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ANALYSTS' FORECAST ACCURACY IN AN UNLISTED COMPANY

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Abstract

The purpose of this study is to investigate the optimism of analysts and the impact of the forecast period length on the accuracy of forecasts in unlisted companies. Previous research shows an optimistic bias towards forecasts by analysts in listed companies, and forecast error is positively correlated with the length of the forecast period. However, there is a lack of previous research on forecast optimism and accuracy for unlisted companies. This study aims to bridge this research gap and contribute to the understanding of forecast behavior in this context.

The research questions and hypotheses of this study are derived from previous studies. Hypothesis 1 states that analysts make optimistic forecasts at the beginning of the fiscal year, while Hypothesis 2 proposes a positive correlation between forecast errors and the length of the forecast period. The data used in the study includes analysts' one-year-ahead forecasts and the actual earnings and EBITDA figures for the corresponding period.

The findings of this study reveal that analysts' earnings forecasts in unlisted companies are also optimistic. Furthermore, the accuracy of these forecasts diminishes as the forecasted period extends. The accuracy of earnings forecasting significantly decreases from the seventh month onward, indicating that analysts can effectively forecast the first seven months. In contrast, there is no observed significant deterioration in the accuracy of EBITDA forecasting over time within the fiscal year. Thus, while the hypothesis regarding earnings is supported, the hypothesis concerning EBITDA is not supported by the results.

In conclusion, this thesis contributes to the understanding of analysts' forecasting behavior in unlisted companies. The results highlight the importance of considering the forecasted periods' length and the positive bias when evaluating the analysis in unlisted companies. It is recommended to be meticulous for investors and financiers when relying on analysts' long-term forecasts for unlisted companies.

Further investigation is required to explore the accuracy and optimism of forecasts with a greater sample size. The study confirms the hypothesis that analysts tend to be optimistic when forecasting earnings for unlisted companies. This finding suggests the need for further research to explore the sources of this optimism and understand the underlying reasons, especially regarding the generalizable optimism.

Keywords
Analysts' forecast, forecast error, forecast bias, positive bias

Additional information

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1 INTRODUCTION

1.1 Background and motivation

Analysts play a settled role in financial markets. They act as information intermediaries by conducting market and company research and producing forecasts, recommendations, and target prices for the target securities. A literature on the role of equity analysts indicates that analyst reports are valued by stakeholders.

Stakeholders utilize the information provided by analysts to fill information gaps and make decisions regarding the company. Analysts’ research saves many investors the trouble of performing time-consuming expertise that requires analysing the company themselves and reduces information asymmetry. Moreover, analysts often possess professional skills in gathering and evaluating financial information.

In his study, So (2013, p. 618) aknowledges the valuable contribution of analysts by highlighting that the market's assessment of a company's value is greatly influenced by the information provided by analysts. Collective literature however shows that analysts' forecasts and recommendations are often biased and and relying solely on these forecasts can result in biased estimates of a company's value. Therefore, it is crucial for both financial markets and stakeholders who utilize analysts' forecasts to be able to identify and account for this bias in order to accurately evaluate companies.

Studying the accuracy of analysts' earnings forecasts is relevant not only for investors and stakeholders but also for the companies themselves. Numerous previous studies on this topic differ in terms of analysis period, location, and research design, and the reported findings vary. A consistent bias found in the prior literature is that analysts' earnings forecasts tend to be optimistic on average (e.g., Abarbanell and Lehavy 2003, Cifci, Mashruwaland and Weiss 2016). The concerns and evidence of potential bias in analysts' forecasts have sustained research interest in this field. The literature review in this thesis will delve into these topics in more detail.

Forecast accuracy, is commonly defined as the absolute value of the percentage difference between realized and forecasted (Hutira, 2016). When assessing forecast accuracy, it is often evaluated by considering either analysts' characteristics or company-level characteristics. The literature review in this thesis will follow this order as well. It is worth noting that the included studies generally assume the presence of systematic errors in forecasts. Therefore, the initial focus of these studies is to identify the factors that contribute to forecast errors.

The literature review also covers the role of analysts who specialize in researching and analyzing unlisted companies, commonly referred to as business analysts. These analysts are responsible for making forecasts for various purposes. For instance, a critical aspect of valuation involves constructing reliable financial forecasts for the future development of the company. Given that the value of a company is determined by its future profits or cash flows, accurate valuation necessitates forecasting these future financial indicators.

1.2 Previous literature

Instead of random errors, this thesis as well as previous literature focus on forecasts errors that are systematic due to some specific issue. While a number of early research do not definitely always document systematic errors or these do not identify significant differences in forecast accuracy, it can be noticed that more recent studies document systematic differences. When previous literature examines forecast accuracy, it mostly assumes that forecast error exists. After this, the literature looks for reasons and explanations for the occurrence of the forecast error. Several factors have been identified as determinants of financial analysts' forecast accuracy, and as consensus, two culprits can be found as the source of the forecast error which are the analyst itself and the company being analysed.

Intuitively, the existence of first impressions can be found in all disciplines, in human interaction, in everything. According to the literature, the existence of first impression biases among financial professionals is undeniable. Hirshleifer, Lourie, Ruchti & Truong (2021) present evidence of first impression bias among finance professionals in the field. If a company performs particularly well (poorly) in the year before an analyst follows it, that analyst tends to issue optimistic (pessimistic) evaluations.

Consistent with negativity bias, they find that negative first impressions have a stronger effect than positive ones.

What comes to forecast horizon, number of prior studies finds that the forecast horizon, the time between an analyst submits a forecast and the announcement by the company of the actual realized, affects the accuracy of forecasts significantly. (Richardson, Teoh, & Wysocki, 1999; Burgstahler & Eames, 2003; Hutira, 2016). Particularly, analysts particularly make optimistic forecasts at the start of the year and then 'walk down' their estimates to a level the company is likely to beat by the end of the year. In addition, in contrast to the analysts' optimism were reported, Richardson et al. documented analyst pessimism, which happen in the final months closest to the earnings announcement. The forecast pessimism was strongest for companies with the highest incentives to avoid earnings disappointments like high market-to-book companies and high market capitalization companies.

In 2003, Abarbanell and Lehavy looked back as far as four decades and analysed previous studies related to analysts' forecasts and the rationality of forecasts. Their results were somewhat puzzling relative to many other studies, as they showed that some widely held beliefs about the tendency of analysts to make systematic errors (e.g., the common belief that analysts tend to make optimistic forecasts) did not support a larger analysis of the distribution of forecast errors well. Thus, their results did not give the clear answer to analysts' rationality, and they highlighted that research should be continued that explores the real goal towards which analysts' forecasts are directed. It is a prerequisite for defending or opposing analysts' rationality.

Usual reason to analysts' effort and decisions to follow companies and their systematic optimism or pessimism in their forecasts and recommendations is different incentives. Financial analyst forecasting literature have recognized several incentives that analysts have. (Ramnath, Rock & Shane, 2008; Groysberg, Healy & Maber, 2011; Capstaff, Paudyal & Rees, 2001; Lim, 2001.)

According to Ramnath et al. (2008) incentives have related to analysts' career concerns, underwriting and trading incentives of their employers and how the incentives of, and communication with, company management influence analysts' behaviour. Selection bias results from analysts initiating and maintaining coverage only for companies for which they expect good prospects. The incentive structure of analysts has also been detected to cause association between forecast accuracy and the earnings types like profits, losses, year over year increases or decreases. Analysts who issue a negative recommendation risk their relationships with the firm's management and thus their access to information or even incentive. (Lim, 2001.)

Capstaff et al. (2001) argue that differences in the performance of analysts' forecasts are due to differences in earnings. They examine that if earnings are weakly relevant for future returns, analysts may devote less efforts and resources to earnings forecasting. According to them, the low value-relevance of earnings may discourage analysts to spend time on earnings forecasting. Capstaff et al. argue also that differences in the performance of analysts' forecasts are due to differences in the accounting practises. The differences in the accounting practices may complicate the task of financial analysts and influence the incentives for them to produce accurate earnings forecasts.

Also, Groysberg et. al (2011) argue, that trade commission act as important incentives for analysts. Analysts provide optimistic and biased forecasts to generate trade commission for their employers and to secure promotion and trade commission for themselves. On the other hand, analysts are incentivized to produce accurate forecasts and recommendations, because forecast accuracy is important for an analyst's career, and it allows them to achieve and maintain high status (Hilary and Hsu, 2013).

According to previous literature, also work experience affects to forecast accuracy. More experienced analysts are able to provide more accurate forecasts, larger employers enable access to greater resources. Also, stock prices react more strongly to more experienced analysts' forecasts. (Mikhail, Walter and Willis, 1997.) These have also been founded by Clement (1999). His results show that accuracy increases with experience and the size of the employer and decreases with larger number of companies and industries followed. Confusingly, the study of Bolliger (2004) doesn't instead find relationship between forecast accuracy and analysts' job experience and the size of the bank employing the analyst. Instead, Bolliger focuses also on local versus foreign brokerage houses and finds an advantage for local brokerage houses.

Analysts' skill to correctly forecast company's expenses has a substantial impact on the accuracy of earnings forecasts. Cifci et al. (2016) suggest that if financial analysts make no errors in estimating variable costs or sticky costs, then the earnings forecast errors should be symmetric across favourable and unfavourable sales surprises of equivalent amounts. Their findings, though, show earnings forecast errors that are significantly smaller when sales beat expectations than when sales miss expectations by an equivalent amount. Their evidence is thus inconsistent with analysts perfectly incorporating available information on firms’ cost behaviour.

Also, other prior study, a study of Kim and Prather-Kinsey (2010) has been dedicated to cost forecast accuracy. Their aims to examine whether analyst forecast systematic errors are due costs they forecast. They test whether analysts’ earnings forecast errors are a function of analysts’ use of so-called proportionate cost model (PCM) in which the growth rate for both expenses and sales are assumed to be equal. Their study suggests that such an assumption leads to forecast errors when expenses change at a different rate than sales. The study show that analysts do not fully understand the impact of fixed costs on cost and earnings behaviour.

According to the previous studies presented above, the factors affecting the accuracy of the forecast error are related to the knowledge, skills, and other characteristics of the analyst. Forecast accuracy is also affected by issues that the analyst has no chance to influence. The issues are caused from within the company, and often they are not revealed to the analyst.

The information published by company itself about the business operations reduces the asymmetry of information and increase consensus among analysts and thus, contributes to the accuracy of forecasts. It happens, especially if more forthcoming disclosures and addition information given by company itself. (Lang and Lundholm, 1996.)

Forecast accuracy is said to increase with higher quality disclosures and with stronger enforcement of accounting standards. The findings of Hope (2003) suggest that higher quality information and more tight accounting standards provide stronger information for analysts’ forecasts, when increases the reliability of accounting. We can count on the fact that accounting values are more accurate since the 21st century. Namely, according to Choi, Peasnell and Toniato (2013) accounting Standards Board (IASB), who develops and approves International Financial Reporting Standards (IFRSs), has succeed its stated goal to create a set of standards which are more useful for forecasting.

From an analyst's point of view, what kind of information the company shares about itself is a high quality? According to previous literature, the information environment has overall improved over the past decades and thus, forecast accuracy has improved also. What comes to information included in, the forecasting models based on financial and textual information are more accurate than models using financial variables alone. However, an overly complex and difficult to understand publication does not necessarily increase the accuracy of forecasts, instead may even decrease it. (Chaudhury and Sahoo, 2022; Bochkay and Levine, 2019; Plumlee, 2003.)

The impact of earnings management and earnings quality on forecast accuracy is well investigated. The term “earnings management” refers to actions undertake by management that undermine earnings quality and thus the ability of analysts to issue accurate forecasts (Scott, 2003). Some of the proxies for earnings quality examined in prior studies include specific financial accounting manipulations, such as discretionary accounts, transaction-timing, and reporting incentives (Salerno 2014). According to Salerno higher earnings quality is associated with improved forecast accuracy, which is intuitively understandable.

There are several motivations for earnings management and study of Embong and Hosseini (2018) shows that one of the factors is managers’ intent to meet or beat analyst forecasts. If analysts fail to account for earnings management, it is possible that earnings manipulation in the previous year may mislead analysts and affect forecast accuracy for current and future years. Thus, relationship between earnings management and forecast accuracy is endogenous or reciprocal when managers react upon analysts’ forecasts and analysts use reported earnings to make forecast.

According to Athanasakou, Strong and Walker (2009), especially during a recession, large companies move the actual operating expenses to the income statement as incidental expenses, so that the actual operating result would be closer to the analysts' forecasts.

In addition to accurate and coherence of revenue or accounting, literature has also made progress in understanding companies' cost behaviour and its relationship to forecasting accuracy. The studies provide evidence that costs increase more when sales rise than they decrease when sales fall by an equivalent amount meaning that costs are sticky. Weiss (p. 1445) shows that sticky costs cause greater earnings forecast errors. Also, Banker and Chen (2006) argue, that analysts unaware about the effect of cost stickiness on their forecasts, cannot forecast accurate.

In summary, the literature identifies two clear main sources of forecast accuracy deficits: characteristics of the analyst and the company itself. The literature review of this thesis covers these two entities more carefully.

1.3 The objective and scope of the study

Theoretical background opens perspective needs related to the research of the analysts' systematic forecast errors. It is supposed to draw a comprehensive picture to the reader to understand the factors behind the systematic errors in analysts' forecasts and the meaning of the existence of the errors. Simultaneously, it reveals that the accuracy of analysts' forecasts has been studied almost exclusively for analysts following listed companies. Literature review explains differences between forecasting needs of unlisted companies and listed ones and introduces the reader to the drivers of forecast errors.

The objective of this thesis is look for common features of the analysts' forecast accuracy of unlisted companies' forecasts than what the literature offers about analysts' forecasts and their accuracy with listed ones. Since the bias in listed companies is on average that analysts' profit forecasts are optimistic (e.g., Abarbanell and Lehavy 2003, Cifciet al. 2016), and forecast error is positively correlated with the length of the forecast period, could the bias be similar on average for unlisted companies as well. The needs for forecasting the future of unlisted companies are often much more diverse. The forecasts are prepared at least for valuation, which is needed for a planned ownership arrangement, for an acquisition or merger or for a financing arrangement. The forecasts are prepared also for the business development and proactive company management.

The different context provided by unlisted companies raises a whole new empirical question, are analyst' forecast still optimistic and forecast error positively correlated with the length of the forecast period? Since a typical forecast formed by an analyst is based on figures obtained from history as well as on management's statements about their future goals, the forecasts produced from diverse needs do not necessarily differ too much. Therefore, results like the theoretical background can be expected.

The thesis is a custom order for a company where analyses have only been done for a few years. Thus, the factor affecting the applicability of the above assumed theoretical background assumption in this thesis is at least the limited sample size. A small sample size may affect the statistical significance of the results. The research questions of previous studies (Richardson et al. 1999), are also suitable as the research questions of this study, and thus serve as the research questions and hypotheses of this thesis.

Hypothesis 1:

Analysts make optimistic forecasts at the start of the fiscal year.

Hypothesis 2:

A forecast error is positively correlated with the length of the forecast period.

1.4 The structure of the study

This thesis consists of six main chapters. After the introduction, the literature review focuses more on the practical side. The second part of the thesis focuses on the role of analysts in serving stakeholders. The third chapter continues the theoretical background. It drills down to one of the most important parts of an analysis produced by analysts: forecasting a company's future performance and its accuracy. The third part present also hypothesis of the topic.

Chapters four to six focus on empirical side of this thesis. Fourth chapter covers methodology used in the empirical section and the data used, and how it was acquired. Chapter five presents result of the thesis. Last, chapter six is reserved for conclusion.

2 ANALYSTS ROLE IN SERVING STAKEHOLDERS

Financial analysis and forecasting have spanned a wide range of studies in the past which is no surprise considering how central part of finance these topics represent. In the next two chapters, theoretical references and observations related to the topic of the thesis are reviewed. First, the role of analysts is discussed and the discussion about the role is deepened to deal with analysts' analysing unlimited companies in accordance with the thesis topic. The second part of the literature review deals with the generation of forecasts produced by analysts and the accuracy of forecasts. Finally, the factors that affect the accuracy of forecasts produced by analysts is examined.

2.1 The role of analyst

Analysts' role is to collect and interpret information about companies and distribute it ahead. They thus linking the information produces and consumers. Through their analysis and by using their expertise they generate or discover new information that is not readily available such as company valuations, earnings forecasts, and long-term growth rates. Analysts' role is thus producing their own comprehensive analyses, research reports, and the report can be divided into four phases: business analysis, financial statement analysis, forecasting, and valuation. Analysts use a variety of information sources and significant amounts of data in their work. (Soffer & Soffer, 2003.)

As So (2013, p. 618) and Chen, Cheng and Lo (2010, pp. 206) highlighted, analysts have an important role in financial markets making market operations more efficient. Financial analyses and forecasts prepared by analysts is relevant for all the different stakeholders who require information about the economic situation of a company. Suppliers and customers are interested in the financial situation of the company. Also, competitors monitor the company's performance for benchmarking. Furthermore, investors evaluate the company's financial performance and analyse its potential as an investment opportunity. Analysts can facilitate stakeholders in their decisions. They can direct the attention of investor to the topics that they consider relevant and important. They can clarify and explain the disclosures by using their own words and they can also assess the management's estimates and statements using calculations.

Additionally, as analysts are seen as independent agents, they can assess the reliability of management's statements. On the other hand, they are free to disclosure their opinion. The researchers find that both information discovery and interpretation activities of analysts trigger market reactions that suggest that these functions bring value to investors. (Barth & Hutton 2004, pp. 59-96; Healy & Palepu 2001, pp. 405–440; Kirk 2011, pp. 184). Most, it is preferable to use financial analysis reports prepared by different analyst services. However, for some the significance of the financial analysis in decision making is of such importance that they conduct it themselves, such as banks.

The existence of analyst does not only benefit companies' stakeholders but also companies themself in a variety of ways as numerous studies have shown (Merton 1987, pp. 483-510; Brennan & Subrahmanyam 1995, pp. 361–381; Irvine 2000, pp. 224; Kirk 2011, pp. 182–200). Analysts have unquestionable role reducing agency problem and costs between company management and owners through the sufficient analyst coverage and their monitoring. Their close monitoring of companies can help investors and owners detect managerial misbehaviours. It has also detected that with decreased analyst coverage companys' cash holdings contribute less to shareholder value, the companys' CEOs receive higher excess compensation, and the management is more likely to make value-destroying acquisitions and engage in earnings management. Analysts can even serve as an external governance mechanism by providing direct monitoring by regularly interacting with the companys' management and analysing the financial statements. Value of analysts for listed companies is also that the commencement of analyst coverage may results in positive stock returns and improves the liquidity of stocks, when the institutional investors that did not own the stocks, increase their holdings. (Demiroglu & Ryngaert, 2010). On the other side, the decrease in analyst following, caused by the companies' closures, may reduce share prices and liquidity, and decreases retail investors' demand for the stocks (Kelly & Ljungqvist, 2012).

Professional analysts can be divided into buy-side analysts and sell-side analysts. The differences between analysts are mainly related to who their employer is. Buy-side analysts work in investment funds, insurance companies and institutions managing investment portfolios, and the analyses they make are usually intended for internal use alone. To name the most common ones, they evaluate potential securities suitable for their funds and make buy or sell recommendations. Sell-side analysts work for brokerage companys like investment banks and banking companies, and their research is widely disseminated to institutional and retail clients. They follow specific stocks and industries and produce reports of them. They also make buy, hold, and sell recommendations for the brokerage company's clients. Independent analysts do not have an employer, they prepare paid analyses for their clients. (Groysberg, Healy & Chapman, 2008.)

The purpose of analysts is to produce added value for their clients and for this reason, it is of the utmost importance that analysts' forecasts are right, and not too much large forecast errors would occur. Revenue forecasting is however a complex task. A measure commonly used in studies to evaluate the accuracy of forecasts is the analysts' forecast error. The forecast error is calculated as the difference between the forecasted and the actual realized value. The smaller the error (i.e., the closer the forecast is to the actual realized value), the more accurate the forecast is. (Schipper 1991, Rees 1995: 131.)

2.2 Analysts in unlisted company

The role of analyst is most easily considered of as buy-side or sell-side analysts who produce analyses for listed companies, as stated in the previous paragraph. Also, unlimited companies need help in finding potential solutions to business issues and opportunities. It has become apparent that this requires a new set of skills to support business managers in achieving it. These factors have led directly to the development of the business analyst role there. (Cadle, Paul & Turner, 2014.)

According to Cadle et al. (2014), business analysis has developed into a specialist discipline that can really add value to companies and its stakeholders. And the place of analysis within the business change lifecycle is critical if organizations are to benefit from those changes. Business analysts offer objective views that can challenge the received wisdom and identify where real business benefits can accrue. Over the last few years, business analysts have continued to develop their skills such that the breadth of work they can engage in has become extensive. Business analysts can improve areas where success has traditionally been a struggle, such as the achievement of forecasted business benefits.

Organizations may use external consultants to be employed to deal with a specific issue on an as-needed basis, to bring a broader business perspective and to be provide a dispassionate, objective view of the company. In addition to using external consultants, business analysts are employed to their organizations. These analysts may lack an external viewpoint, but they are knowledgeable about the business domain and crucially, will have to live with the impact of the actions they recommend. Reason for using internal business analysts, apart from lower costs, include speed and retention of knowledge within the organization. There has been increasing number of business analysts working as internal or external consultants over the last decade. An area where most business analysts work are strategy implementation and business case production. (Cadle et al., 2014.)

During the enterprise analysis phases, the business analyst conducts a competitive analysis and benchmark studies, identifies potential solutions to business problems, conducts feasibility studies to determine the optimum solution, and prepares the business case for the proposed new initiative to arm the executive team with the information it needs to make quality project investment decisions. A high-quality decision made by analysts is one that is likely to attain the goals of the organization, is well reasoned, and is consistent with available information and with organizational goals and objectives. (Lindbergh et al. 2007.)

The goal of both listed and unlisted company analysis is thus to achieve a deep understanding of the company's business operations and business environment, and then to build reliable forecasts. Forecasts is needed for several varied reasons. For instance, the key point of valuation is to build reliable financial forecasts of the company's future development. Since the value of a company is equal to its future profits or cash flows, valuation requires forecasting future profits and cash flows. (Kallunki and Niemelä, 2012, p. 111–112.)

Valuation is inevitably accompanied by uncertainty due to the difficulty of forecasting the company's future success. Because in present value models the company's value is influenced especially by assumptions about the company's future growth and risk, analyst has to do careful background work about company analysis. Despite of that, even the most educated estimate of the company's future is not certain. (Kallunki & Niemelä, 2012, p. 233.)

Analysing the economy includes forecasting is usually done through budgeting. Budgeting is prepared one to three years ahead, and the future is roughly assessed even after that. Previous literature does not mention the accuracy of budgeting done by analysts. It is therefore necessary to find out whether the forecasts made by the analysts of unlisted companies follow the bias of the forecasts of listed ones stated before. If so, can the causes of forecast bias be found in the same places, either in the characteristics of the analyst or in the companies themselves. Investigating this covers the empirical part of this thesis.

3 ANALYSTS EARNINGS FORECASTS

Kolmoskappaleen tarkoitus on mennä syvemmäksi tutkimuksen tutkimuskysymyksiä, kun puhutaan analyytikoiden ennustamisesta.

As said, financial analysis and forecasting have spanned a wide range of articles in the past which is no surprise considering how central part of peoples' and companies' finance these topics represent. Like this thesis, also Ramnath et al. (2008) went through financial analyst forecasting literature. Their effort was to find out the roles that financial analysts play in economic field and because of their article they categorized research into seven categories:

1. Analysts' decision process
2. The nature of analyst expertise and the distributions of earnings forecasts
3. The information content of analyst research
4. Analyst and market efficiency
5. Analysts' incentives and behavioural biases
6. The effects of the institutional and regulatory environment
7. Research design issues

Of these seven topics, the literature review section of this thesis focuses most closely on the information content of analyst research and opens aspects related to analyst characteristics, such as incentives and behavioural bias. Furthermore, this thesis opens aspects related to company characteristics on the creation of forecast bias.

3.1 Analysts' information sources

Several studies have examined what information affects the development of analysts' research reports, forecasts, and recommendations. The starting point to a source of analysts' information is the company's financial statements contained in the annual report. It provides quantitative financial data in the income statement, balance sheet, and statement of cash flows. The annual report contents also qualitative data in the form of management commentaries and accounting policies used and those are also important source of information to analysts. The accompanied disclosures and notes of the annual reports provide a more detailed breakdown of the information. Annual report thus serves as a basis for analysts' forecasts, but analysts use numerous other sources as well. They follow the companies' press releases and interim reports and articles in newspapers and magazines. Usually, they also are directly interacting with the company's management and customers, and they employ other analysts' reports and forecasts. Essential information are also company-specific stock market information, generic market data, and information about competitors. In addition to information specific to a company, analysts consider the industry reports on market conditions and trends. (Rees 1995: 27–33, Soffer & Soffer 2003: 3–5.)

More than twenty years ago Rogers & Grant (1997) found that financial statements (income statement, balance sheet and cash flow statement) provide however only 26% of the content in analyst reports. The narrative sections of annual reports provide an additional 26% of the content in analyst reports, with management discussion and analysis (MD&A) being the most important section of that. The remaining 48% of the content in analyst reports comes from external information sources. Also, Epstein & Palepu (1999) found that two primary sources of analysts' information are private contacts and analyst meetings, and annual reports ranked only as third.

Also, the findings of Daniel, Lee & Naveens' research (2016) suggest that analysts use significant amounts of non-financial information both from annual reports and outside sources when they prepare research reports and forecasts. In addition, they find that 17% of reports contain new information generated by the analysts. Among reports containing information discovery, 79% contain discovery from management sources such as personal meetings or conversations with management, conference calls, and analyst meetings and the remaining contain discovery from non- management sources.

As can be seen analysts use a variety of information sources. Previous research shows that the information analysts need for their analyses may not be available in the annual reports and financial statements, and thus it must be found from outside sources. Also, the information that is available may not be presented in a suitable format for analysis and will need to be reorganized and adjusted. Huang, Lehavy, Zang & Zheng (2018) study shows that analysts play the information intermediary roles by discovering information beyond corporate disclosures and by clarifying and confirming public corporate disclosures. The majority of previous studies conclude that analysts add value through information discovery and through interpretation of public information. Nonetheless, financial statements provide important essential information for forecasts.

3.2 Forecasting

Forecasts are significant products of analysts' work and valued by the capital markets. Forecasts are often essential as they can be used as direct inputs in many valuation models. And more accurate forecasts, more accurate company valuations and better investment decisions. (Rees 1995: 134.)

In an efficient capital market, analyst forecasts perform several key roles. First, almost all financial valuation models are based on earnings forecasts in some way. Forecasts drive significant movements in the level and variability of equity prices and returns and as thus play a key role within the economy. Second, research by both regulators and academics relies extensively upon the financial statement analyses and recommendations provided by analysts. Given the importance of forecasts, prior studies claim that errors can lead to increased corporate agency costs and reduced informational efficiency within financial markets. That is why a significant body of research has been devoted to identifying those factors that drive systematic errors within forecasts. Prior research has focused on multiple determinants of forecast accuracy. These studies cover factors ranging from firm specific indicators to the quality and type of analysts covering the firm, to the state of the economy. (Hutira, 2016.) This thesis cover factor from analyst's characteristic to company specific characteristic.

To accurately forecast a company's future performance and determine its value, analysts need to have a thorough understanding of the that. it is the most essential to understand the key business drivers and risks of the company. It is needed understanding of both internal and external environment of the company, when knowledge of internal environment includes issues such as the company's products and services, its marketing and manufacturing methods, distribution processes, business model and strategy. Knowledge of external environment consists of matters such as industry economics, competitive environment and the company's competitive advantage, customers, and legal, regulatory and political environment. (Soffer & Soffer 2003: 14–15, Penman 2004: 512.

A deep understanding of the company's numbers is also essential. Analyst has to examines the financial statements to find out about the company's current and historical profitability, growth, and resource needs. The analyst aims to understand the connections between the financial variables and the company's activities, and how these might change in future. The analyst also considers the company's accounting policies and choices and how these affect the reported numbers. As accounting standards give management some freedom of choice on accounting methods, the analyst must adjust for any distortions. Therefore, analysts often modify the financial statements into a more suitable format for analysis, excluding non-recurring items and possibly including others. The financial statement analysis prepared by analyst translates the observations made in the business analysis phase into concrete measurements. Through analysis it can be seen changes of the margins easier. Through analysis it can also be evaluated whether current earnings and history are a good indicator of future earnings. With the understanding of company's historical and present performance, the analyst can then begin to forecast the future. (Soffer & Soffer 2003: 15, Penman 2004: 382–382, 512.)

By employing information gathered in the business and financial statement analysis, the analyst makes forecasts about the company's future financial performance. Forecasting can be divided into mechanical and non-mechanical forecasting. (Foster 1986: 262–263, Soffer & Soffer 2003: 16.)

In the mechanical forecasting, data is combined in a prespecified way so that using the same data and forecasting model will always yield the same result. An example of mechanical forecast would be a model that calculates next year's earnings to be the weighted average of past five year’s earnings. Other example of mechanical forecast would be a regression model that uses two or more variables to forecast earnings, such as data about economy and industry. (Foster 1986: 262– 264, Penman 2004: 501–502, 510.)

In a non-mechanical forecasting, the data is not combined in a prespecified way, so depending on the analysts the same data inputs could lead to different results. An example of non-mechanical one would be to observe a visual earnings curve or plot and to subjectively estimate the future earnings. Multivariate non-mechanical forecasting is the one typically used by analysts. It employs the many different information sources, such as financial statements, economy and industry data, and information about competitors and customers. The weights given to different information sources may vary from forecast to forecast and there is rarely a clearly observable link between the data inputs and the forecast results. (Foster 1986: 262–264, Penman 2004: 501–502, 510.) Numerous studies have compared the accuracy of earnings forecasts between non-mechanical models made by analysts and mechanical models and these show that analysts produce superior forecasts to those of mechanical models.

As stated above, analysts’ role is thus producing analyses, research reports, and the report can be divided into four phases: business analysis, financial statement analysis, forecasting, and valuation. After first three phase, business analysis, financial statement analysis and forecasting the company's future, the analyst is ready to determine the company's value. In this phase the analysts use some valuation method to determine the company’s value. There are several different valuation methods. Methods involving forecasting are the ones based on discounted cash flow models and the most common techniques of these are dividend discount model, free cash flow model, and residual income model. A method that does not involve forecasting is multiples valuation where the company is valued by comparing it to comparable companies. The choice of valuation method is affected by its costs and benefits and where it is needed. Simpler methods are faster whereas more complex methods can provide a more reliable valuation, but they are more time-consuming. (Soffer & Soffer 2003: 16, Penman 2004: 17–18, Kallunki & Niemelä 2004: 102–103.)

The previous literature provide support for valuation models emphasizing future earnings. it also indicates the usefulness of fundamental accounting analysis in investment decisions. Loh & Mian (2006) investigated the relation between analyst forecast accuracy and profitability of stock recommendations and they found that expending time and resources on forecasting is rewarded with more accurate and profitable valuations. According to them, analysts who issue more accurate earnings forecasts also issue significantly more profitable investment recommendations compared to analysts issuing inferior forecasts. The results suggest that in an imperfectly efficient market the more slow and costly activity of information gathering to provide superior forecasts leads to better valuations and thus higher returns.

3.3 Factors affecting the accuracy of forecasts

Within this thesis, the term “forecasts” refers to annual assessment of the company financial succeed provided by analysts. The accuracy of analysts’ forecasts is commonly evaluated by measuring the error and error means difference between the forecasted value and the subsequent actual realized value. According to previous literature, the accuracy is defined as the absolute value of the percentage difference between realized and forecasted. The smaller the difference between the estimated and actual realized value, the more accurate the forecast is. (Rees 1995: 131-132.)

Two common error measurements are forecast error (FE) and absolute forecast error (AFE) in the following formulas (1). The first is forecast error, which thus is calculated as the difference between the realized earnings (RE) and median forecast for the period (F). Finally, it is divided by the realized earnings. (Rees, 1995: 131–132; Hutira, 2016.)

$$FE = \frac{RE - F}{|RE|} \tag{1}$$

The second formula (2) is the absolute forecast error (AFE), which is the non-negative value of the forecast error.

$$AFE = |FE| \tag{2}$$

According to Rees (1995: 131-132) measurements are mean absolute error and mean square error. Here formulas' (3) A equals the actual realized value, F equals forecasted value, N is the number of forecasts, and X is the deflator. The deflator is often used as the deflator X, but other measures can be used as well, such as the company's stock price at the time of the forecast.

$$MAE = \frac{\sum_{1}^{n} \left|\frac{A_i - F_i}{x_i}\right|}{N} \tag{3}$$

Mean absolute error measures the average of all the errors in the sample and gives equal weighting to each error. Furthermore, mean square error (4) is the same as mean absolute error but it gives greater weighing to high error values than to low values.

$$MSE = \frac{\Sigma_{1}^{n} \left[\frac{Ai - F_i}{x_i}\right]^2}{N} \tag{4}$$

Instead of random errors, this thesis as well as prior studies focus on errors that are systematic due to some specific issue. Previous literature provides mixed results about whether systematic differences in financial analysts' forecast accuracy exist. While a number of early research do not definitely always document systematic errors or these do not identify significant differences in forecast accuracy, it can be noticed that more recent studies document systematic differences. When previous literature examines forecast accuracy, it mostly assumes that forecast error exists. After this, the literature looks for reasons and explanations for the occurrence of the forecast error.

However, there are some early studies that find a systematic error in the accuracy of the forecasts. Already Elton, Gruber & Gultekin (1984) analysed the errors and their sources in analysts' earnings forecasts. They found that majority of forecast errors are due to analysts' incorrect estimates of industry and company performance, and errors due to economy itself are marginal. Furthermore, misestimating company performance was a greater source of errors relative to industry performance. They found that some companies and industries are more difficult to forecast than others. Similarly, they observed that if analysts provided a poor forecast for a company in any year, they would likely provide a poor forecast for the same company in the subsequent year. Several factors have been identified as determinants of financial analysts' forecast accuracy, and as consensus, two culprits can be found as the source of the forecast error:

1. the analyst itself

2. the company being analysed

Also, this chapter 3.3 proceeds in this order. First, it reviews the literature where the source of forecast error is the analyst. In the second part, we familiarize ourselves with the literature, where the source of the forecast error is the company being analysed.

3.3.1 Analyst's characteristics and skills

Prior research has shown analysts to have even the ability to drive security prices and corporate financing activity. That is the reason why there has been a lot of research into the functioning of these important information mediators. Forecast accuracy is affected by issues which most often have been caused by analysts themselves. It does not mean, however, that the analyst's actions to achieve imprecision are always intentional or conscious. On the contrary, their actions or ways of thinking are mostly subconscious and therefore completely unintentional, that, however, does not eliminate the need to study the topic. Studies is motivated also by the strong concern expressed by regulators about the behaviour of analysts' forecasts, as well as investors needs to fill information gaps and make decisions regarding the company.

Prior studies aim to find out what causes the systematic forecast errors, when the assumption of the point is that a forecast error occurs. When studies deal with the topic that analysts' actions influence the generation of forecast errors, these suppose, for instance, that analysts are too optimistic, or they suffer from first impressions. Some argue that analysts make coarser analyses at the beginning of the financial year, i.e., larger forecast errors and refine their forecasts during the financial year. Some argue that local analysts are more accurate than non-local ones or forecast costs incorrectly causing distortion in the forecast of the revenue. According to many prior studies reason to analysts' effort and decisions to follow companies and their systematic optimism or pessimism in their forecasts and recommendations is different incentives.

Several psychological research shows that information received first tends to overshadow information received later, and first impressions have a lasting effect on perceptions and future behaviour. The first impression bias causes a decision-maker, assessing the outcomes of some process, to place undue weight on experiences that contribute to an initial impression. If the first impression is clearly positive, then assessments about the future tend to be unduly positive; the reverse is the case if the first impression is negative. (Hogarth & Einhorn, 1992.) Intuitively, the existence of first impressions can be found in all disciplines, in human interaction, in everything. According to the literature, the existence of first impression biases among financial professionals is undeniable. According to Hirshleifer et al. (2021), analysts' forecasts suffer from first impressions. If the company has performed particularly well or poorly in the year before the analyst follows it, the analyst will tend to give optimistic or pessimistic estimates. In line with the negativity bias, Hirshleifer et al. find that negative first impressions have a stronger effect than positive ones. Furthermore, they show that a set of professionals in the financial analysts, apply U-shaped weights to their sequence of past experiences, meaning that with greater weight on first experiences and recent experiences than on intermediate ones.

What comes to forecast horizon, number of prior studies finds that accuracy decreases as the horizon increases. The forecast horizon, the time between an analyst submits a forecast and the announcement by the company of the actual realized, thus significantly affects the accuracy of forecasts. Like intuitively, the further out one makes an estimate, the greater the probability of error. (Richardson, Teoh, & Wysocki, 1999; Burgstahler & Eames, 2003; Hutira, 2016). Richardson et al., investigated the claim that analysts make optimistic forecasts at the start of the year and then 'walk down' their estimates to a level the company is likely to beat by the end of the year. They found strong evidence of a switch from upward-biased to downward-biased forecasts of annual earnings as the announcement date approaches. Thus, in contrast to the analysts' optimism reported in all prior studies of their study, on annual earnings forecast errors, they also documented analysts' pessimism, which happen in the final months closest to the earnings announcement. The forecast pessimism was strongest for companies with the highest incentives to avoid earnings disappointments. These companies included especially high market-to-book companies and high market capitalization companies. They also found that companies that beat analysts' forecasts often include large discretionary items, such as special items and accruals, in their final reported earnings. This evidence is consistent with the allegation that companies systematically manage analysts' earnings expectations and tailor their final reported earnings to beat the analysts' forecasts. The subject of earning management is discussed more in section 3.3.2 of this thesis.

In 2003, Abarbanell and Lehavy looked back as far as four decades and analysed previous studies related to analysts' forecasts and the rationality of forecasts. According to them, the results were somewhat puzzling, as the most accurate statements on which critics of earnings forecasters seemed ready to agree were those for which there was only weak empirical support. Abarbanell and Lehavy (2003) showed that some widely held beliefs about the tendency of analysts to make systematic errors (e.g., the common belief that analysts tend to make optimistic forecasts) did not support a larger analysis of the distribution of forecast errors well. The results also raised questions about whether analysts are expected or motivated to forecast discretionary manipulations of companies' reported results. At the same time, the results also highlighted the fact that research that explores the real goal towards which analysts' forecasts are directed is a prerequisite for defending or opposing analysts' rationality.

Prior research has shown analysts to have even the ability to drive security prices and corporate financing activity. That is the reason why there has been a lot of research into the functioning of these important information mediators. Usual reason to analysts' effort and decisions to follow companies and their systematic optimism or pessimism in their forecasts and recommendations is different incentives. Financial analyst forecasting literature have recognized several incentives that analysts have. (Ramnath et al., 2008; Groysberg et al., 2011; Capstaff et al., 2001; Lim, 2001.)

According to Ramnath et al. (2008) incentives have related to analysts' career concerns, underwriting and trading incentives of their employers and how the incentives of, and communication with, company management influence analysts' behaviour. Instead, selection bias results from analysts initiating and maintaining coverage only for companies for which they expect good prospects. At the same the literature has shown that economic incentives and behavioural biases can create underreactions in analysts' forecasts. The incentive structure of analysts has also been detected to cause association between forecast accuracy and the earnings types like profits, losses, year over year increases or decreases. This is because of analysts who issue a negative recommendation risk their relationships with the firm's management and thus their access to information or even incentive. (Lim, 2001.)

Capstaff et al. (2001) argue that differences in the performance of analysts' forecasts are at least due to differences in earnings. Capstaff et al. compared accuracy and bias across nine European countries report differences in forecast bias and they argue that if earnings are weakly relevant for future returns, analysts may devote less efforts and resources to earnings forecasting. According to them, the low value-relevance of earnings in some European countries (e.g., Germany and Switzerland) may discourage analysts to spend time on earnings forecasting. Capstaff et al. argue also that differences in the performance of analysts' forecasts are due to differences in the accounting practises. The differences in the accounting practices under which European companies report may complicate the task of European financial analysts and influence the incentives for European financial analysts to produce accurate earnings forecasts. All at all, in their European sample, analysts' forecasts are most accurate in the United Kingdom and least accurate in Italy.

That is the reason why there has been a lot of research into the functioning of these important information mediators. How, for example, incentives affect the recommendations they give or the forecasts they make. According to Groysberg et. al (2011) trade commissions from buy-side analysts act as important incentives for sell-side analysts. Analysts provide optimistic and biased forecasts to generate trade commission for their employers and to secure promotion for themselves. They also show that buy-side analysts make more optimistic and less accurate earnings forecasts than sell-side. On the other hand, analysts are incentivized to produce accurate forecasts and recommendations, because forecast accuracy is important for an analyst's career, and it allows them to achieve and maintain high status (Hilary and Hsu, 2013).

More experienced analysts are able to provide more accurate forecasts, larger employers enable access to greater resources. Mikhail et al. (1997) studied if forecast experience explains the differences in forecast accuracy of financial analysts. Examining quarterly earnings forecasts and stock recommendations, they show that more experienced analysts issue more accurate forecasts. Furthermore, they show that stock prices react more strongly to their forecast revisions. These have also been founded by Clement (1999), when he investigated how the analyst's ability, resources and affect their forecast accuracy. Clement documents a positive relationship between analysts' relative forecast accuracy and analysts' firm specific and general experience, which means learning-by-doing. His results show that accuracy increases with experience and the size of the employer and decreases with larger number of companies and industries followed. Confusingly, the study of Bolliger (2004) doesn't find relationship between forecast accuracy and analysts' job experience or the size of the bank employing the analyst. The study of Bolliger investigates the determinants of financial analysts' forecasts differential accuracy in European stock markets. Analysts forecast accuracy is positively associated with analyst company specific experience and is negatively associated with the number of countries followed by analysts and the age of the forecast. Instead, Bolliger focuses on local versus foreign brokerage houses and finds an advantage for local brokerage houses.

Analysts' skill to correctly forecast company's expenses has a substantial impact on the accuracy of earnings forecasts. Cifci, Mashruwaland and Weiss (2016) examine whether inappropriate utilization of information on cost behavior leads to analysts' earnings forecast errors. They suggest that if financial analysts make no errors in estimating variable costs or sticky costs, then the earnings forecast errors should be symmetric across favourable and unfavourable sales surprises of equivalent amounts. Their findings, though, show earnings forecast errors that are significantly smaller when sales beat expectations than when sales miss expectations by an equivalent amount. Their evidence is thus inconsistent with analysts perfectly incorporating available information on firms' cost behaviour. The earnings forecast errors, if any, should namely be symmetric across favourable and unfavourable sales surprises of equivalent amounts if financial analysts make no errors in estimating costs. Ciftci et al. show that analysts' partial understanding of the costs also induces a systematic error in their forecasts.

Also, other prior study, a study of Kim and Prather-Kinsey (2010) has been dedicated to cost forecast accuracy. Their aims to examine whether analyst forecast systematic errors are due costs they forecast. They test whether analysts' earnings forecast errors are a function of analysts' use of so-called proportionate cost model (PCM) in which the growth rate for both expenses and sales are assumed to be equal. Their study suggests that such an assumption leads to forecast errors when expenses change at a different rate than sales. The study show that analysts do not fully understand the impact of fixed costs on cost and earnings behaviour.

3.3.2 The company itself

Forecast accuracy is also affected by issues that the analyst has no chance to influence. The issues are caused from within the company, and often they are not revealed to the analyst. How much information the company is willing to disclose? To what extent can the analyst trust the company's financial numbers? What is the impact of earnings management? What about sticky costs? Does the company's industry affect the accuracy of the forecast? How has the change in the information environment over time affected forecasting?

The information published by company itself about the business operations reduces the asymmetry of information and thus contributes to the accuracy of forecasts. According to Lang & Lundholm (1996) more forthcoming disclosures given by company itself also increase consensus among analysts. In other words, the narrower information a company shares about itself, the more inaccurate the analysts' earnings forecasts about the company are. Lang and Lundholm studied the effect of company's disclosure practices on analyst following and earnings forecasts. They found that companies that voluntarily provide additional information, relative to minimum requirements set by regulations, and more informative disclosures have larger analyst following, more accurate earnings forecasts, less dispersion among individual forecasts, and less volatility in forecast revisions. Hope (2003) examined the relations between forecast accuracy and the company level disclosures as well as the relation between forecast accuracy and enforcement of accounting standards. The findings document that forecast accuracy increases with higher quality disclosures and with stronger enforcement of accounting standards. The findings suggest that disclosures provide stronger information for analysts' forecasts. The findings suggest also that more tight accounting standards increases the reliability of accounting, and thus reduces analysts' uncertainty about future earnings.

Bochkay and Levine (2019) combine traditional measures of operating performance with MD&A text, allowing us to assess the incremental information value of MD&A. They find that forecasting models based on financial and textual information are more accurate than models using financial variables alone and that MD&A helps improve companies' information environments. More general level of study on the impact of the information environment did Chaudhury and Sahoo (2022). They show that the improvement in forecast accuracy of analysts over the past two decades is mainly due to the improved information environment, when their study cover India region.

However, an overly complex and difficult to understand publication does not necessarily increase the accuracy of forecasts, instead may even decrease it. Plumlee (2003) studied the effect of information complexity on analysts' use of that information. The researcher investigated the relation between six tax-law changes and accuracy of analysts' effective tax rate forecasts. The results show that the forecasts include information from the less complex tax-law changes but fail to incorporate the effects of the more complex tax-law changes. The results suggest that increased complexity of information reduces the accuracy of forecasts based on that information because of a lack of ability in understanding more complex information or because the costs of using the information outweigh the benefits.

Financial reporting is considered a tool and a window for users of external information to obtain insider information. The result and key figures are the focus of financial reporting, and both analysts and stakeholders make their decisions based on the information provided by financial reporting. The quality of the income is created in this situation. Although all financial transactions related to the company are reflected in the financial statements, company insiders can manipulate this information in the financial statements, leading to inaccuracy of the information. Supervisors tend to have more confidential information than stakeholders. They may be tempted to withhold vital information or report biased accounting information to outsiders for gain. Thus, they play with the income numbers to achieve their goals regardless of other consequences. Consequently, the quality of earnings is not as good as forecasted. That is called an earnings management. (Scott, 2003.)

The impact of earnings management and earnings quality on forecast accuracy is well investigated. The term “earnings management” thus refers to actions undertake by management that undermine earnings quality and thus the ability of analysts to issue accurate forecasts. Some of the proxies for earnings quality examined in prior studies include specific financial accounting manipulations, such as discretionary accounts, transaction-timing, and reporting incentives (Salerno 2014). According to Salerno higher earnings quality is associated with improved forecast accuracy, which is intuitively understandable.

The paper of Embong and Hosseini (2018) address the relationship between earnings management and analyst forecast accuracy. There are several motivations for earnings management and study of Embong and Hosseini shows that one of the factors is managers’ intent to meet or beat analyst forecasts. If analysts fail to account for earnings management, it is possible that earnings manipulation in the previous year may mislead analysts and affect forecast accuracy for current and future years. Thus, relationship between earnings management and forecast accuracy is endogenous or reciprocal when managers react upon analysts’ forecasts and analysts use reported earnings to make forecast.

Although the direct examination of the specific mechanism of earnings management is outside of the scope of this thesis, however one source of debate has been the observed discontinuity in earnings around zero. Prior studies have noted a statistically significant difference in those companies having slightly negative vs. slightly positive earnings, with a larger than expected number of firms reporting slightly positive earnings. More recent studies using more current data suggests however that this discontinuity has disappeared for realized earnings, although not necessarily for analyst forecasts (Gilliam et al. 2015). It is caused by earnings management. Also, Burgstahler and Eames (2003) find that analysts exhibit significant forecast pessimism, overestimating earnings, for those companies that report zero earnings and significant forecast optimism, underestimating earnings, for those firms associated with zero earnings forecasts. They thus find that analysts have higher than expected forecasting errors around zero. These results have also been corroborated by Gilliam et al. (2015).

Athanasakou et al. (2009) have also investigated the earning management. They studied the extent to which the management of UK companies use earning managements to influence the financial statements to ensure that the numbers are in line with analysts' expectations. Their study cover recession. The study found no connection between unusual, earnings-enhancing working capital periods and the probability of predictions coming true. Instead, it was stated that especially during a recession, large companies move the actual operating expenses to the income statement as incidental expenses, so that the actual operating result would be closer to the analysts' forecasts.

Company performance prediction, gross profit and gross profit margin are widely used as indicators to evaluate the basic performance level of enterprises. However, less attention is be paid to the potential problems of the indicator itself. How is profit generated? How about costs, what costs are included for the financial year? Are the sales and costs reliable, so that one can conclude something from them or predict the future?

We can count on the fact that accounting values are more accurate since the 21st century. Namely, according to Choi et al. (2013) accounting Standards Board (IASB), who develops and approves International Financial Reporting Standards (IFRSs), has succeed its stated goal to create a set of standards which are more useful for forecasting. Their study cover to argue that IFRS forecasts are more accurate and less dispersed than domestic GAAP in the target country of the study, UK. The IFRS standard has been in use since 2005. It was created by the IASB when a need for international standards was discovered. Due to the internationalization of business and investment, it was important that financial statement information is comparable between different countries. Often, the accounting practices of different countries differed, so the information contained in the financial statements is not comparable. That is why there was a need to harmonize accounting practices internationally. The need for harmonization steamed from the need for information from stakeholders, especially investors.

Gross profit margin is the most commonly used index to evaluate the profitability of companies' basic business performance. Gross profit it is the difference between revenue and cost of sales when gross profit margin is the proportion of gross profit to revenue. Gross profit margin is the starting point index to analyse the profitability of company. It is of great significance to use it to investigate the market competitiveness of companies' products horizontally and the stability and development trend of enterprise's operation vertically. Paper goal of Shi, Huang, Wu & Jin (2021) paper is to analyse the limitations of the gross profit margin in China and explore how high the gross profit margin of the company listed is. Overall, the index of gross profit margin is overestimated in China, they say. According to them, the current revenue includes some unrealized items such as in-price tax, bad debt loss and cash discount in order to obtain the revenue. It thus is not completely consistent with the definition of revenue from the perspective of accounting and lead to the overestimation of gross profit margin. The paper thus found the overestimation of revenue. The findings can help us to recognize the limitations of gross profit margin and to recognize implications for various stakeholders and for further use of the gross profit margin information. It thus can help us to get rid of the misunderstanding of relying too much on gross profit margin for instance when preparing forecasts. If the gross profit margin calculated based on the current revenue cannot reflect the real basic business profitability of enterprise, it will mislead the decision-making of stakeholders and reduce the usefulness of accounting information.

In addition to accurate and coherence of revenue or accounting, literature has also made progress in understanding companies' cost behaviour and its relationship to forecasting accuracy. The studies provide evidence that costs increase more when sales rise than they decrease when sales fall by an equivalent amount meaning that costs are sticky. Weiss (p. 1445) shows that sticky costs cause greater earnings forecast errors on both favourable, high sales demand, and unfavourable, low sales demand, scenarios even if analysts perfectly understand cost stickiness and that the absolute forecast errors in the two scenarios are expected to be equal. According to Weiss "the absolute forecast error when activity levels decline as well as when activity levels rise is greater under sticky costs than under anti-sticky costs." Also, Banker and Chen (2006) argue, that analysts unaware about the effect of cost stickiness on their forecasts, cannot forecast accurate. Analysts cannot be able to predict efficiently by earnings alone. Through their study they concluded that inserting cost stickiness variables to the forecasting models of earnings will lead to higher level of accuracy to their forecasts, where neglecting it will lead to bias on these models hence lower accuracy of their forecasts. They conclude, that although the great importance of cost stickiness in the modern accounting environment, it is not received enough attention about its effect on the outcomes of financial reporting. Cost behaviour is one of the most determinants of future earnings predictability because it can draw the potential level of uncertainty related to the production environment.

The literature identifies two clear main sources of forecast accuracy deficits: characteristics of the analyst and the company itself. The literature review of this thesis covers these two entities. Doubtless, there are other separate factors affecting the accuracy of the forecast, such as macroeconomic conditions. According to Chopra (1998) study, the forecasts are most accurate during a time of continuous strong economic growth, and the least accurate when the economic growth is either accelerating or decelerating. The analysts' forecasts tend to be very optimistic and in a time of strong economic growth the actual realized earnings move closer to the optimistic forecasts, thus reducing the forecast errors.

3.4 Hypotheses

The purpose of the theoretical background is to provide a comprehensive understanding of the factors contributing to systematic errors in analysts' forecasts and the significance of such errors. Additionally, the theoretical background helps identify areas that require further research on the systematic forecasting errors of analysts. It serves as the foundation for the hypotheses formulated in this thesis.

The literature consistently supports the notion that analysts' earnings forecasts tend to be optimistic. This phenomenon is believed to be driven by various factors, including analysts' personal and institutional incentives to support their own and their employers' earnings development, as well as to influence the stock price of the target company. Moreover, the literature highlights the importance of information transparency and accounting accuracy in improving the accuracy of analysts' forecasts. Additionally, earnings management practices by companies have been identified as a crucial factor affecting the accuracy of revenue forecasting.

Do these phenomena, such as the positivity bias, which have been predominantly observed in listed companies, also apply to unlisted companies? Intuitively, analysts in the unlisted companies may have a preference for more cautious forecasts when predicting the future of a company. To investigate whether the same patterns hold true for unlisted companies, further research is needed in this specific context.

The existing literature primarily focuses on the accuracy of analysts' forecasts in the context of listed companies. It acknowledges the important role played by analysts in both the unlisted and listed companies, emphasizing the need for accurate forecasting in both settings. However, the specific examination of forecast accuracy in the unlisted companies, is limited. Further research exploring the accuracy and biases of analysts' forecasts in unlisted companies would contribute to a more comprehensive understanding of the forecasting practices.

The aim of this thesis is to examine the accuracy of analysts' forecasts for unlisted companies and compare it with the findings from previous literature. The needs of unlisted companies when it comes to forecasting are often much more diverse. Forecasts are prepared for the valuation required for ownership arrangements, such as business acquisitions, mergers, or financing arrangements. Forecasts are also prepared for business development and proactive business management purposes. Previous studies on listed companies have shown a bias towards optimistic profit forecasts by analysts, and this bias is positively correlated with the length of the forecast period (e.g., Abarbanell and Lehavy, 2003; Cifci, Mashruwala, and Weiss, 2016). The thesis aims to investigate whether a similar bias exists in the forecasts of unlisted companies.

The different context provided by unlisted companies raises a whole new empirical question: Is the analyst's forecast still optimistic and forecast error positively correlated with the length of the forecast period? Intuitively, since the analyst's forecast is typically based on historical figures and information provided by the management about their future goals, it can be expected that the forecasts produced for different needs may not differ significantly. Therefore, similar results can be expected to be found in the thesis as presented in the theoretical background.

The thesis is a custom order. There are factors that may affect the applicability of the assumed theoretical background, such as the limited sample size. A small sample size can impact the statistical significance of the results. The research questions of previous studies, such as Richardson, Teoh, and Wysocki (1999), are deemed suitable for the research questions of this study and therefore serve as the research questions and hypotheses of this thesis.

Hypothesis 1:

Analysts make optimistic forecasts at the beginning of the year.

Hypothesis 2:

A positive forecast bias is positively correlated with the length of the forecast period.

4 DATA AND METHODOLOGY

The empirical part of this thesis aims to address the following research questions: Are the forecasts made for unlisted companies optimistic? Do the realized profit margins of companies systematically fall below the profit margin forecasts provided by analysts for unlisted companies? Is there a specific point at which the forecasted and realized profit margins start to diverge? Is there a continuous growth in the deviation as the fiscal year progresses?

To answer these questions, this thesis employs a statistical research method. Quantitative or statistical research is commonly used to address questions related to numerical data and percentages. This method is often employed to examine relationships between research variables or to analyze changes that have occurred within the subject of interest. The results obtained from the study sample can be generalized to a larger population, allowing for real-life implications (Heikkilä 2014, p. 15).

The primary objective of analyzing both listed and unlisted companies is to develop a comprehensive understanding of their business operations and the surrounding business environment, which forms the basis for building reliable forecasts. However, the analysis and valuation conducted by analysts inherently involve uncertainty due to the challenges associated with predicting a company's future success. Despite conducting thorough background research on the company, even the most informed estimate of its future performance remains uncertain (Kallunki & Niemelä, 2012, p. 233).

In the case of unlisted companies, economic analysis and forecasting are typically conducted through budgeting processes. The existing literature does not extensively discuss the accuracy of analysts' budgeting for unlisted companies. Hence, it becomes necessary to examine whether the forecasts made by analysts for unlisted companies exhibit similar biases to those observed in the forecasts of listed companies, as mentioned earlier. Additionally, it is crucial to identify whether the sources of forecast bias are similar, either in terms of analyst characteristics or company-specific factors.

Investigating these aspects forms a significant part of the empirical analysis in this thesis.

The next three chapters will address the research questions outlined in the thesis. Chapter four will begin by presenting the data utilized in the study, along with introducing the research methodology and structure. Chapter five will cover the main components of the study. Finally, in chapter six, the analysis findings will be presented and discussed.

4.1 Data

The thesis aims to examine the impact of the forecast period length on analysts' forecasts in Finnish unlisted companies. It is specifically tailored for a company that offers accounting, financing, and business analysis services to its clients. The analysts at this company are responsible for preparing budgets for clients, which serve various purposes such as securing financing or providing guidance for business success and implementation of changes. The budgeting process also allows for monitoring the adequacy of working capital for clients. Since its establishment in 2005, the company has a proven track record of preparing forecasts, and stakeholders, including partner banks, have acknowledged the company's high standards in analysis for its customers.

The sample used in this study consists of budgets prepared by analysts for the fiscal year, as well as the actual realized data for the same period. The sample includes a total of 22 client companies for which both the budgeted and actual figures for the fiscal year are available. The sample period spans from 2020 to 2022, depending on the specific accounting period of each client. It is important to note that the data used in this study is collected from the databased of the long-term clients, ensuring a comprehensive and consistent dataset, rather than relying on one-time client cases.

The data utilized in the study comprises analysts' forecasts of the fiscal year's earnings and operating profit margin (EBITDA), along with the actual realized earnings and EBITDA figures during that period. These forecasts were prepared by analysts shortly before the commencement of the new fiscal year, ensuring that the most recent information was considered for the forecasting process. This approach enables a more precise estimation throughout the entire fiscal year. It is important to note that while the forecasts might undergo refinement during the fiscal year in practice, the refined forecasts have not been included in the sample utilized for this study.

Earnings and EBITDA were chosen as variables in this study due to their widespread use in forecasting. Earnings forecasts involve analysts estimating both the revenue or sales and the expenses to determine the earnings for a specific period. On the other hand, EBITDA forecasts require analysts to estimate not only the revenue and expenses but also the fixed costs.

It is worth noting that the sample for this study is not restricted to specific clients or industries. Instead, it includes all potential clients for whom both forecasted and actual realized data are available for the same fiscal period between 2020 and 2022. This approach ensures a broader representation of companies across various sectors and enables a more comprehensive analysis of forecasting accuracy.

After collecting the earnings data, it was found that three companies had forecast errors that resulted in outliers in more than half of the 12 months. As a result, the decision was made to exclude the data of these companies from the sample. Consequently, the final dataset for earnings consists of 19 companies. Similarly, for EBITDA, the forecast errors of up to eight companies resulted in outliers in more than half of the 12 months. Therefore, it was decided to remove these companies from the sample as well. This reduced the final dataset for EBITDA to 13 companies.

However, it is important to acknowledge that the small sample size can impact the reliability and representativeness of the study. A smaller sample size may limit the generalizability of the findings and increase the risk of sampling bias. It is crucial to interpret the results with caution and recognize the limitations imposed by the sample size. The findings should be considered as indicative rather than conclusive, and further research with a larger and more diverse sample would be beneficial to enhance the reliability of the study.

4.2 Research method and structure

This thesis builds on the same kind of like quantitative methods of previous studies on the accuracy of the forecasts (Hope, 2003; Capstaff, 2001). In quantitative research, is typically tested theories deductively to either support or refute hypotheses. By contrast, in inductive approach, qualitative researchers gather information from individuals, which allows them to develop theories from the themes they identify. Deductive reasoning approach begins with the general and ends with the specific, whereas an inductive reasoning approach moves from the specific to the general. This thesis uses a deductive approach meaning that the thesis is begun with a theory, forms hypotheses, gathers and uses data to complement or contradict the initial theory after completing empirical tests on the gathered data (Soiferman, 2010).

To test the hypothesis introduced earlier in this thesis, the relationship between the variables is examined using regression. More carefully, it is run a regression to examine which factors influence the magnitude of the forecast error. The results tell what the share of an individual month or control variable is when the other factors on the variable to be explained has been taken into account. A coefficient of determination, mostly indicated by R2, describes the explanatory power of the model and it shows how much of the variation in the dependent variable can be explained by the model. The p-value of an estimated regression coefficient indicates the significance of the explanatory variables. Regressions used to determine if the connection between variables are statistically significant. When the p-value is less than 0.05, the association between the variables is statistically significant, in other words, the variable can be said to explain the forecast error.

In this thesis, the null hypothesis of the regression test is that there is no relationship between the forecast error and the length of the period forecasted. The test is one-sign, meaning that it tests whether there is a connection between the forecast error and length of the period. Thus, the greater the forecast error, the further away the period is. The one-sign of the testing affects the significant value, p-value, so that the value is half the value of the corresponding two-sided testing. A significance level of 5% is used throughout the empirical part of this thesis.

Regression coefficients measure the effect of a change in an independent variable has on the dependent variable, holding all other explanatory variables constant. The coefficients can be positive or negative, indicating the relationship between the independent variable and the dependent variable.

Before running the regression, mean median of the forecast errors will be compared and tested between the months during the fiscal year to observe any significant changes. After that, Pearson correlation analysis is conducted for data of earnings and EBITDA. The correlation analysis describes the pairwise correlation between the variables in the regression analysis, and it is used for variables with interval-scale of measurement, such as month. Finally, a regression analysis will then be carried out to determine whether the changes, if any, are statistically significant. Investigating these three, covers the empirical part of this thesis.

When the thesis will study the accuracy of analysts' forecasts in unlisted companies by measuring forecast error, two types of forecasts will be studied, earnings' forecasting and operating profit margins' (EBITDA) forecasting. Forecast error is the difference between the forecasted and the actual realized value, in this study the difference between forecast earnings and EBITDA, and the realized figures of earnings and EBITDA.

The method used in this study is derived from a study by Capstaff et al. (2001), and it measures forecast accuracy of both types of forecasts. The error metric used is analysts' forecast error (AFE) where the forecasts are contrasted with actual realized earnings or EBITDA. To compute the analysts' forecast error from the data a following equation (5) is used:

$$AFE = \frac{F_i - A_i}{A_i} \tag{5}$$

Where AFE = Analysts' forecast error, F_i = forecasted earning or EBITDA of company i, and A_i = Actual realized earning or EBITDA of company i. Variable AFE is considered in term of absolute.

The deflator used is the actual realized values of earnings and EBITDA. According to Rees (1995) Using the actual values as the deflator will help to standardize the errors across companies of different sizes. At the same, it will present how many percent the error differs from the actual value. So, for instance a value of 0.15 would tell us that the average forecast error was 15% of the actual realized value of earnings or EBITDA.

When using actual values as the deflator it should be considered that if the value of the deflator is remarkably close to zero it will result in high value of the AFE variable and thus the creation of outliers. For instance, forecasted value of 10 for earnings deflated with the actual value of 0.01 would result in absolute forecast error even 99900%. Comparing this to a forecast of 150 for earning when the actual value was 200 would result in absolute forecast error of 25%. When using actual values as the deflator it should be also considered that if difference between actual realized value and forecasted ones is high, it will produce outlier meaning that forecast error is remarkably high. Therefore, forecast errors that were more than 100% were eliminated as outliers as per Capstaff et al. (2001) with the distinction that Capstaff et al. have used 200% as an eliminate value.

The median of the error variable AFE in each month of fiscal year will be considered in both earnings and EBITDA to see whether there are changes in the trend of errors i.e. the accuracy of forecasts during the fiscal period, and in which direction the trend i.e development is headed.

To test whether the earning and EBITDA trends in the forecast accuracy are statistically significant a regression analysis is used. The purpose of the regression analysis is to explain the dependent variable (AFE) with the independent variables to see if these factors have a statistically significant effect on the forecast errors. Regression analysis is performed on the whole data and the regressions are run for forecast errors for both earnings and EBITDA separately.

The regression formula (6) is used both earning and EBITDA is following:

$$AFE = \beta_0 + \beta_1 D_2 + \beta_2 D_3 + \cdots + \beta_{12} D_{12} + \beta_{13} DEBT + \beta_{14} ROI + B_{15}\, ln\, ASSET$$

(6)

Where AFE= the dependent variable, analysts forecast error for earnings of EBITDA for whole data

$\beta_0 = \text{Intercept}$

D2–D12 = Dummy variables for months, where January, D2 is February, D3 is March, etc.

DEBT = Net gearing ratio to control for indebtedness of the company in the end of the fiscal year

ROI = Return on investment to control for profitability of the company in the end of the fiscal year

LnASSET = Natural logarithm of the balance sheet to control for the size of the company in the end of the fiscal year

5 EMPIRICAL RESULTS

5.1 Univariate T-test and Wilcoxon test

The first objective of this thesis is to examine whether the positive bias observed in analysts' forecasts of listed companies also exists in the earnings forecasts analyzed in this study. To achieve this, the mean and median values for both forecasted and realized earnings are calculated. Statistical tests are then conducted to determine if there are significant differences between the forecasted mean and realized mean, as well as between the forecasted median and realized median.

The alternative hypothesis being tested is a one-tailed assumption that the forecasted values are greater than the realized values. This hypothesis suggests that there is a positive bias in the analysts' forecasts, indicating that the forecasted earnings tend to be higher than the realized earnings. By conducting statistical tests, the aim is to determine if these differences are statistically significant, providing evidence to support or reject the alternative hypothesis.

Table 1. Measures of Mean and Median Around Analysts' Positive Bias

Variable	Mean EST	Mean ACT	Median EST	Median ACT	Difference-in-Mean (P-value)
1st Month	569.54	541.88	156.91	121.83	0.114
2nd Month	593.45	596.34	199.96	158.68	0.478
3rd Month	662.04	743.84	213.36	204.70	0.182
4th Month	667.46	728.45	221.53	132.24	0.279
5th Month	680.82	636.31	235.29	198.27	0.134
6th Month	735.88	710.36	282.58	214.66	0.283
7th Month	713.05	511.99	253.05	163.71	0.031**
8th Month	809.88	658.49	252.17	198.85	0.023**
9th Month	759.99	752.68	260.54	185.25	0.466
10th Month	765.55	623.40	225.58	148.38	0.034**
11th Month	759.07	644.77	265.00	148.98	0.028**
12th Month	719.84	911.44	275.14	230.89	0.139

P-value: ** significant at 5%; *** significant at 1%.

Table 1 displays the mean values of forecasted and realized earnings for each month of the fiscal period. The statistical analysis reveals that there are significant differences between the forecasted and realized earnings in the seventh, eighth, tenth, and eleventh months at the 5% significance level. These findings support the acceptance of the alternative hypothesis, which suggests a positive forecast error.

The size of the companies can influence the mean values, and therefore, the statistical significance is also examined using the median. Table 1 displays the median values of forecasted and realized earnings for each month of the fiscal period. Non-parametric Wilcoxon tests, which were not included in the Table 1, provide clearer results compared to the mean values. The hypothesis of equal forecasted median and realized median is rejected at the 0.05 significance level, supporting the acceptance of the alternative hypothesis of a positive forecast error.

Both T-tests and Wilcoxon tests indicate a significant difference between the forecasted and realized earnings, providing further support for the hypotheses. These findings demonstrate that the positive bias observed in analysts' forecasts of listed companies also exists in the forecasts of unlisted companies, confirming the presence of a positive forecast error.

5.2 Regression result of analysts' forecasts accuracy

5.2.1 Descriptive Statistic and Pearson Correlation Coefficient

Next, forecast errors are computed for both earnings and EBITDA data. The forecast error is the difference between the forecasted value and the realized value. Additionally, the trend of medians is analyzed to gain a preliminary understanding of the accuracy of the forecasts and their direction. By examining the medians over time, trends can be identified. For example, if the median forecast error for earnings consistently shows positive values, it suggests a systematic overestimation of earnings. Conversely, if the median forecast error for EBITDA consistently shows negative values, it indicates a systematic underestimation of EBITDA.

Table 2. Descriptive statistics for variables for the whole data

Variable	mean	median	Max	Min	Std.dev.
Earnings (N=19)					
|FE|1	0.2069	0.0979	1.0000	0.0001	0.2607
|FE|2	0.2285	0.1072	1.0000	0.0006	0.2828
|FE|3	0.2137	0.1651	0.6834	0.0174	0.1777
|FE|4	0.3414	0.2274	1.0000	0.0179	0.3373
|FE|5	0.2954	0.2043	1.0000	0.0008	0.2841
|FE|6	0.2342	0.2028	0.9064	0.0127	0.2386
|FE|7	0.4839	0.4512	1.0000	0.0148	0.3800
|FE|8	0.3786	0.3594	1.0000	0.0285	0.3004
|FE|9	0.3562	0.2767	1.0000	0.0356	0.2695
|FE|10	0.3229	0.2067	1.0000	0.0163	0.2860
|FE|11	0.3416	0.2660	1.0000	0.0111	0.2952
|FE|12	0.3918	0.3331	1.0000	0.0079	0.3286
DEBT	1.3969	0.7420	15.2079	-4.3798	3.8688
ROI	0.0539	0.0504	1.4406	-1.8687	0.6315
LnASSET	3.3354	3.2601	4.6400	2.5021	0.5774
EBITDA (N=13)					
|FE|1	0.6149	0.6812	1.0000	0.0023	0.3766
|FE|2	0.6566	0.6531	1.0000	0.0234	0.3241
|FE|3	0.5811	0.4946	1.0000	0.0399	0.3962
|FE|4	0.6921	0.7255	1.0000	0.1943	0.3498
|FE|5	0.5796	0.5681	1.0000	0.0189	0.3605
|FE|6	0.7656	0.9944	1.0000	0.1060	0.3345
|FE|7	0.7658	1.0000	1.0000	0.0467	0.3756
|FE|8	0.5777	0.6881	1.0000	0.0491	0.3735
|FE|9	0.5277	0.4098	1.0000	0.0295	0.3668
|FE|10	0.6948	0.8306	1.0000	0.0482	0.3356
|FE|11	0.5525	0.5396	1.0000	0.0671	0.3623
|FE|12	0.6738	0.6985	1.0000	0.1320	0.3342
DEBT	1.9430	0.2919	15.2079	-1.0570	4.3569
ROI	0.1077	0.0847	1.4406	-1.8687	0.7520
LnASSET	3.3110	3.2836	4.6400	2.5021	0.5567

N = Number of obsevations

Table 2 presents the descriptive statistics for all variables for both earnings and EBITDA in the regression. Both mean and median forecast errors for earnings and EBITDA seem to have increased during fiscal year overall. The standard deviation has also increased for earnings during fiscal year overall and that could indicate increased dispersion of forecasts. The standard deviation has stayed a quite stabile for EBITDA and it could indicate non-dispersion of forecasts.

For earnings, the average forecast errors have increased from 20.7 percent to 39.2 percent, indicating that forecasting has generally become more challenging as the forecast horizon extends. The median forecast errors have increased from 9.8 percent to 33.3 percent, suggesting a higher number of larger errors.

Regarding EBITDA, the average forecast errors have increased from 61.5 percent to 67.4 percent, while the median errors have increased from 68.1 percent to 69.9 percent. These findings suggest that the forecast errors for EBITDA have also generally increased, although the growth appears to be less pronounced compared to earnings.

Based on the initial observation of the descriptive statistics for the entire dataset, it can be inferred that the forecast errors have, on average, increased throughout the fiscal year. Furthermore, the increase appears to be more significant for earnings than for EBITDA.

Testing the correlation between variables serves two purposes. Firstly, it allows for preliminary conclusions about the relationships between the variables based on initial correlation figures. This analysis helps determine, for example, how the forecast error at the beginning of the fiscal year correlates with the level of indebtedness. Secondly, testing correlation helps identify multicollinearity among the explanatory variables. Multicollinearity occurs when there is a high correlation between the explanatory variables. To avoid multicollinearity, it is important to examine the individual correlations between the explanatory variables. If the correlation is substantial and significant, the variables should not be included in the same regression model. Typically, a correlation coefficient of 0.7 is considered a critical level of correlation between explanatory variables (Anderson, Sweeney & Williams, 2014).

Table 3. Pearson Correlation Coefficients matrix for Earnings

	Pearson Correlation Coefficients, N = 19													
	|FE|2	|FE|3	|FE|4	|FE|5	|FE|6	|FE|7	|FE|8	|FE|9	|FE|10	|FE|11	|FE|12	DEBT	ROI	lnASSET
|FE|1	0.5565	0.3617	0.3053	0.3161	0.4527	0.3456	0.3656	0.3522	-0.0032	0.3128	0.1739	0.4009	0.0135	-0.3141
|FE|2		0.2840	0.5747	0.6632	0.7235	0.4736	0.4368	0.5383	-0.0895	0.3678	0.0256	-0.0499	0.2733	-0.2246
|FE|3			0.3771	0.2665	0.2723	0.2462	-0.2228	0.1416	-0.1705	-0.1038	-0.1123	-0.1352	0.1936	-0.1721
|FE|4				0.9086	0.6679	0.2283	0.3949	0.5800	0.1970	0.2577	0.1735	-0.1239	0.2157	-0.2471
|FE|5					0.6010	0.2138	0.3984	0.6116	0.2452	0.3712	0.2003	-0.0554	0.1530	-0.1968
|FE|6						0.5602	0.6272	0.7835	0.0589	0.4998	0.0480	-0.1551	0.0286	-0.3319
|FE|7							0.4460	0.7151	0.3296	0.7069	0.3984	0.2409	-0.2699	-0.0863
|FE|8								0.6038	0.3829	0.6945	0.3638	0.2664	0.0062	-0.2186
|FE|9									0.3090	0.7129	0.4662	0.0545	-0.3746	-0.2826
|FE|10										0.7068	0.6785	0.5696	0.0724	-0.1047
|FE|11											0.6732	0.5069	-0.1954	-0.3027
|FE|12												0.4847	-0.2416	-0.4169
DEBT													0.0034	0.0755
ROI														-0.0491

N = Number of observation

Table 4. Pearson Correlation Coefficients matrix for EBITDA

Pearson Correlation Coefficients, N = 13														
	|FE|2	|FE|3	|FE|4	|FE|5	|FE|6	|FE|7	|FE|8	|FE|9	|FE|10	|FE|11	|FE|12	DEBT	ROI	lnASSET
|FE|1	0.4146	0.1716	0.0913	0.2500	-0.2104	0.1044	-0.0649	0.3203	0.5143	0.4012	-0.4144	0.0936	0.1618	-0.3952
|FE|2		0.5919	0.6454	0.1742	0.2013	-0.0306	-0.2779	0.3282	-0.0275	0.3644	-0.0892	0.0280	0.3973	-0.2277
|FE|3			0.4753	0.2826	-0.0485	0.3777	0.0992	0.2747	0.0178	0.5734	-0.1063	0.0993	0.3247	0.2035
|FE|4				0.2267	0.6774	-0.0149	0.0438	0.5637	-0.3231	0.3841	0.5360	-0.3107	0.2880	-0.4454
|FE|5					0.2397	0.3296	0.1356	0.5093	0.4839	0.6878	-0.0666	0.1283	0.2900	-0.3365
|FE|6						0.0162	0.1722	0.3890	-0.4652	0.0223	0.6073	-0.4132	0.3430	-0.5456
|FE|7							0.1668	0.3934	0.3203	0.4300	-0.1497	0.1603	0.4860	0.1854
|FE|8								0.2862	0.0449	0.0529	-0.0646	-0.5648	0.0189	-0.1619
|FE|9									0.1598	0.5959	0.0153	-0.4002	0.0545	-0.3104
|FE|10										0.2727	-0.3667	0.1090	0.3025	0.0896
|FE|11											-0.1709	0.3549	0.0628	-0.2806
|FE|12												-0.3055	0.2152	-0.2013
DEBT													-0.0350	0.0311
ROI														-0.1164

N = Number of observation

The correlation analyses for earnings in Table 3 and Appendix 1 indicate that the explanatory variables are not strongly correlated with each other. The dependent variable |FE|1 shows a positive correlation with other individual months, with a stronger correlation observed between closer months compared to distant months. For example, the correlation between |FE|1 and |FE|2 is higher than the correlation between |FE|1 and |FE|6. This suggests that there is a relationship between the forecast error and the length of the forecasted period. As the forecasted period becomes further away, the relationship weakens and the forecast error increases. However, the statistically significant correlations at the 5% level are quite rare in Table 3, indicating that there is no significant correlation between the variables. Therefore, the generalization of these correlations to the population is not supported. Additionally, there is no observed multicollinearity between the forecast error and the control variable.

Similarly, the correlation analyses for EBITDA in Table 4 and Appendix 2 indicate that the explanatory variables are not strongly correlated with each other. The dependent variable |FE|1 does not exhibit a significant correlation with the explanatory variables at any time, and the correlation coefficients are relatively low, with some even being negative. There is no observed multicollinearity between the forecast error and the control variable.

5.2.2 Multivariant regression analysis

To test the statistical significance of the observed changes in forecast errors, a regression analysis can be employed. The linear regression model allows us to examine the impact of the forecasted period's length on analyst forecast errors. By analyzing the coefficients and hypothesis test, we can assess whether there is a significant relationship between the forecasted period and forecast errors.

Table 5 displays the average regression results for earnings, where the forecast errors were regressed against lagged company characteristics. The adjusted R^2 value of 0.17 indicates that approximately 17 percentage of the variability in the dependent variable (forecast errors) can be explained by the explanatory variable included in the regression analysis. However, it is important to note that the sample size in this thesis was significantly small, which may have contributed to the relatively low adjusted R^2

value. The statistical insignificance of most individual variables, as shown in Table 5, is likely a result of the limited sample size and should be interpreted with caution.

Similarly, regression analysis is prepared also for EBITDA to test, whether these observed changes in forecast errors are statistically significant. Table 5 displays the regression results for EBITDA, where the forecast errors were regressed against lagged company characteristics. The adjusted R^2 value of 0.06 indicates that only approximately 6% of the variability in the dependent variable (forecast errors) can be explained by the independent variables included in the regression analysis. As mentioned before, the small sample size in this thesis could be a contributing factor to the low adjusted R^2 value. Similarly, the statistical insignificance of most individual variables, as shown in Table 5, is likely a result of the limited sample size and should be interpreted with caution.

Table 5. Regression results for forecast errors for Earning and EBITDA

Variable	AFE (Earning)	AFE (EBITDA)
Intercept	0.8797***	0.9755***
	(0.000)	(0.000)
D2	0.0053	0.0623
	(0.4781)	(0.2718)
D3	-0.0249	-0.0626
	(0.3975)	(0.2708)
D4	0.0670	0.0296
	(0.2426)	(0.3863)
D5	0.0438	0.0287
	(0.3238)	(0.3897)
D6	0.0112	0.0969
	(0.4536)	(0.1726)
D7	0.2354***	0.1372
	(0.0073)	(0.0908)
D8	0.1235	-0.0348
	(0.0993)	(0.3670)
D9	0.1251	-0.0588
	(0.0964)	(0.2832)
D10	0.0964	0.0784
	(0.1576)	(0.2224)
D11	0.1125	0.0076
	(0.1207)	(0.4703)
D12	0.0966	0.0675
	(0.1571)	(0.2551)

DEBT	-0.0056***	-0.0037***
	(0.0000)	(0.0004)
ROI	-0.0416	0.0892***
	(0.1124)	(0.0082)
LNASSET	-0.1741***	-0.0887***
	(0.0000)	(0.0114)
Observations	264	252
Adjusted R-Squared	0.1658	0.0609

P-value in parentheses; ** significant at 5%; *** significant at 1%, 1-sided.

Examining the regression results in Table 5, it is observed that for the forecast errors in earnings, the length of the forecasted period starts to have a significant influence on forecast accuracy from D7. The length of the forecasted period is found to be statistically significant at a 1% level with a p-value of 0.007, and the coefficient has a positive sign. These results indicate that an increase in the length of the forecasted period leads to a significant increase in the forecast error starting from the seventh month in the forecasted period.

Furthermore, the results show that the control variables, such as the indebtedness of the company and the company's size, have a significant impact on reducing the forecast error at a 1% level. This implies that forecasting the earnings of a company becomes easier when the size of the company increases and when the company's level of indebtedness increases.

It is important to note that the small sample size in this thesis may have influenced the significance and interpretation of the regression results. Therefore, caution should be exercised in generalizing these findings to a larger population.

The regression output for EBITDA in Table 5 indicates that none of the dummy variables are statistically significant, as their p-values are greater than the usual significance level of 0.05. The variable D7 has the lowest p-value of 0.09. Since the p-values for all the dummy variables are greater than the 5% significance level, there is not enough evidence to conclude that an increase in the length of the forecasted period leads to a statistically significant increase in the forecast error for EBITDA.

In summary, the sample data for EBITDA does not provide sufficient evidence to reject the null hypothesis for the entire population. The findings suggest that the length of the forecasted period does not have a statistically significant impact on the forecast error for EBITDA in the forecasted period, based on the available sample.

6 CONCLUSIONS

The purpose of this thesis was to investigate whether analysts' earnings forecasts are optimistic in unlisted companies and whether the length of the forecasted period has an impact on the accuracy of analysts' forecasts in unlisted companies. Based on previous research findings for listed companies, the hypotheses were that analysts make optimistic forecasts at the start of the fiscal year and that forecast error is positively correlated with the length of the forecast period.

The research results in this thesis show that analysts' earnings forecasts are optimistic in unlisted companies. In addition, the results show that the accuracy of earnings forecasting decreases the further away the forecasted period is. More carefully, the accuracy of forecasted earnings decreases statistically significant from the seventh month onwards, meaning that the analyst can accurately forecast the first seven months.. According to the results, when forecasting EBITDA, there is no deterioration in forecast accuracy over time when examining the period of the fiscal year. For earnings, the results confirm the hypothesis of this study, but for EBITDA, the results do not confirm the hypothesis.

This study this contributes to the existing literature on analysts' forecasting accuracy and optimism by examining these factors in unlisted companies and provide novel insights. Previous literature has not explored the optimism and forecasting accuracy of analysts for unlisted companies, as it has mostly focused on listed companies. Examining the forecasting of earnings for unlisted companies is both interesting and necessary since it can differ from the forecasting of listed companies. For instance, the positive bias brought by the analyst's business incentives is eliminated, and thus analysts may feel to free to provide more conservative assessments of a company's future forecasts. Additionally, companies seeking financing may prefer a cautious rather than an optimistic forecast of their financial prospects.

The research results showed that analysts are optimistic in their analyses of unlisted companies, and the accuracy of their earnings forecasts decreases as the forecasted period moves further away in time. However, the accuracy of EBITDA forecasting does not deteriorate over time. The research results can be generalized to the entire base population in terms of optimistic bias and forecast accuracy over time. Nevertheless, given the small sample size in this study, generalizations should be approached with caution. Probably, the small sample size in this study caused at least the fact that the forecast accuracy of EBITDA did not deteriorate statistically significantly over time. intuitively and based on previous literature, it would be thought that EBITDA deteriorate over time just like earnings does.

The results of this study highlight the importance of considering the forecasted periods' length when evaluating the accuracy of analysts' forecasts in unlisted companies when the findings suggest that analysts' forecasts become less accurate as the forecasted period becomes longer. It is recommended to be meticulous by investors and financiers when relying on analysts' long-term forecasts for unlisted companies.

The limitations of this study include the small sample size and the fact that it only examined the forecasting optimism and accuracy of analysts of the one company. Further investigation is required to explore the accuracy and optimism of forecasts made by analysts in several companies and with the greater sample size at all. The study confirms the hypothesis that analysts tend to be optimistic when forecasting earnings for unlisted companies. This finding raises questions about the factors that influence analysts' optimism and suggests the need for further research to explore the sources of this optimism to understand the reasons especially behind the generalizable optimism. Are there generalizable incentives for analysts or companies? For instance, what is the role of the earnings management in the accuracy of the forecasts in unlisted companies?

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APPENDIX 1

P-VALUES OF PEARSON CORRELATION COEFFICIENTS FOR EARNINGS

P-values of Pearson Correlation Coefficients for Earnings, N = 19

	|FE|2	|FE|3	|FE|4	|FE|5	|FE|6	|FE|7	||FE|8	|FE|9	|FE|10	|FE|11	|FE|12	DEBT	ROI	lnASSET
|FE|1	0.0133	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500
|FE|2		0.0500	0.0101	0.0020	0.0005	0.0405	0.0500	0.0174	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500
|FE|3			0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500
|FE|4				0.0000	0.0018	0.0500	0.0500	0.0092	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500
|FE|5					0.0065	0.0500	0.0500	0.0054	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500
|FE|6						0.0126	0.0041	0.0001	0.0500	0.0293	0.0500	0.0500	0.0500	0.0500
|FE|7							0.0500	0.0006	0.0500	0.0007	0.0500	0.0500	0.0500	0.0500
|FE|8								0.0062	0.0500	0.0010	0.0500	0.0500	0.0500	0.0500
|FE|9									0.0500	0.0006	0.0442	0.0500	0.0500	0.0500
|FE|10										0.0007	0.0014	0.0109	0.0500	0.0500
|FE|11											0.0016	0.0268	0.0500	0.0500
|FE|12												0.0354	0.0500	0.0500
DEBT													0.0500	0.0500
ROI														0.0500

N = Number of observation

APPENDIX 2

P-VALUES OF PEARSON CORRELATION COEFFICIENTS FOR EBITDA

P-values of Pearson Correlation Coefficients for EBITDA, N = 13

	|FE|2	|FE|3	|FE|4	|FE|5	|FE|6	|FE|7	|FE|8	|FE|9	|FE|10	|FE|11	|FE|12	DEBT	ROI	lnASSET
|FE|1	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500
|FE|2		0.0331	0.0172	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500
|FE|3			0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0405	0.0500	0.0500	0.0500	0.0500
|FE|4				0.0500	0.0110	0.0500	0.0500	0.0448	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500
|FE|5					0.0500	0.0500	0.0500	0.0500	0.0500	0.0094	0.0500	0.0500	0.0500	0.0500
|FE|6						0.0500	0.0500	0.0500	0.0500	0.0500	0.0277	0.0500	0.0500	0.0500
|FE|7							0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500	0.0500
|FE|8								0.0500	0.0500	0.0500	0.0500	0.0443	0.0500	0.0500
|FE|9									0.0500	0.0316	0.0500	0.0500	0.0500	0.0500
|FE|10										0.0500	0.0500	0.0500	0.0500	0.0500
|FE|11											0.0500	0.0500	0.0500	0.0500
|FE|12												0.0500	0.0500	0.0500
DEBT													0.0500	0.0500
ROI														0.0500

N = Number of observation