-side expectations for the sectors Consumer Discretionary, Consumer Staples, and Utilities.

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Appendix

A1 Interview answers

Table A1.1: Survey Results. The survey results show the answers from several Equity Research employees from different Investment Banks covering a variety of sectors. We refer to section 4.1.4 for the survey questions.

Candidate	Sector	Response to Q1	Response to Q2	Response to Q3
Arctic Securities				
Daniel Stenslet	E&P	No	N.A.	Model all D&A on PPE, roll over other items
Alexander Jost	Shipping	Yes	Yes	Yes
Øyvind Hagen	E&P	Yes, for most companies	Yes, if "Yes" on Q1	Only for PPE and lease
Ivar Ryttervold	Renewables	Yes, if sufficient info	Yes, but not for all companies	Yes, but not for all companies
Kristian Spetalen	TMT	Yes	Yes, but not for every firm	Yes, but not for every firm
Kristoffer Barth Skeie	Shipping	Yes	Yes	Yes
Axel Jacobsen	Aquaculture	No, roll over	N.A.	No, model all D&A on PPE
Ole H. Berg	Oil Service	Yes, model lease payments	Yes	Yes
Roy Tilley	Financials	No, rolling over	N.A.	Model all D&A on PPE
Carl Frederick Bjerke	Retail	No, roll over	N.A.	No, model all PPE on D&A
Jeppe Baardseth	Retail & Industrials	No, roll over	N.A.	Model all PPE on D&A
Pareto Securities				
Olav Rødevand	Industrials	Yes, if available info	Yes if 1	Yes, if available info
Fridtjof S. Fredricsson	TMT	Yes, model entire lease payment	Yes	Separate D&A in each non-current asset
Danske Markets				
Victor Waage Sand	Renewables	No	N.A.	Model all PPE on D&A
ABG Sundal Collier				
Ali Al-Shemmari	TMT	No	N.A.	Model all D&A on PPE
Anonymous	Asset-heavy	No	N.A.	Model all PPE on D&A

A2 Robustness test after excluding *Financials* sector

Table A2.1: Regression Results. It reports the results of Eq.(3.2) excluding the *Financials* sector based on Q4/2022 to Q1/2010 forecast error. This model regresses ForecastError (intercept) on the Post_IFRS16 (dummy), logged number of analysts (Log_NAnalysts), logged market cap (Log_Market_Cap), and standard deviation of ROE (StdvROE). This model takes *Industry Dummies* as additional control variables.

	Dependent Variable: Error					
	Coef.	Std. Err.	z	P>|z|	[0.025	0.975]
Intercept	0.1512	0.010	14.764	0.000	0.131	0.171
Post_IFRS16***	-0.0068	0.002	-4.363	0.000	-0.010	-0.004
Log_NAnalysts***	-0.0258	0.002	-10.656	0.000	-0.030	-0.021
Log_Market_Cap***	-0.0032	0.000	-7.283	0.000	-0.004	-0.002
StdvROE***	0.0160	0.004	3.803	0.000	0.008	0.024
Sector Dummies	*Yes*					
Country Dummies	*No*					
R^2	0.345					
Adjusted R^2	0.343					

**significant at 10%; **significant at 5%; ***significant at 1%*

Table A2.2: Regression Results. It reports the results of Eq.(3.2) excluding the *Financials* sector based on Q4/2022 to Q1/2010 forecast error. This model regresses ForecastError (intercept) on the Post_IFRS16 (dummy), logged number of analysts (Log_NAnalysts), logged market cap (Log_Market_Cap), and standard deviation of ROE (StdvROE). This model takes *Industry Dummies* and *Sector Dummies* as additional control variables.

	Dependent Variable: Error					
	Coef.	Std. Err.	z	P>|z|	[0.025	0.975]
Intercept	0.1774	0.012	14.431	0.000	0.153	0.201
Post_IFRS16***	-0.0049	0.002	-2.896	0.004	-0.008	-0.002
Log_NAnalysts***	-0.0218	0.003	-8.462	0.000	-0.027	-0.017
Log_Market_Cap***	-0.0043	0.001	-7.433	0.000	-0.005	-0.003
StdvROE***	0.0156	0.005	3.456	0.001	0.007	0.024
Sector Dummies	*Yes*					
Country Dummies	*Yes*					
R^2	0.354					
Adjusted R^2	0.351					

**significant at 10%; **significant at 5%; ***significant at 1%*