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School of Business and Management
Strategic Finance and Business Analytics

Master's Thesis

Predicting earnings and analysts' forecast errors; characteristic approach in Nordic countries

Jaakko Mantila 2019
Examiners: Associate Professor Sheraz Ahmed
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ABSTRACT

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The objective of this research is to predict sell-side analysts' forecast errors for Nordic companies' earnings. Analysts' forecasts of earnings are found to exhibit persistent error, most often arising from misalignment incentives. Implementing the characteristic approach, firstly introduce by So (2013), this study relies on cross-sectional earnings forecasts instead of time-series fitting of past forecast errors, for the prediction of future forecast errors. Lagged firm characteristics are utilized in annual cross-sectional regressions, and the coefficients applied to current characteristics to obtain characteristic earnings predictions. By comparing analysts' forecast to the unbiased characteristic forecast, signals of firms' fundamentals are accessed, and inferences of the portion of expected earnings that are not yet incorporated into analysts' forecasts can be drawn.

The characteristic forecasts show better performance over analysts' forecasts, as more accurate forecasts were achieved using the characteristic forecast. Even though, the characteristic forecast was not able to predict analysts' forecast errors, the investment strategy implemented managed to generate noticeable returns, showing the effectiveness of the characteristic approach in predicting future abnormal returns. By generating positive returns, the investments strategy developed reveals that investors are constantly overweighting analysts' forecasts. This suggests that when making investment decisions the investors should, instead of using analysts' forecasts directly, incorporate additional information into their decision-making in order to make well-advised investment decisions. Biases in analysts' forecasts are affecting the efficient allocation of capital; hence the regulators should be concerned over the credibility of the forecasts.

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Tämän tutkimuksen tarkoituksena on osakeanalyytikoiden virheen ennustaminen Pohjoismaiden markkinoilla. Analyytikoiden tulosennusteet sisättävät lukuisten tutkimusten mukaan vinoumia, jotka usein johtuvat analyytikoille ilmenevistä houkutteista vääristää ennusteita. Tämä tutkimus nojaa poikkileikkausaineston hyödyntämiseen analyytikoiden virheen ennustamisessa, ja jättää huomiotta aikasarja-ainestoa hyödyntävän menneisiin analyytikoiden virheisiin keskittyvän metodologian. Yristysten edellisten vuosien tunnuslukuja hyödynnetään tutkimuksessa vuositasolla ajetuissa poikkileikkaus-regressioissa. Regressiokertoimet asetetaan yritysten seuraavan vuoden tunnuslukuihin ja näin saavutetaan tunnusomaiset tulosennusteet yrityksille. Yritysten tunnusluvuissa piileviin signaaleihin päästään käsiksi vertaamalla näitä ennusteita analyytikoiden ennusteisiin, ja tätä kautta pystytään tekemään havaintoja yritysten odotettavista tuloista, jotka eivät vielä näy analyytikoiden ennusteissa.

Tunnusomainen menetelmä onnistui tämän tutkimuksen perusteella tuottamaan tarkempia tulosennusteita analyytikoiden ennusteisiin verrattuna. Vaikka tunnusomainen menetelmä ei onnistunut analyytikoiden virheen ennustamisessa Pohjoismaiden markkinoilla, tutkimuksessa kehitetyn investointisuunnitelman tulos jäi positiiviseksi ja tämä kertoo siitä, että sijoittavat asettavat liian suurta painoarvoa analyytikoiden ennusteille. Vastaisuudessa sijoittajien ei tulisi investointisuunnitelmia laatiessaan luottaa analyytikoiden ennusteisiin sellaisenaan, vaan hyödyntää myös täydentävää informaatiota päätöksenteon tueksi, tehdäkseen viisaampia sijoituspäätöksiä. Analyytikoiden ennusteissa piilevät kallistumat vaikuttavat pääoman tehokkaaseen liikkumiseen markkoilla, ja tästä syystä sääntelyviranomaisten tulisi olla huolissaan ennusteiden luotettavuudesta.

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In Helsinki 22.04.2019

Jaakko Mantila

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List of abbreviations

AF:	Mean/Median consensus sell-side analysts' forecast for fiscal year one-year ahead earnings.
BLUE:	Best Linear Unbiased Estimate.
CF:	Characteristic Forecast for fiscal year one-year ahead, calculated by utilizing lagged firm characteristics in a regression fitted to current firm characteristics.
CO:	Characteristic forecast optimism, defined as the characteristic forecast minus the corresponding analysts forecast divided by firms total assets at year end.
HCCM:	Heteroscedasticity-Consistent Covariance Matrix.
HC0 to HC3:	Heteroscedasticity-Consistent Covariance Matrix estimators 0, 1, 2 and 3.
IBES:	Institutional Broker's Estimates System.
IPO:	Initial Public Offering.
LSDV:	Least Squares Dummy Variable.
ME:	Mean error of the forecast.
MSE:	Mean Squared Error.
OLS:	Ordinary Least Squares.
OLSCM:	Ordinary Least Squares Covariance Matrix estimator.
SEC:	U.S. Securities and Exchange Commission
SEO:	Seasoned Public Offering.

1 Introduction

Analyst's act as intermediaries in the capital markets. Their objective is to find and incorporate information into forecasts of firms' future earnings and cash flows and provide the information to other market participants, thus alleviating information asymmetry. Analysts' actions and the competition among them is often perceived as enriching the information in the market and enhancing the formation of share prices. (Frankel, Kothari & Weber 2006) Analysts can bring additional value to investors by finding the relevant pieces of information and processing this information into their forecasts of future share prices. Analysts may also have access to private information, such information that is unattainable or at least not as easily attainable by investors. (Ivkovic & Jegadeesh 2004)

It is widely acknowledged by the academic literature that analysts' forecasts and recommendations offer valuable information to the market (Gintschel & Markov 2004). However, forecasts into an unknown future always exhibit some degree of error, as do analysts' forecasts. Somewhat, this error can be explained with the unpredictability of financial data, but analysts' forecasts are also found to exhibit error due to external incentives (Lo & Elgers 1998). There are numerous studies revealing an incentive misalignment between the analysts' forecasts and the end user who exploits these forecasts into investment decisions. Investors, especially small investors, rely on analysts' forecasts heavily, without considering the possibility of biases in the forecasts (So 2013). This study will concentrate on the analysts' forecast error and its predictability, by exploiting a cross-sectional model developed by So (2013). The way analysts' forecasts affect the distribution of welfare among agents makes this research area socially important. Regulators should also be concerned about the effect on efficient allocation of capital (So 2013).

The majority of the research focusing on analysts' forecast errors have incorporated time series of realized errors into their forecasts (Hughes, Liu & Su 2008; Ali, Klein, & Rosenfeld 1992; Elgers & Murray 1992; Lo & Elgers 1998; Frankel & Lee 1998). These kinds of research will be referred to as the traditional approach on forecasting analysts' forecast error throughout this study. In his paper, So (2013) argues that the traditional approach has a fundamental flaw in its formulation, thus letting researchers draw false conclusions based on these models. So (2013) states that whenever the observable firm characteristics used in the prediction of realized forecast errors are correlated with unobservable inputs, such as incentive misalignment or private information, biases might emerge.

So (2013) introduces a new methodology for predicting analysts' forecast errors, the characteristic approach. This approach contrasts analysts' earnings forecasts with characteristic forecasts of earnings. The characteristic forecast employs publicly available firm characteristics in a cross-sectional regression. There are numerous combinations of characteristics that can be exploited, but So (2013) uses a set of variables introduced by Fama and French (2006) in their paper on the relation between profitability, investment and book-to-market ratio. Based on the predicted forecast error, an investment strategy is drawn in which the firms are divided into quintiles. The quintile division is based on the scaled difference between characteristic and analysts' forecast, and a long position is taken on the highest portfolio where the characteristic forecast is high relative to analysts' forecast and a short position on the lowest portfolio. The goal of the investment strategy is to discover whether investors overweight analysts' forecasts.

The implementation of the characteristic approach in this study follows the methodology by So (2013). The annual characteristic forecasts in this study are found to show better performance than analysts' forecasts, as more accurate forecasts are achieved using characteristic forecast. Analysts' forecasts constantly exceed realized earnings in the sample. Even though, the characteristic forecast was not able to predict analysts' forecast errors with a clear positive relationship, the investment strategy implemented still managed to generate noticeable returns. This shows the effectiveness of the characteristic approach in predicting future abnormal returns and indicates that investors place more than optimal weight on analysts' forecast and less than optimal on characteristic forecast.

Additionally, the objective of the research was to find how the informational quality of the firm affects the degree of error in analysts' forecasts and in characteristic forecast. Two proxies for the informational quality were chosen, the firm size and analysts' coverage. The results regarding informational quality of the firm are somewhat contradicting, as firm size was found to affect both forecast errors with a negative sign, but the coverage of the firm was found to have an unexpected positive sign.

The research on analysts' forecasts errors has mainly focused on the U.S. stock market. Though, there can also be found international studies covering multiple markets in a single study. This study will concentrate solely on the Nordic countries' stock markets. The motivation in studying these markets bounds from the fact that the region is similar in many aspects, while very different to the U.S. market and other European regions. The Nordic market is usually perceived as highly transparent. However, the average number of analysts' covering the firms in the Nordic countries is usually small, and most companies are small in terms of market capitalization. These factors create an interesting setting for a study on earnings predictability and analysts' forecast errors, in that the results can be very different than results from larger markets.

Earnings prediction is an area of research that usually draws attention for its importance to securities market practices. The study contributes to the earnings prediction literature, by providing evidence on the cross-sectional predictability of earnings. Analysts' forecast has also caught the attention of a vast academic research in accounting and finance, and this study enriches the earlier findings in these fields. The implication that analysts tend to be overly optimistic strengthens the findings of Frankel and Lee (1998) and Lin and McNichols (1998), among others. Also, the implication that investors place more than optimal weight on analysts' forecast supports the work by So (2013). These being considered, this research supports the implementation of the characteristic approach in predicting analysts' forecast error in the Nordic markets. The study can be of use for investment decisions, when considering the predictability of earnings and profitability, and for studying whether investors overweight analysts' forecasts.

1.1 Research problem and research questions

The traditional approach has been used in the existing literature repetitively, and the researchers has provided the academia with proof of its utility with various datasets. However, So (2013) argued that the formation of a typical model under the traditional approach leads to biased estimates and he introduced the characteristic approach. So (2013) showed that a cross-sectional model like the characteristic approach provides more reliable estimates of future earnings. These earnings can then be used in the predictions of analysts' forecast error. Specifically, So's (2013) empirical prediction is that the characteristic forecast optimism (CO), derived as the characteristic forecast minus the analysts' forecast scaled by firm's total assets, positively predict analysts' forecast error. The objective of this study is to determine how the characteristic approach works in the context of the Nordic stock market. Derived from So's (2013) empirical prediction, the study seeks to answer the following research question:

1. *”Does the characteristic forecast optimism, CO, positively predict analysts' forecast error?”*

Also, through the investment strategy presented later in this study, the objective is to answer the following question:

2. *“Does the characteristic forecast optimism, CO, positively predict future abnormal returns?”*

And lastly, by examining closer the reasons behind the analysts' forecast error and the characteristic forecast error, the research attempts to find an answer to the following question:

3. *“Does the informational quality of the firm affect the degree of analysts' forecast error and/or characteristic forecast error?”*

1.2 Delimitations

A broad distinction on analysts' forecast research can be drawn between consensus analysts' research and research of individual analysts' properties (Kothari 2001). This study focuses on the former, hence no conclusion on the properties of an individual analysts can be drawn based on the findings of this study. Specifically, this study focuses on the mean consensus earnings forecasts of sell-side analysts for the current fiscal year. The study is delimited to the stock exchanges of Finland, Sweden, Denmark and Norway. Currently (December 1st 2018) there are only 18 companies traded in the Iceland Stock Exchange, so after the removal of outliers the exchange contributed only a handful of companies each year, therefore the exchange was left outside the sample altogether.

The replication of this study could be possible in a different time series as well as in different markets. For example, in one of the Nordic stock exchanges alone, say Helsinki or Oslo. However, the sample size in a single market study might become an issue. A study concentrating exclusively on Finland for example, would most likely be insufficient, as there is relatively small amount of publicly listed companies in the Helsinki Stock Exchange and the coverage for most of them is inadequate for significant results. Therefore, I chose to concentrate on the whole region.

Other models than So's (2013) on predicting analysts' forecast error are not covered for the length of this thesis. For further research, it could be interesting to see the effectiveness of the characteristic approach with varying firm characteristics. Also, analysts' growth forecasts, recommendations or target prices could be used as dependent variables in further specifications of the model.

1.3 Structure of the study

The remainder of this study is constructed as follows. Section 2 provides theoretical background on the subject, through earlier academic literature. Theoretical foundations of the traditional and the characteristic approached will be discussed in detail. Also, arguments in favour of cross-sectional research in the context of analysts' forecast error will be provided in section 2. Section 3 moves on to the data collection and introduction of the methodology concerning all three research questions. Panel regressions used for the third research question and for robustness checks will also be discussed. A thorough clarification on the timeline of the analysis will be provided in its own sub-chapter. Section 4 describes the results of the empirical analysis in detail, comparing the results with the previous literature. Section 5 summarizes the study and presents the final conclusions.

2 Theoretical framework

This section will introduce some of the earlier findings on analysts' forecast error and relating fields and introduce a variety of traditional approaches used in the literature and the characteristic approach for predicting analysts' forecast errors. Concerns relating these methods are also discussed. A thorough derivation of the fundaments of the traditional approach will be described in sub-chapter 2.2 and the characteristic approach in 2.3.

2.1 Literature review

As Zhang (2006b) categorized them, the explanations behind observed analysts' forecast errors can be divided to categories of economic incentive -based explanations (Michaely & Womack 1999), behavioural explanations (Easterwood & Nutt 1999) and earnings-management arguments (Abarbanell & Lehavy 2003). Examples throughout the literature of each of the categories will be discussed in the following literature review. The review will also gather and discuss the most important studies in the field employing the traditional approach on predicting analysts' forecast error. As most of the research on analysts' forecast error focuses on the U.S. market, the literature review will mostly consist of studies from the U.S., but will also bring an international perspective with studies focusing on Europe, and the Nordics especially.

2.1.1 Analysts' role and information

The information gathered by analysts can come from either public or private sources. The public type can be essentially any publicly available piece of information concerning the company under observation; such information is usually also easily accessible by other market participants, including investors. Whereas private information often is not as easily accessible, for example the information held by the company management and other stakeholders of the company. Analysts most often have a better access to private information than do investors. (Ivkovic & Jegadeesh 2004)

Barniv and Myring (2006) studied the performance of two valuation models in an international setting. The first model is a analysts' forecast based model, that uses one and two-year ahead analysts' forecasts to discount the current value of the firm and the second one is a model based on the historical earnings and the book value of the firm. The results show that analysts' forecasts are value relevant in most of the markets, including the Nordic counties. Also, compared to the historical model the analysts' forecasts seem to exhibit more explanatory power on future earnings in Finland and Denmark. However, in Sweden and Norway the two models show similar results. They also studied the characteristics of the market and analysts' and the results indicate Sweden and Norway being countries where analysts are less active and their forecasts "noisy", compared to their Nordic counterparties.

The Nordic markets are often perceived as highly transparent. The transparency can be measured for example with disclosure scores, which Hope (2003) found to be among the highest for Sweden and Finland in his sample on 22 developed countries around the world. The researcher found the disclosure increasing the accuracy of analysts' forecasts. Hodgdon, Tondkar, Harless and Adhikari (2008) studied companies' compliance with the IFRS disclosure requirements and its effect on analysts' forecast error. They found more disclosure again leading to more accurate forecasts. Their sample included three of the four countries chosen for this study.

In the Nordics, the independence of the media is highly valued. The media independence has been found to affect analysts' forecasts, as Kim, Li and Zhang (2017) found the state ownership of media increasing the forecast error in their sample of 52 different nations. The sample included all the Nordic countries under observation in this study and the researchers showed that in all these markets the media is highly independent.

In a U.S. based study, Das, Levine, and Sivaramakrishnan (1998) found that greater analysts' forecast optimism will usually be evident in low predictability firms. They argue that private information for analysts is more valuable on firms for which future earnings cannot be as easily forecasted from publicly available information, as for other firms. Also, that overly optimistic forecasts allow analysts an access to private information through managers of the companies, hence forecasts for the low predictability firms will more likely be overly optimistic.

Analysts' early access to private information has also been criticized. As a result, it has been regulated to some extent, for example with Regulation Fair Disclosure in the U.S. According to this regulation, managers must disclose information simultaneously to all market participants. It was implemented by the U.S. Securities and Exchange Commission (SEC) in 2000. The regulation has had a noticeable effect on the informational content of analyst's reports, since the absolute price impact following a report was significantly lower in the years immediately after its implementation (Ivkovic & Jegadeesh 2004; Gintschel & Markov 2004).

Lopez and Reez (2002) showed the effect of analysts' forecast on companies' share price by studying the consequences of beating and missing forecasted earnings. The study indicates that the forecasts exhibit significant informational content, as the market penalizes companies that miss forecasts, regardless of the size of the forecast errors. Companies that beat the forecast, and especially those that do so consistently, are given a higher earnings multiple in valuations by investors. This shows evidence that analysts' play a major role in the price discovery process nowadays, as Lopez and Reez (2002) also states that between 1984-1992 outplaying the market was not as vital for a company and only roughly half of the companies met or beat the forecasts, but in the years after 1992 this percentage increased to approximately 65.

Frankel et al. (2006) studied individual analyst's reports in trying to explain why for some stocks the information disclosed causes more volatility than for others. The study was conducted on a cross-section, examining the average price impact of a report on a stock, and the objective was to draw conclusions on the informativeness of the analyst's report. The researchers found analyst's information increasing with higher trading volume and return volatility, indicating that when the earnings opportunities of trading for investors increases so does the analysts' reports information content. The information content was found to decrease for firms that operate in multiple industries, as analysts rarely have the expertise and deep knowledge of multiple industries, thus investors benefitting less from reports on such firms.

Additionally, to the information provided by analysts' reports and forecasts, analysts' forecast revisions offer simple and fast information to the investors about firms' future profitability. Revisions, being issued throughout the quarter, are a vital source of information on the prospects of the company, as opposed to quarterly earnings announcements. Informational technology development has made revisions available for a wider group of end-users and in real time. (Gleason & Lee 2003)

Share price changes tend to move in tandem with analysts' forecast revisions, indicating that analysts' forecasts contribute to the price discovery process (So 2013). Gleason and Lee (2003) finds that there is a delayed market reaction to analysts' forecast revisions, and that subsequent revisions boosts one another, acting as catalysts in the price discovery process. They divide the revisions in to two extreme categories based on the informational content of the revision, to those that simply adjust towards the consensus, and to those that are unequivocally providing new information, and find that market does not make a sufficient distinction between these two. The price discovery process is also found to be faster for firms with wider coverage. Focusing on the sign of the revision, Frankel et al. (2006) found negative forecasts revisions to affect the stock price of a company more than positive revisions. This would indicate that analysts have more information on the negative factors that affect the firms' stock price or that investors react to positive revisions with more caution.

2.1.2 Incentives to bias forecasts

Great level of dispersion in consensus analysts' forecast for an observed company raises questions about the source of the dispersion. While this simply might be the output of the uncertainty in the company's cash flows, the level of dispersion might as well be a function of the analysts' incentives. There exists a strong evidence that analysts' estimates are often biased, but also their choice on whether to adjust to or to deviate from the consensus estimate might be an output of their career concerns. (Johnson 2004) These kinds of issues over the liability of analysts' estimates and recommendations will be considered in this sub-section.

Biases in the analysts' forecasts and recommendations often arise simply from a traditional structure of an investment bank. The divisions within an investment bank may have differing objectives. For example, the objective of the corporate finance division is to complete transactions for its clients, such as initial public offerings (IPOs), seasoned equity offerings (SEOs) and mergers. However, the brokerage division and its equity research department generate their income by providing accurate information and recommendation for their clients. One major source of conflicting interests arises from the compensation structure of an analyst of such investment bank. Commonly a significant factor in the compensation plan comes from the analyst's "helpfulness" in the work of colleagues in the corporate finance division. Another factor is the analyst's external reputation, which is a direct output of the precision of the analyst's forecasts. Clearly, there is a risk that these two objectives may collide. (Michaely & Womack 1999)

Irvine (2004) agrees when it comes to the obligations of a brokerage house analyst. The analyst's main objective is to issue trustworthy analysis, but one must also keep in mind the objectives of the firm and maintain goodwill with the management and other departments of the firm, by doing so also growing their compensation package. Irvine (2004) studied the brokerage firm analysts' earnings forecasts and recommendations to find out whether they can help to create trading for the brokerage-firm on the stock under consideration. He found that forecasts that significantly positively differ from the consensus increases the employer's market share of trading in the underlying stock, in the two weeks after the forecast issued. Michaely and Womack (1999) also questions the liability of brokerage analysts by studying their recommendations. They find that brokerage analysts' valuations tend to be more biased than those of unaffiliated analysts', by showing that the firms that receive a "buy" recommendations from the former perform more poorly than those given the same recommendation by the latter. They also show that this bias is not fully recognized by the market.

Lin and McNichols (1998) researches the analysts' affiliation in an underwriting of a seasoned equity offering. They create two groups of affiliated analysts, one for the lead underwriter's analysts and one for the co-underwriter's analysts, and compare their earnings forecasts, growth forecasts and recommendations with those of unaffiliated analysts. They find no difference in the earnings forecasts in current nor the subsequent year. However, they find lead and co-underwriters growth forecasts and recommendations to be more favourable than those of unaffiliated analysts'.

Lin and McNichols (1998) also describes the decision-making of the issuer company in choosing an underwriter with two scenarios. In a non-strategic scenario, the forecasts and recommendations of an affiliated analyst are correlated with the decision-making, but the analyst makes his/hers forecasts non-strategically. In this scenario, the reports by lead underwriter's analysts will be upward biased, but only due to choices made by issuing company rather than the analysts. Non-strategic reporting is expected from analysts if the costs are less than benefits of biased reporting. When it comes to strategic scenario, they assume that analysts do in fact issue biased reports in order to win the underwriting contract. They argue that when the issuer has announced the issue, but has not yet chosen the underwriter, the analysts of the lead and co-underwriters from the previous issue are expecting their firm to be chosen as an underwriter for the new issue. Hence, their reports will be biased with a higher probability, because of the benefit to their company, compared to unaffiliated analyst' companies.

Kothari (2001) also talks about the decision making of the issuing company in his review on capital markets research in accounting. He concludes that the final decision is most likely dependent on which analyst is the most optimistic about the firm's prospects. Kothari (2001) recognizes the two explanations behind analysts' bias, the incentive based -explanation as in Michaely and Womack (1999) and the aforementioned explanations arising from the issuing company by Lin and McNichols (1998). He believes that it is difficult to make a distinction between the two.

In an initial public offering situation, it is reasonable that the underwriter has a good view of the issuing firm's prospects, otherwise it would not be a very favourable deal for the underwriter, as one analyst put it:

"It goes without saying that if you do a company's IPO, you are going to have a buy [on the stock], because frankly if you don't you shouldn't be doing the deal." (Raghavan 1997).

To put it in other words, if the issuer chooses the underwriter on the based on the terms of the underwriting, and these terms being dependent on the prospects of the issuer by the eyes of the analyst, then the chosen underwriter's analyst's views naturally are optimistic. (Lin and McNichols 1998)

As a conclusion from this sub-section, as long as these discussed incentives exists, the possibility of biased forecasts and recommendations prevails. However, forecasts are not always biased on purpose and the next sub-section will talk more about these unintentional biases.

2.1.3 Unintentional biases and informational uncertainty

The uncertainty of information in the context of analysts' forecast has been capturing the interest of academics as well. Information uncertainty can stem from volatile fundamentals of the underlying firm or from poor information (Zhang 2006a). The dispersion in analysts' consensus is a commonly used proxy for uncertainty (for example Johnson 2004), it being relatively easy to measure, other such proxies include firm size, firm age, analyst coverage, return volatility, and cash flow volatility (Zhang 2006b). Uncertain information environment can lead to forecast error regardless of the analyst's incentives.

Despite being transparent, there is usually a small number of analysts' following the companies in the Nordic markets (Hope 2003; Lang 2004), which can create an uncertain environment for earnings prediction. For example, Coën, Desfleurs and L'Her (2009) studied this in a sample comprising 18 countries. They measure the mean consensus analysts' forecast error as the difference between the forecast and realized earnings scaled by the absolute value of realized earnings. They observe the error with two measures. The first one is the absolute value of the error, considering only the magnitude and the second one, bias, considers also the direction of the error. For all the Nordic countries, the absolute forecast error is far above the mean, in fact, it being the highest in the whole sample for Norway and third highest for Finland. Yet again, when it comes to the bias, that also considers the sign of the error, Finland, Norway and Denmark are among the four countries with the lowest bias. This suggest that in these markets, analysts' forecasts are not necessarily biased, an issue that was discussed in the previous sub-section but can be inaccurate for other reasons. Most certainly, one of these reasons being the relatively thin coverage of firms by analysts in these markets.

Coën et al. (2009) also researched the effect of coverage on the forecast error by dividing the stocks into four categories according to their coverage. They found a significant difference in the absolute forecast error between the category for the stocks with largest coverage and the one with the smallest, the accuracy increasing with more coverage, as expected. The same effect was found also earlier by Alford and Berger (1999) who document, using simultaneous equations that greater forecast accuracy is associated with wider coverage. They emphasize that analysts' private information mitigates the information uncertainty, rather than substituting for other factors that increase the certainty in the market.

Zhang (2006a) measures the uncertainty with dispersion in consensus estimates and accesses the magnitude of analysts' forecast errors through their forecast revisions. Zhang (2006a) affiliates upward revisions with good news and downward revisions with bad news, both providing new information to the primal uncertain state. The findings indicate that greater uncertainty in information predicts more positive forecast errors and vice versa, and also that, bad news over good news affect analysts' behavior much more, in an uncertain informational setting.

Gu and Wang (2005) found industry characteristics to affect the analysts' forecast error. More specifically, they found a positive correlation between the error and intangible intensity of a firm, such that deviates from the industry norm. For firms that are using diverse and innovative technologies, the analysts' forecast error was found to be even more severe.

Barron, Byard, Kile and Riedl (2002) came to similar conclusions, finding the analyst' estimates to be more widespread for firms with higher levels of intangible assets. This is due to the uncertainty of firms' future earnings increasing with the level of intangibles. What comes to the industry, their study also shows high-technology firms with great levels of R&D investments, to have the lowest levels of consensus.

2.1.4 Incentives for managers to bias earnings

Abarbanell and Lehavy (2003) researches whether reported earnings are the best benchmark for measuring analysts' bias and inefficiency. They believe that simple motivations for managers to manipulate earnings can be perceived as analysts' errors. Earnings management is perceived all around the world, also in the Nordic markets there is evidence of earnings management, even though the Nordic exchanges are known for their transparency. For example, using a dataset from Finnish companies' financial statements, Martikainen (2002) found that companies tend to fine tune earnings, meaning that the management of the company uses discretionary assets to manage earnings in the favourable direction. This naturally affects the profitability of the firm, and the researcher did find that lagged earnings management significantly affects the future profitability of the company. She also makes a notion that lagged earnings management, contains information that cannot be directly observed from the past profitability nor the stock price.

The aforementioned study by Lopez and Reez (2002) found meeting the analysts' forecasts to be extremely important for a company, because of its effect on the market value. This also creates a major incentive for managers to fine tune earnings when they are unable to meet the analyst's forecast. On the other hand, when earnings are above the consensus, management can choose to report the realized earnings or reduce the reported earnings to the forecasted level (Payne 2008). Reducing the earnings will create reserve for discretionary accruals that can be utilized in the future (Payne & Robb 2000). The evidence shows that, whether the company exceeds or falls short of the analysts forecast, managers are actively using their discretion in reporting earnings to benefit their company (Lopez & Reez 2002; Payne & Robb 2000).

2.1.5 Investor attention

Lin and McNichols (1998) study whether investors account for the difference between the recommendations of affiliated versus unaffiliated analysts. In a 3-day period after the announcement of an SEO, they found no difference in the performance of the stock following a “strong buy” and “buy” recommendations, but for “hold” recommendations, investors seem to perceive the difference between a recommendation given by the lead underwriter’s analysts and unaffiliated analysts, as the returns for the former are significantly more negative.

The distribution of welfare between different investor groups might be affected by how they perceive analysts’ forecast. Malmendier and Shanthikumar (2007) studied the informational content of analysts’ recommendations, by measuring the reactions of small and large investors to the recommendations. The finding of the study reveal that large investors do consider the possible upward bias of analysts’ recommendations, and react to “hold“ recommendations significantly and negatively and show no reaction to “buy” recommendation, while a significant positive reaction was found only for “strong buy” recommendations. Whereas, small investors take recommendations more literally, showing positive reaction to both “strong buy” and “buy” and no reaction to “hold”. Also, the researchers found no significant difference in the reaction of small investors to recommendations between affiliated and unaffiliated analysts, while again large investors on average knew how to account for the greater possibility of a biased recommendation. Same kind of setting is formed by Mikhail, Walther and Willis (2007) in reasoning the concerns behind regulations. Where their study differs is that they also include the recommendation revisions. They find that large investors trade more following recommendation revisions, where small investors trade more following the issuance of the actual initial recommendation. Small investors also trade more on the basis of recommendations upgrades and “buys”, which are classified as less credible. These results support the regulators concerns over the less aware small investors not adjusting for the credibility of analysts’ recommendations.

2.2 The traditional approach on predicting analysts' forecast error

Since 1983, the Institutional Brokerage Estimate System (IBES) has been collecting data on analysts' estimates. Each observation in the data set represents a single forecast by a single analyst for a specific reporting period and taken all these together, one can observe the consensus estimate for the selected company. (Johnson 2004) For the traditional approaches this data is commonly the main source for measuring the forecast error of analysts.

Frankel and Lee (1998) find that a modest portion of the errors in IBES consensus estimates are predictable. The predictable portion, however, shows consistency and therefore the researchers proceed to implement a trading strategy based on the predictions. The model developed predicts the cross-sectional returns annually from 1977 to 1991. The model includes four firm characteristics as independent variables, the book-to-market ratio, past sales growth, analyst consensus long-term earnings forecast and a new variable they call analyst optimism. The model explains some 7% of the cross-sectional variations in the IBES estimates.

Ali et al. (1992) find that analysts constantly underestimate the importance of past forecast errors in forecasts of future earnings. Analysts overestimate the next periods EPS and their forecasts exhibit significant positive autocorrelation. They compare the results of an adjusted model, where past time series properties of earnings are used, with the results of the original unadjusted model, and discover the adjusted model to be significantly more accurate in terms of mean squared error (MSE). For the adjusted model, they access the price/earnings ratios of the companies, and identify those with extreme ratios with a binary variable.

Similarly, Lo and Elgers (1998) uses four different adjustment methods. The systematic error adjustment simply uses the forecast error of the prior periods, in forecasting the future. This method is used as a benchmark to measure the effectiveness of the rest of the models. The second model, the composite forecast adjustment, uses a random walk with drift forecast of earnings change, in addition to the previous model. The drift is measured as the average per share earnings change over the prior five years. The third model is the one introduced by Ali et al. (1992), described above. The last model adjusts for the prior performance of the firm through the prior year's earnings, earnings changes and security returns. By dividing the MSE in to three components, Lo and Elgers (1998) find that the prior performance adjustment model is the only model that affects the random error or the unsystematic error component of the MSE. Remaining models only affects the systematic parts of the MSE; the bias and the residual components, providing insignificant improvements to the benchmark model. On the other hand, prior performance adjustment reduces the MSE of the unadjusted forecasts (IBES consensus) considerably.

Hughes et al. (2008) accesses the relationship between predictable market returns and predictable analyst forecast error. They use a set of under-reaction and over-reaction variables introduced in earlier studies and perform regressions in two stages. In the first stage regressions, they estimate predictable component of analysts' forecast error and market returns, in a one-year horizon, in-sample and out-of-sample. The out-of-sample regressions are based on the prior 5 years of data, in order to predict the forecast errors and market returns, at one month after the annual earnings release. In the second stage regressions, the researchers use significant coefficients from the first stage, applied to the current values of the variables, to predict the forecast errors and abnormal returns for the upcoming year. They find that while the market seems to comprehend the predictable component of analysts' error, the analysts does not seem to comprehend the predictable abnormal returns, indicating the market being more efficient.

In a recent study by Monte-Mor, Galdi and Costa (2018), the authors implement a bit different approach in trying to understand the forecast errors by analysts. They divide the error into two components, those that emerge from accounting fundamentals and to those from "other information", the latter meaning such information that cannot yet be observed directly from the financial statement. The authors find that the common conclusion in the literature of analysts being optimistic do hold for errors concerning accounting fundamentals, but in their processing of other information, analysts tend to be pessimistic, also, that on average analysts incorporate good news in to their forecasts with pessimism but process bad news with a more optimistic mind-set.

2.2.1 Concerns with the traditional approach

The traditional approach on predicting analysts forecast errors, used by Hughes et al. (2008) among others, exploits publicly available lagged firm characteristics in a regression against realized forecast errors, applying the obtained coefficients to create a fitted prediction of future forecast errors. In his paper, So (2013) expresses concern over the traditional approach, which will be discussed in this sub-section.

To begin the explanation of the methodology behind the traditional approach, we shall write the firms realized earnings in an equation form:

$$\boldsymbol{E_{j,t} = \Sigma_{i=1}^{M} \beta_i \cdot X_{i,j,t-1} + \epsilon_{j,t},} \tag{1}$$

where $X_{1,j,t-1} \ldots X_{M,j,t-1}$ stands for publicly observed set of *M* characteristics for firm *j* in year *t-1* and $\epsilon_{j,t}$ for the component of earnings not predicted by the firm characteristics. Similarly, analysts forecast in *t-1* for year *t* can be written as:

$$\boldsymbol{AF_{j,t-1} = \Sigma_{i=1}^{M} \gamma_i \cdot X_{i,j,t-1} + \Sigma_{i=1}^{K} \delta_i \cdot Z_{i,j,t-1} + \eta_{j,t-1},} \tag{2}$$

where $Z_{1,j,t-1} \ldots Z_{K,j,t-1}$ stands for analysts private information and any possible incentive to bias their forecasts, discussed above (2.1.2) and $\eta_{j,t-1}$ for the component of earnings not predicted by the analyst. Combining equations (1) and (2), we can write realized forecast error as:

$$\boldsymbol{FE_{j,t} \equiv E_{j,t} - AF_{j,t-1} = \Sigma_{i=1}^{M} (\beta_i - \gamma_i) \cdot X_{i,j,t-1} + \epsilon_{j,t} - \Sigma_{i=1}^{K} \delta_i \cdot Z_{i,j,t-1} + \eta_{j,t-1}.} \tag{3}$$

In the traditional approach, usually the researcher regresses realized forecast errors against the lagged firm characteristics. Derived from equation (3) the error term from such regression can be written as:

$$\boldsymbol{\Omega_{j,t} \equiv \epsilon_{j,t} - \Sigma_{i=1}^{K} \delta_i \cdot Z_{i,j,t-1} + \eta_{j,t-1}.} \tag{4}$$

Now we can see that the regression error is dependent on the unobservable inputs of the analyst $Z_{i,j,t-1}$, and the estimated values of $(\beta_i - \gamma_i)$ in equation (3) are subject to bias. Also, there is evidence that the error term $\Omega_{j,t}$ in equation (4), might be correlated with the forecast error $FE_{j,t}$ or the set of control variables $X_{i,j,t-1}$, making the regression subject to a risk of correlated omitted variable bias.

Moving on with the traditional approach, in the second stage, the researcher uses the estimated values of $(\beta_i - \gamma_i)$ with the current firm characteristics as in:

$$\widehat{\boldsymbol{FE}^{T}}_{j,t+1}=\boldsymbol{\Sigma}_{i=1}^{M}(\widehat{\boldsymbol{\beta}_{\iota}-\boldsymbol{\gamma}_{\iota}})\cdot\boldsymbol{X}_{i,j,t}. \tag{5}$$

The resulting fitted value $\widehat{\mathrm{FE}^{T}}_{j,t+1}$ equals the researchers estimate of the analyst forecast error for *t+1*, calculated under the traditional approach denoted by the superscript *T*. Using biased coefficients results in a prediction of analyst error that does not equal the expected value of the realized forecast error. The forecast error $\widehat{\mathrm{FE}^{T}}_{j,t+1}$ can be above or below the realized forecast error and is dependent of the sign and magnitude of the bias. The bias arises from the methodological flaw that causes the difficulty for the researcher to observe external factors affecting analysts' forecasts, such as private information and incentives, denoted as $Z_{i,j,t-1}$ in equation (2). It is possible to control for some of these factors (as Lin and McNichols (1998) controls for the affiliation of the analysts,) but it is impossible to detect all the unobservable inputs that might bias the information issued by the analysts, So (2013) argues.

There are also concerns in using the IBES data for studying the forecast error. The researcher must be careful in using the correct data. Since the typical IBES estimates are adjusted with a split factor and rounded to the nearest two decimal places, one can come across a measurement error. This problem is especially severe in cases where IBES estimates shows zero forecast error, when the actual non-adjusted error would be non-zero in fact. (Payne & Thomas 2003)

2.3 Characteristic approach

So (2013) introduces a new method for predicting analysts' forecast errors, the characteristic approach. This approach contrasts analysts' earnings forecasts with characteristic forecast of earnings, and measures both several months before the earnings announcement of a company. For the forecast of earnings So (2013) uses a set of variables introduced by Fama and French (2006), in their paper on the relation between profitability, investment and book-to-market ratio.

In the characteristic approach the researcher directly estimates future earnings (instead of using realized forecast errors), by estimating equation (1) for the following year presented as:

$$\boldsymbol{\hat{E}_{j,t+1} = \Sigma_{i=1}^{M} \hat{B}_i \cdot X_{i,j,t}}. \tag{6}$$

Next, the researcher uses the estimated future earnings $\hat{E}_{j,t+1}$ with analyst consensus forecast for *t+1* earnings:

$$\boldsymbol{\widehat{FE}^{C}{}_{j,t+1} = \hat{E}_{j,t+1} - AF_{j,t+1} = E_t[E_{j,t+1} - AF_{j,t+1}] = E_t[FE_{j,t+1}]}, \tag{7}$$

thus, achieving the predicted forecast error $\widehat{\mathrm{FE}}^{C}{}_{j,t+1}$, where the C-superscript indicates the predicted forecast error estimated with the characteristic approach. The result is an unbiased estimate of the realized analysts' forecast error. (So 2013)

The selection of the variables for the characteristic approach by So (2013) is based on a comprehensive justification from Fama and French (2006). For example, the book-to-market ratio is found to be negatively related to profitability by Fama and French (1995; 2006) among others, suggesting that value firms tend to be less profitable. Also, a wide range of literature spawned by Sloan (1996) show evidence that accruals predict profitability with a negative relationship. Sloan (1996) studied the cash flow and accrual components of earnings to specify to which extent this information is reflected in stock prices. He found a negative relationship between the level of current accruals and future stock returns, since the accrual component of earnings is less persistent than the cash flow component, meaning that high current levels of the accrual component leads to lower future earnings. What comes to the effect of dividends, it is widely acknowledged that dividend-paying firms are usually more profitable, but grow at a slower rate, Fama and French (2001) also shows evidence on this. However, the characteristic approach on predicting analysts' forecast error is not limited on a specific selection of variables but allows the researcher to choose from any publicly available inputs, and by exploiting a cross-sectional model, the range from which to choose from is wider.

As Hou, van Dijk and Zhang (2012) reminds, cross-sectional models, like the one presented here, usually outperform past returns models already because of data availability. Cross-section studies only require data on limited selection of variables, and normally only from two consecutive years. Whereas, the precision of past return models is heavily dependent on the availability of past data and these models are also subject to survivorship bias. Cross-sectional forecasts may incorporate additional variables, such as accruals and dividend, which are found to increase the explanatory power for future profitability. Additionally, So (2013) expressed concern over the accuracy of time series models compared to analysts' forecasts, potentially making them an inadequate measure on which to compare analysts' forecast error.

3 Data and methodology

This chapter presents the data collection, with sub-chapters on the selection of the companies and on the selection and transformation of the variables. After having described the data collection, the methodology of the study will be introduced. Also, the research questions will be repeated, with explanations on how the research aims to answer to these questions. Lastly, the timeline of the empirical analysis will be explained.

The data for this research was obtained mainly from Thomson Reuters Eikon. The IBES estimates, realized earnings and other firm characteristics were accessed through this database, and its Microsoft Excel add-in. Fundamental data was needed for 2007-2016, in order to run regressions and obtain coefficients for 2010-2016 to predict the earnings for 2011–2017. Thus, a total of 10 years of data was extracted and transformed to produce an outcome of predictions for seven consecutive years, which equals 1345 firm-years after the removal of outliers.

3.1 Companies

The regressions are ran for each company traded in the stock exchange of Stockholm, Copenhagen, Oslo or Helsinki, for which a non-missing value of all the nine characteristics is found for the particular year and a non-missing value is found for the dependent variable the following year. Firms with negative book-to-market ratio will be excluded from the sample, as well as financial firms. Financial firms will be excluded from the sample, as their industry norm highly leveraged balance sheets could cause biased results (Fama & French 1992). The annual sample size for the earnings predictions and the contribution of each exchange to the sample is illustrated in Figure 1 below.

Following Fama and French (2006) I trim the independent variables for the earnings regressions, but instead of 0.5 and 99.5 percentile, I use 1.0 and 99.0 percentiles due to the differing sample size. Meaning that, if an independent variable is below the 1^{st} or above the 99^{th} percentile, the observations is removed from the sample altogether. After the elimination of outliers, the sample size ranges from a low of 179 in 2011 to a high of 204 in 2015 and 2017. As can be easily observed from Figure 1, the Stockholm Stock Exchange is the marketplace for most of the companies' stocks in the sample. Total 46% of the companies in the full sample are traded in the Stockholm Stock Exchange. Helsinki Stock Exchange represents 28% of the total sample, while Oslo Stock Exchange and Copenhagen Stock Exchange share the remainder.

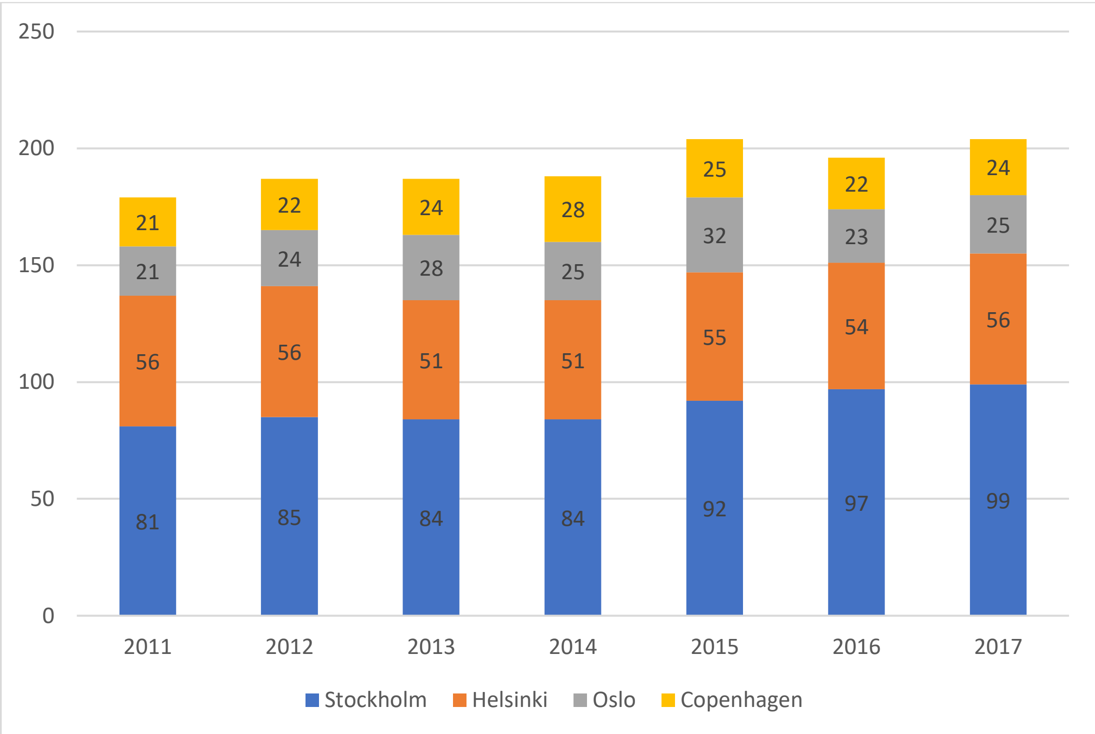


Figure 1 Number of firms in the sample each year and in each exchange.

3.2 Variables

Table 1 lists all the variables used in the empirical analysis in the first column and the items utilized in the formation of the desired variables from Eikon database in the last column, as well as a short description of each variable in the middle. Full descriptions of the items as presented in Eikon can be accessed from Appendix 1. As this thesis follows the methodology by So (2013), the same variables, introduced by Fama and French (2006) will be used. Most of the variables were extracted and loaded with the Microsoft Excel add-in of the Eikon software. The manipulation of the variables was performed with SAS code using SAS Enterprise Guide -software.

Table 1 Variables used in the study and the item used in formation of the variable from the Eikon database.

Variable	Description	Items in Eikon
EPS NEGE	Earnings per share Loss indicator	EPS actual
ACCN ACCP	Negative accruals per share Positive accruals per share	Total current assets Notes payable/short-term debt Cash and short-term investment Total current liabilities
AG	Asset growth	Total assets reported
DD DIV	Zero dividend indicator Dividends per share	Dividend per share actual
BTM	Book-to-market ratio	Price / book value per share
PRICE	Share price	Hist fscl period price close (fin cur)
AF	Analysts' forecast	Earnings per share - Mean
TA	Total assets	Total assets reported
TR	Total return	Total return
TOTAL	Total number of shares	Basic weigted average shares
COV	Average analyst coverage	Analyst coverage

In order to achieve better comparability between the forecasts, Eikon item EPS actual was used. This item corresponds to the EPS that the analyst perceives as the one with which to value a security. Naturally, the loss indicator NEGE, which is assigned a value of one for companies reporting negative earnings and zero otherwise, was also calculated using this item. Negative and positive accruals were calculated as the change in total current assets plus the change in notes payable/short-term debt minus the change in cash and short-term investment and minus the change in total current liabilities. Negative outcomes of this equation were assigned to ACCN and zero or above to ACCP, while the counterpart variable for the observation was assigned a zero. Asset growth was calculated as the percentage change of total assets reported. DIV uses dividend per share actual, which corresponds to the common stock dividend divided by the average number of common shares outstanding for the fiscal year and DD is a dummy variable assigned a value of one for non-dividend paying firms and zero otherwise. The book-to-market ratio was not directly found from the database so the price-to-book value per share was loaded instead and transformed to book-to-market. The closing price of the fiscal period was used for the PRICE variable. Following So (2013), and against the common method of using median analyst consensus estimate, the mean consensus estimates were used, denoted as AF. However, for robustness checks the median consensus estimates were also used. The estimates are the latest available estimates on May 31st of each year. The variables that yet were not on per share basis were divided by basic weighted average shares denoted as TOTAL. Total assets, denoted as TA, are used in the denominator of characteristic forecast optimism and total returns, TR, in the investment strategy. Analysts' coverage COV is utilized in the third research question and it is defined as log of average analysts following the firm during the previous fiscal year.

Table 2 shows descriptive statistics of the nine characteristics for the full panel data. Some interesting observations can be made from the descriptive statistics already. We can see the mean for the accrual variables ACCP and ACCN are almost the same in absolute terms. Also, the mean stock price is above 10 and this variable exhibit by far the largest standard deviation, expectedly. Mean values for the binary variables NEGE and DD, by being closer to zero than one, indicates that more firms report positive earnings than do negative and that more firms pay dividends than do not.

Table 2 Descriptive statistics of the nine characteristics for the full panel data.

	Min	Mean	Median	Max	Std Dev
EPS	-7.584	0.678	0.456	13.667	0.289
NEGE	0.000	0.100	0.000	1.000	0.041
ACCP	0.000	0.290	0.000	12.950	0.203
ACCN	-8.567	-0.298	-0.001	0.000	0.156
AG	-0.382	0.070	0.048	1.343	0.024
DIV	0.000	0.339	0.233	4.191	0.080
DD	0.000	0.178	0.000	1.000	0.044
BTM	0.023	0.799	0.501	15.818	0.206
PRICE	0.038	10.859	7.681	159.419	3.627

Notes: Description of each variable is presented in Table 1 and a full description as shown in Eikon database is presented in Appendix 1. The yearly characteristics are derived from firms' financial statements using the Eikon database. The table shows the minimum, mean, median, maximum and the standard deviation of the variables.

3.3 White's heteroscedasticity-consistent standard errors

Any conclusion drawn on the basis of ordinary least squares (OLS) standard errors, when heteroscedasticity is present can be wrong. The final effect on the results depends on the form of the heteroscedasticity (Brooks 2014). Through methods of plotting the data and White's general test, heteroscedasticity was found in the residuals of the regressions in this study. The form of the heteroscedasticity was unclear; therefore, White's (1980) heteroscedasticity-consistent standard errors were applied. The White's standard errors are larger relative to the OLS standard errors, which makes hypothesis testing require more evidence before the null hypothesis can be rejected (Brooks 2014).

To define the heteroscedasticity-consistent covariance matrix (HCCM) estimator for OLS let us consider the following standard linear regression model:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\epsilon} \tag{8}$$

where $E(\epsilon) = 0$ and $E(\epsilon\epsilon') = \Phi$, that is a positive definite matrix. Under the specifications underlined, the OLS estimator $\hat{\beta} = (X'X)^{-1}X'y$ is the best linear unbiased estimator (BLUE) with a variance of

$$\mathrm{var}(\hat{\boldsymbol{\beta}}) = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{\Phi}\mathbf{X}\,(\boldsymbol{X}'\boldsymbol{X})^{-1}. \tag{9}$$

In the absence of heteroscedasticity, that is $\Phi = \sigma^2 I$, the equation can be simplified to:

$$var(\hat{\boldsymbol{\beta}}) = \boldsymbol{\sigma}^2(\boldsymbol{X}'\boldsymbol{X})^{-1}. \tag{10}$$

The residuals can be defined as $e_i = y_i - x_i\hat{\beta}$, where x_i is the i^{th} row of X. Now the covariance matrix estimator for ordinary least squares (OLSCM) can be estimated as:

$$OLSCM = \frac{\Sigma e_i^2}{N-K}(X'X)^{-1} \tag{11}$$

where N represents the number of observations and K the number of elements in β. When the standard assumptions of a linear regression model hold, only then is the OLSCM an appropriate approach in evaluating the model. In the presence of heteroscedasticity, one of the assumptions is broken and the OLSCM will lead to biased estimates.

Correcting for the heteroscedasticity of a known form, the researcher can proceed by utilizing equation (9). However, more often the form is unknown and a HCCM should be applied. As shown by White (1980), the basic form of the HCCM the HC0 is a consistent estimator of $var(\hat{\beta})$ when heteroscedasticity is present. To derive HC0, the basic idea is to use e_i^2 to estimate Φ_{ii}, described differently we are estimating ϵ_i with a single observation: $\widehat{\Phi_{ii}} = (e_i - 0)^2 / 1 = e_i^2$. Now, let $\widehat{\Phi} = diag(e_i^2)$, and the HC0 estimator can be expressed as:

$$HC0 = (X'X)^{-1}X'\widehat{\Phi}X\,(X'X)^{-1} = (X'X)^{-1}X'diag(e_i^2)X\,(X'X)^{-1}. \tag{12}$$

HC0 is the most commonly used estimator, but it is not well designed for small samples. As a solution for this, MacKinnon and White (1985) introduced three additional covariance matrix estimators, HC1, HC2 and HC3. More recently, Long and Ervin (2000) studied the performance of the three estimators and found that they generally work better for small samples than the original HC0. Specifically, for sample sizes less than 250 observations, the HC3 estimator was found to be the best fit. The average sample size in this study is 192, thus the HC3 method will be applied. Even so, all three specifications of the HCCM will be shortly presented here. The first one, HC1, makes a degrees of freedom adjustment to inflate the residuals by a factor $\sqrt{N/(N-K)}$. Not having to re-write the HC0 estimator the HC1 estimator can be written as:

$$HC1 = \frac{N}{N-K}HC0. \tag{13}$$

For the second estimator, we must remember that $\widehat{\Phi}$ in equation (12) is based on the OLS residuals e, not the errors $\boldsymbol{\epsilon}$. We can define $h_{ii} = x_i(X'X)^{-1}x_i'$, then:

$$var(e_i) = \sigma^2(1 - h_{ii}) \neq \sigma^2, \tag{14}$$

where $var(e_i)$ underestimates σ^2, because $1/N \leq h_{ii} \leq 1$. The HC2 estimator is based on suggestion made by equation (14), that even though e_i^2 is a biased estimator of σ^2, e_i^2 / h_{ii} will be less biased, therefore MacKinnon and White (1985) introduced the second estimator:

$$HC2 = (X'X)^{-1}X'diag\left[\frac{e_i^2}{1-h_{ii}}\right]X(X'X)^{-1}. \tag{15}$$

The final estimator is very similar, in which e_i^2 is further inflated by dividing it with $(1 - h_{ii})^2$:

$$HC3 = (X'X)^{-1}X'diag\left[\frac{e_i^2}{(1-h_{ii})^2}\right]X(X'X)^{-1}. \tag{16}$$

The purpose of the HC3 estimator is to adjust for the effect of observations with excessive influence and large variances. (Long & Ervin 2000)

3.4 Characteristic approach

For the first two research questions this thesis will follow the methodology by So (2013), with minor alterations. To begin with, the following equation will be estimated cross-sectionally:

$$EPS_{j,t} = \beta_0 + \beta_1 EPS_{j,t-1} + \beta_2 NEGE_{j,t-1} + \beta_3 ACCN_{j,t-1} + \beta_4 ACCP_{j,t-1} + \beta_5 AG_{j,t-1} + \beta_6 DD_{j,t-1} + \beta_7 DIV_{j,t-1} + \beta_8 BTM_{j,t-1} + \beta_9 PRICE_{j,t-1} + \epsilon_{j,t-1}. \tag{17}$$

Equation (17) expresses firm *j*'s earnings per share in year *t* as a function of *t-1* lagged firm characteristics. The characteristics are as described above in sub-chapter 3.2. Next step of the characteristic approach involves applying the estimated coefficients from equation (17) to the current characteristics of the firm. The characteristic earnings forecast equals:

$$CF_{j,t} = \widehat{\beta}_0 + \widehat{\beta}_1 EPS_{j,t} + \widehat{\beta}_2 NEGE_{j,t} + \widehat{\beta}_3 ACCN_{j,t} + \widehat{\beta}_4 ACCP_{j,t} + \widehat{\beta}_5 AG_{j,t} + \widehat{\beta}_6 DD_{j,t} + \widehat{\beta}_7 DIV_{j,t} + \widehat{\beta}_8 BTM_{j,t} + \widehat{\beta}_9 PRICE_{j,t} \quad (18)$$

where $CF_{j,t}$ denotes the characteristic forecast for year *t* earnings for firm *j*. The prediction of the consensus analysts' forecast error, according to the characteristic approach, equals the characteristic forecast of earnings deflated by the analysts' forecast for year *t* earnings ($AF_{j,t}$). Lastly the firms are ranked each year according to characteristic forecast optimism ($CO_{j,t}$), which is derived in the following equation:

$$CO_{j,t} = \frac{CF_{j,t} - AF_{j,t}}{TA_{j,t}}, \quad (19)$$

where $\mathrm{TA}_{j,t}$ is firm *j*'s total assets per share. The difference between the forecasts is scaled by total assets (TA) instead of price, because of the risk that the two could move in tandem.

Characteristic forecast optimism will be exploited in the main analysis to predict analysts' forecast error, as presented in the first research question. The empirical prediction is that characteristic forecast in excess of analysts' forecast predict realized earnings in excess of analysts' forecast, thus CO positively correlates with analysts' forecast error (So 2013). It is based on the assumption that when characteristic forecast is high relative to analysts' forecast, firms' fundamentals signals future expectations that are not yet incorporated into analysts' forecasts, meaning analysts are overly pessimistic, and vice versa. Firms will be ranked into quintiles of CO, and the forecast error is expected to be most severe in the high CO firms. (Different division to rankings was also tested for robustness checks.) Through this methodology I will be able to answer the first research question being:

1. *"Does the characteristic forecast optimism, CO, positively predict analysts' forecast error?"*

Similarly, the assumption behind the abnormal earnings possibilities lies behind the characteristic forecast optimism. In high CO firms, the earnings potential in firm fundamentals has not yet been incorporated into the share price, thus investing into these companies will predictably result in future abnormal returns. The empirical prediction is that characteristic forecast optimism positively predicts future abnormal returns. The investment strategy will be based on this prediction; thus, a long position will be placed on firms in the high CO quintile and short position on those in the low CO quintile. The outcome of the investment strategy will be the resulting annual return. The higher goal of the investment strategy is to discover whether investors overweight analysts' forecasts. This is achieved by comparing the two forecasts with characteristic forecast optimism, and allocating each firm to the quintiles, accordingly, thus receiving an answer to the second research question:

2. *"Does the characteristic forecast optimism, CO, positively predict future abnormal returns?*

3.5 Panel regressions

Panel regressions allow the researcher to draw more robust conclusions based on the entire sample. With panel techniques the researcher can account for fixed effects of the time series or the cross-sectional observations, using a one-way fixed effects model or both by using a two-way fixed effects model. However, if the outside effects on the regression disturbance term are less easily observable, the random effect model can be applied. The fixed effects model normally is a better fit for a study that utilizes a sample comprising an entire population, in this instance the population being all the stocks in a certain market. (Brooks 2014) A two-way fixed effects model is applied in this study for robustness purposes, and a one-way fixed effects model in order to find an answer to the third research question.

Fixed effects models assume that a change in a regressor, whether it's a change from one time-period to another or a change from one individual to another, has the same effect for all betas (Verbeek 2008). The entity-fixed effects should be used when it is assumed that the residuals are correlated across time for a given firm. The residual of such model is described as unobservable individual effect by Baltagi (2005), whereas for a time-fixed effects model where the residuals are expected to be correlated across firms in a given year, they are described as unobservable time effects. Both models can be estimated using the least squares dummy variable (LSDV) approach. The following represents the entity-fixed effects model:

$$y_{it} = \beta x_{it} + \mu_1 D1_i + \mu_2 D2_i + \mu_3 D3_i + \cdots + \mu_N DN_i + v_{it} \tag{20}$$

where $D1_i$ for example represents a dummy variable, taking a value of 1 for the first cross-sectional observation and zero otherwise *(i=1,...,N)* and v_{it} the remainder disturbance term that accounts for everything that is left unexplained about y_{it}. In equation (20) the unobservable individual effect μ_N can be thought of as anything that affects y_{it} cross-sectionally but do not vary between time periods. The intercept (α) has been removed from the equation to avoid the so-called dummy variable trap. In a typical financial data setting, like the one in this study, where the number of cross-sections is relatively large to the number of time periods, the number of dummy variables to be estimated increases, and the *N* becomes large. If the researcher is not willing to estimate so many variables and lose the degrees of freedom, there are two further options, the within transformation and the between estimator, which can be exploited.

In similar fashion the model can also be fixed time-wise. Now the unobservable time effect, denoted as λ_t in equation (21), would capture everything that affects y_{it} between time periods, but do not vary over cross-sectional units. The model containing the dummy variables would get the following form:

$$y_{it} = \beta x_{it} + \lambda_1 D1_t + \lambda_2 D2_t + \lambda_3 D3_t + \cdots + \lambda_T DT_t + v_{it} \tag{21}$$

where $D1_t \ldots DT_t$ represents dummy variables, taking a value of 1 for the particular time period and 0 otherwise (*t = 1,...,T*). (Brooks 2014)

Having defined the fixed effects model with both entity effect and time effect, let us consider the case where both dimensions are fixed in a single model, the two-way fixed effects model. As Wallace and Hussain (1969), among others, described, the disturbance term for such model is as follows:

$$u_{it} = \mu_i + \lambda_t + v_{it} \tag{22}$$

where both the unobservable individual effect μ_i and the unobservable time effect λ_t are represented (*t = 1,…,T; i=1,…,N*). Written in vector form the equation becomes:

$$\boldsymbol{u} = \boldsymbol{Z}_{\mu}\boldsymbol{\mu} + \boldsymbol{Z}_{\lambda}\boldsymbol{\lambda} + \boldsymbol{v} \tag{23}$$

where Z_μ is a matrix of the individual effect dummies, whereas Z_λ represents a matrix of the time effect dummies. Once again, if T is large in the matrix of the time dummies, Z_λ, in equation (23), the same problems will be faced as with one-way fixed effect model, so the within estimator can be utilized. By averaging a normal panel regression model over individuals, we receive the following equation:

$$\bar{\boldsymbol{y}}_{.t} = \boldsymbol{\alpha} + \boldsymbol{\beta}\bar{\boldsymbol{x}}_{.t} + \boldsymbol{\lambda}_{\boldsymbol{t}} + \bar{\boldsymbol{v}}_{.t} \tag{24}$$

and by utilizing the restrictions that $\sum_i \mu_i = 0$ and $\sum_t \lambda_t = 0$ we can deduce the following equation:

$$(\boldsymbol{y}_{\boldsymbol{it}} - \bar{\boldsymbol{y}}_{i.} - \boldsymbol{y}_{.t} + \bar{\boldsymbol{y}}_{..}) = (\boldsymbol{x}_{\boldsymbol{it}} - \bar{\boldsymbol{x}}_{i.} - \boldsymbol{x}_{.t} + \bar{\boldsymbol{x}}_{..})\boldsymbol{\beta} + (\boldsymbol{v}_{\boldsymbol{it}} - \bar{\boldsymbol{v}}_{i.} - \bar{\boldsymbol{v}}_{.t} + \bar{\boldsymbol{v}}_{..}) \tag{25}$$

By running OLS on this model gives $\tilde{\beta}$, the within estimator. The within estimator for this model wipes out both the time-invariant and individual-invariant variables. As a conclusion, OLS ignores both sets of the dummy variables introduced here, whereas the one-way fixed effects model ignores one of them, and if the set of dummies ignored are statistically significant the model will suffer from omission variable bias. (Baltagi 2005)

3.6 Informational quality of the firm

For the purpose of this study I have chosen to use firm size and analyst coverage as proxies for firms' information uncertainty, both variables being easily measured and accessed. The objective is to find out whether informational quality of the firm influences' analysts' forecast error and/or characteristic forecast error. Zhang (2006b) uses similar variables and four additional measures in his study on stock returns, to measure the informational uncertainty of the firm. In this study firm size is measured as the market capitalization at previous year-end and analyst coverage is the average number of analysts following the firm during the previous fiscal year. Furthermore, both measures are transformed to natural logarithms, thus receiving the two explanatory variables SIZE and COV that are utilized in the following panel regressions:

$$\boldsymbol{FE^{A}}_{\boldsymbol{i,t}} = \boldsymbol{\beta_1 SIZE_{i,t-1}} + \boldsymbol{\beta_2 COV_{i,t-1}} + \boldsymbol{\lambda_1 D1_t} + \boldsymbol{\lambda_2 D2_t} + \boldsymbol{\lambda_3 D3_t} + \cdots + \boldsymbol{\lambda_T DT_t} + \boldsymbol{v_{it}} \tag{26}$$

$$\boldsymbol{FE^{C}}_{\boldsymbol{i,t}} = \boldsymbol{\beta_1 SIZE_{i,t-1}} + \boldsymbol{\beta_2 COV_{i,t-1}} + \boldsymbol{\lambda_1 D1_t} + \boldsymbol{\lambda_2 D2_t} + \boldsymbol{\lambda_3 D3_t} + \cdots + \boldsymbol{\lambda_T DT_t} + \boldsymbol{v_{it}} \tag{27}$$

Where $\mathrm{FE}^{A}{}_{i,t}$ stands for absolute analysts' forecast error and $\mathrm{FE}^{C}{}_{i,t}$ for absolute characteristic forecast error. $D1_t \ldots DT_t$ represents dummy variables for each time period (*T=7).* The forecast errors are explained as absolute values as in Coën et al. (2009), because the errors can have either sign, and for this research question I am only interested in the magnitude of the error. The regressions are fixed time-wise, because there is reasonable doubt that the effect of a given year, will be more or less the same for the entire population. The two explanatory variables exhibit near multicollinearity in the model, but the multicollinearity is ignored in this case, because we are not interested in the effects of the individual predictors.

The prediction is that firms' size negatively correlates with both forecast errors. It seems reasonable that smaller firms share less information about their prospects, already because of the costs of information disclosure. Also, for smaller firms less information disclosure is required by regulation than for larger firms. Similarly, coverage is expected to be negatively correlated with both forecast errors. Wider coverage of the company usually conveys more information to the market, analysts distribute information onwards, and simultaneously benefit one another. Hence, less information uncertainty is expected in firms with wider coverage. (Zhang 2006b)

Through this methodology the research attempts to find an answer to the third research question:

3. *"Does the informational quality of the firm affect the degree of analysts' forecast error and/or characteristic forecast error?"*

3.7 Timeline of the analysis

The timeline of the analysis for the first two research questions follow So's approach with minor alterations. The objective is to form the characteristic earnings forecast of year *t* earnings. In order to do so, data from year *t-3* onwards is needed; *t-3* to calculate asset growth and changes in accrual variables for *t-2* and *t-2* to run the regressions using *t-1* EPS as the dependent variable. Once the coefficients are obtained, they are applied on year *t-1* characteristics made available and observed at year *t*, thus achieving the objective of forming the characteristic forecast for year *t* earnings.

To be more specific, for a company using calendar year as fiscal year the financial statements will be available by the end of May. Using this financial statement data, the characteristics of the companies will be calculated, and the analysts' forecasts for year *t* earnings observed on May 31st of year *t*. The next day June 1st, the returns accumulation for the investment strategy will begin, and it will end in May 31st the next year that is year *t+1*. The five-month separation between fiscal year-end and the portfolio formation ensures that all the inputs are available before the selection of the portfolio. The timeline is presented in Figure 2 below.

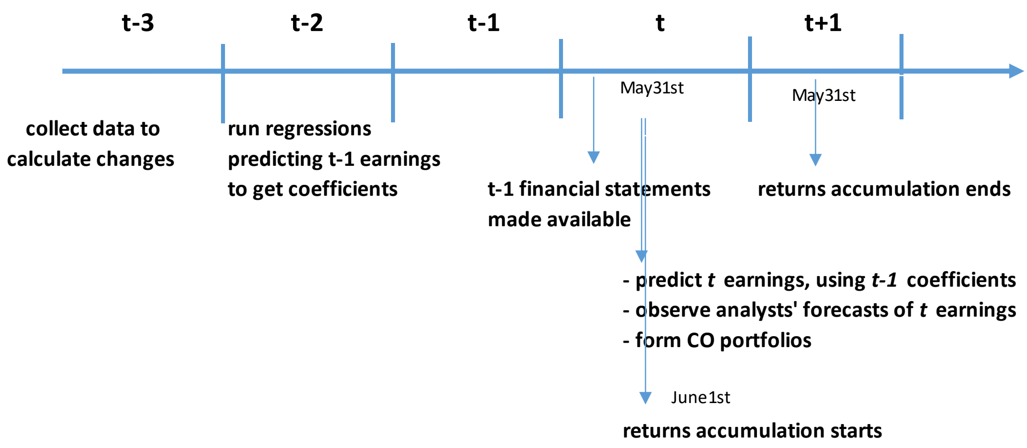


Figure 2 The timeline of the analysis.

Notes: The portfolio division is based on characteristic forecast optimism (CO), which equals the characteristic forecast (CF) subtracted by the analysts’ forecast (AF), divided by firms' total assets per share in the previous year. The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years’ characteristics. Analysts' forecast is the latest available mean consensus forecast on May 31st each year.

4 Empirical results

The results of the empirical analysis will be presented in this section. The regressions were first ran in natural sub-groups as in Fama and French (2006). Nevertheless, the main focus of the research is on the annual regressions with the full set of explanatory variables as demonstrated in the methodology section. Specifically, the results are shown as averages of these annual regression and year-level regression results are not given that much weight. However, the annual regression coefficients will be utilized for the earnings predictions. Additionally, full length of the data is utilized in a panel regression for the whole sample. The empirical analysis of the study is conducted using SAS Enterprise Guide. The data was manipulated, and regression were ran using this software.

4.1 Earnings regression results

First the independent variables were ran in natural subgroup, as in Fama and French (2006). This is done to show that they exhibit explanatory power used individually. There are five subgroups as presented in the first column of Table 3, and three of the groups only have a single independent variable. Total of 35 regressions were thus ran to obtain the results in Table 3. The results shown in Table 3 should be compared with discretion with the results of Fama and French (2006), as some of the explanatory variables are not exactly the same. Fama and French (2006) scales the independent variables with book equity, and also the dependent variable is scaled. Judging by the coefficients, the independent variables seem to have explanatory power on future earnings. However, only coefficients for earnings per share, dividends and stock price have statistically significant coefficients.

Table 3 Average annual results from cross-sectional regressions of earnings per share (EPS) in natural subgroups.

1.	Description	Coefficient	Standard Error	t-statistic	Adjusted-R^2
EPS_{t-1}	Earnings per share	***0.735	0.149	5.727	
NEGE_{t-1}	Loss indicator	-0.107	0.204	-0.342	
ACCN_{t-1}	Negative accruals per share	-0.051	0.148	-0.169	
ACCP_{t-1}	Positive accruals per share	-0.003	0.125	0.130	0.570
2.					
AG_{t-1}	Asset growth	0.303	0.485	0.350	0.006
3.					
DD_{t-1}	Zero dividend indicator	0.127	0.215	-0.497	
DIV_{t-1}	Dividends per share	***1.266	0.267	4.549	0.289
4.					
BTM_{t-1}	Book-to-market ratio	-0.229	0.108	-2.288	0.021
5.					
PRICE_{t-1}	Share price	***0.064	0.011	6.962	0.341

Notes: The yearly characteristics are derived from firms' financial statements using the Eikon database. The subgroups of the characteristic are as presented in the first column from 1 – 5. The last column shows the average adjusted-R^2 for each group. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

Table 4 below shows the average annual results for the yearly cross-section earnings regressions using White's heteroscedasticity-consistent standard errors. The coefficients indicate that negative earnings, negative accruals, positive accruals, asset growth, non-dividends and book-to-market ratio forecasts future earnings with a negative relationship. The signs of the coefficients found by So (2013) and Fama and French (2006) are shown in the last two columns of Table 4. With respect to these studies the signs are the same, except for negative accruals, which Fama and French (2006) did find negative, but So (2013) positive. The lagged EPS have by far the most explanatory power, with a coefficient of 0.492 being 2.507 standard errors from zero. The price variable receives a coefficient of 0.027, which is 3.642 standard errors from zero. None of the coefficients are statistically significant on average, using White's standard errors. However, coefficient for EPS was significant at 95% confidence interval in four out of seven of the annual regressions and for PRICE three out of seven.

Table 4 Average annual results from cross-sectional regressions of earnings per share (EPS) using White's standard errors.

	Description	Coefficient	Standard Error	t-statistic	p-value	So	F&F
Intercept		0.117	0.123	1.087	0.364	+	+
EPS_{t-1}	Earnings per share	0.494	0.228	2.507	0.152	+	+
NEGE_{t-1}	Loss indicator	-0.105	0.279	-0.222	0.629	-	-
ACCN_{t-1}	Negative accruals per share	-0.030	0.137	-0.042	0.339	+	-
ACCP_{t-1}	Positive accruals per share	-0.031	0.134	-0.134	0.578	-	-
AG_{t-1}	Asset growth	-0.192	0.395	-0.736	0.396	-	-
DD_{t-1}	Zero dividend indicator	-0.056	0.235	-0.545	0.439	-	-
DIV_{t-1}	Dividends per share	0.185	0.403	0.392	0.463	+	+
BTM_{t-1}	Book-to-market ratio	-0.106	0.093	-1.093	0.315	-	-
PRICE_{t-1}	Share price	0.027	0.016	1.631	0.223	+	+
Adjusted-R2		0.629					
N		192					

Notes: The yearly characteristics are derived from firms' financial statements using the Eikon database. The last two columns show the sign of the predicted coefficients of referred studies by So (2013) denoted as So and Fama and French (2006) denoted as F&F.

Similarly, to the findings of Fama and French (2006), the explanatory power of dividends largely disappears when used with the full set of explanatory variables in Table 4. Although, Fama and French (2006) used dividend relative to book equity per share and this study uses dividend per share, the two figures are still comparable. When dividends are used in the multivariate regressions their explanatory power most likely shifts to earnings, as dividend paying firms' earnings presumably are relatively high. Also, according to basically any valuation model, for example the one used by Fama and French (2006), expected dividends are considered in the stock price, hence the price variable is another receiver of the explanatory power of dividends. Interestingly enough, the slope for asset growth also turns negative for the multivariate regression, as it does in Fama and French (2006) study. This supports their finding that with controls for additional variables, higher asset growth affects earnings negatively.

The overall average adjusted-R^2 is 0.629, which indicates that the model explains a great portion of the variation in earnings. As a comparison, for So's data the model explained 56.1% on average. The adjusted-R^2 ranged from a high of 0.799 for the regression explaining 2013 earnings to the low of 0.403 for 2010. As can be seen from Table 3, lagged earnings and accruals alone already explains 57% of the variation, so including the remaining independent variables does not have a significant impact to the explanatory power of the model. The average number of firms in the yearly regressions were 192.

Additionally, a panel regression was ran for the whole sample using a two-way error component model described earlier. F-test for restricting the fixed effects to zero yielded a p-value of <0.001, so the restriction is not supported, and the two-way error component model can be applied. This regression utilizes the whole sample, while taking in to account the cross-sectional and time series dependencies of the observations. In similar fashion to the annual regressions, Table 5 shows the key results of the regression, moreover the number of cross-sections as well as the number of time series is displayed. The panel was unbalanced, hence the number of cross sections (318) only indicates the total number of distinct firms in the entire sample, not the number of firms each year. The R^2 for the two-way fixed effects model is 0.747, which is already over 10 percentage points higher than the average adjusted-R^2 in the annual regressions. Also, the statistical significances of the independent variables are more promising, as was expected, since the regression is utilizing the entire sample. Total of five independent variables are significant at 5%. Signs of the coefficients, however, are less expected, as the only negative ones are NEGE, AG, BTM and the intercept. However, the positive coefficients for both accrual variables are not statistically significant. Furthermore, the positive sign for the coefficient of zero dividend indicator -variable DD is significant at 5%, which is unexpected.

Table 5 Results of a two-way error component panel regression of earnings per share (EPS) using the full sample.

	Description	Coefficient	Standard Error	t-statistic	p-value
Intercept		-0.066	0.612	-0.110	0.915
EPS	Earnings per share	0.144	0.032	4.490	***0.000
NEGE	Loss indicator	-0.003	0.096	-0.030	0.974
ACCN	Negative accruals per share	0.031	0.027	1.150	0.252
ACCP	Positive accruals per share	0.005	0.033	0.160	0.870
AG	Asset growth	-0.074	0.114	-0.640	0.520
DD	Zero dividend indicator	0.192	0.081	2.380	***0.017
DIV	Dividends per share	0.555	0.097	5.730	***0.000
BTM	Book-to-market ratio	-0.230	0.040	-5.740	***0.000
PRICE	Share price	0.028	0.004	7.230	***0.000
R^2		0.747			
N of cross-sections		318			
N of time series		7			

Notes: The yearly characteristics are derived from firms' financial statements using the Eikon database. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

4.2 Characteristic forecasts

Table 6 shows an average Pearson correlation matrix for analysts' forecast (AF), characteristic forecast (CF) and realized earnings (RE). The findings are very similar to So's (2013), correlation between AF and RE being 0.122 percentage points higher than between CF and RE, for So (2013) the difference was 0.049. These results indicate analysts' forecast being a better estimate of realized earnings than the characteristic forecast. The average correlation between the two forecast is slightly lower (0.780) than for So's (2013) data

(0.851). The correlations differ only by few percent when using the median analyst' forecast instead of the mean (see Appendix 2).

Table 6 Person correlation matrix of characteristic forecast (CF), analysts' forecast (AF) and realized earnings (RE).

	CF	AF	RE
CF	1		
AF	0.780	1	
RE	0.702	0.824	1

Notes: The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available mean consensus forecast on May 31st each year.

Table 7 shows the annual mean error (ME), defined as realized earnings minus the contributing forecast. The signs for the AF mean errors indicate that on average analysts' forecast are optimistic, supporting the previous literature (Frankel & Lee 1998; Lin & McNichols 1998). These findings are in line with So's (2013), as the average values are very similar in his findings. The absolute values of the mean errors indicate that on average analysts' forecasts are less accurate than characteristic forecasts, the absolute mean error for the full sample being 0.232 for AF and 0.075 for CF. Interpreting the yearly values, the most accurate forecasts were done using CF for 2015 earnings with mean error of only 0.017. Only the values for 2013 and 2014 were negative for CF, making it a pessimistic forecast for most years. The most accurate average AF was for 2017 with mean error -0.117.

Table 7 Mean errors (ME) of characteristic forecast (CF) and analysts' forecast (AF) each year of the sample.

	2011	2012	2013	2014	2015	2016	2017	Avg
CF ME	0.214	0.074	-0.040	-0.031	0.017	0.063	0.228	0.075
AF ME	-0.161	-0.287	-0.292	-0.278	-0.290	-0.197	-0.117	-0.232

Notes: The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available mean consensus forecast on May 31st each year.

The annual forecasts can be seen in the graphical presentation of Figure 3, showing yearly averages for CF, AF and RE. The curve for AF is constantly above of that of RE. The curves for CF and RE move closer to one another, CF being above the curve of RE only in 2013 and 2014, as suggested already by their mean errors above. For 2015 CF is slightly pessimistic, with an average forecast only 0.020 lower than for realized earnings. The difference is highest in 2017 as the average forecast takes the opposite direction compared to RE. The curves follow similar trend with median forecasts, however the curve for CF moves more steeply. The figure for median forecasts can be accessed in Appendix 4.

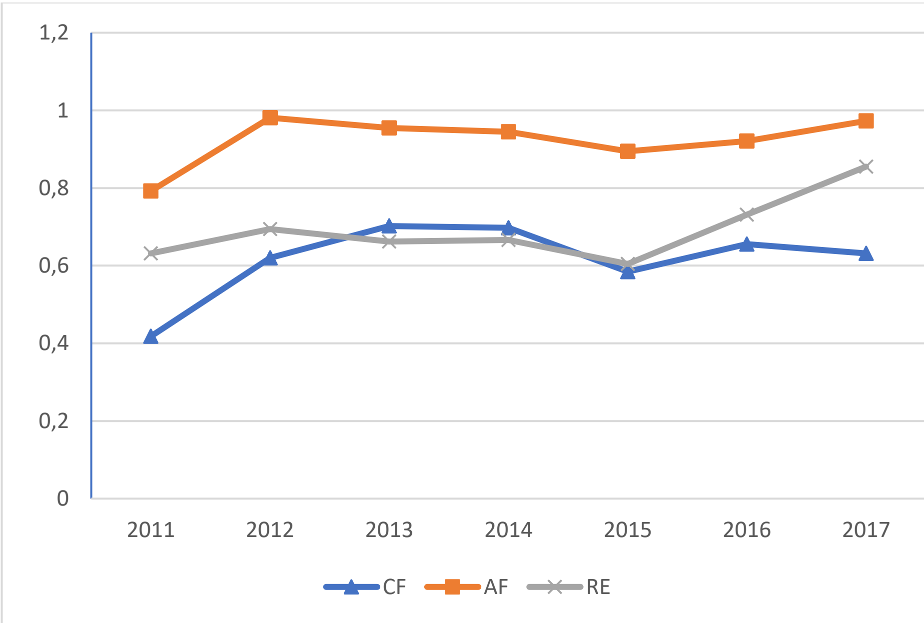


Figure 3 Characteristic forecast (CF), analysts' forecast (AF) and realized earnings (RE) yearly averages.

Notes: The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available mean consensus forecast on May 31st each year.

Having calculated the analysts' forecast and characteristic forecast, the companies were divided into quintiles each year according to characteristic forecast optimism (CO) described in equation (19). Table 8 shows descriptive statistics for CO as well as for CF, AF and RE. The mean value for AF compared to the mean value of RE clarifies the earlier finding that analysts tend to be overly optimistic. Mean value for CF is slightly lower than for RE, indicating that CF is on average pessimistic.

Table 8 Descriptive statistics of characteristic forecast (CF), analysts' forecast (AF), realized earnings (RE) and characteristic forecast optimism (CO) across the full sample.

	CF	AF	RE	CO
Min	-4.937	-1.656	-3.684	-1.636
Mean	0.612	0.919	0.688	-0.036
Median	0.496	0.687	0.516	-0.018
Max	4.872	8.523	7.602	0.547
Std Dev	0.746	0.932	0.890	0.104

Notes: The table shows the minimum, mean, median, maximum and the standard deviation of the variables. The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available mean consensus forecast on May 31st each year. CO equals CF subtracted by AF, divided by firms' total assets per share in the previous year. CO1 is the portfolio for the stocks with lowest CO and CO5 for the stocks with highest CO.

Descriptive statistics for each of the quintiles are also presented separately in Table 9, where CO1 is the portfolio for the stocks with lowest CO, meaning that CF is low compared to AF, correspondingly CO5 is the portfolio for the stocks with highest CO. Figure 4 shows the mean forecasts for each quintile in a graphical presentation, accompanied by the line for realized earnings.

Table 9 Descriptive statistics of characteristic forecast optimism (CO) quintiles.

	CO1 (Low)	CO2	CO3	CO4	CO5 (High)
Min	-1.636	-0.079	-0.046	-0.028	-0.007
Mean	-0.154	-0.037	-0.019	-0.006	0.036
Median	-0.095	-0.035	-0.017	-0.005	0.021
Max	-0.040	-0.019	-0.006	0.009	0.547
Std Dev	0.177	0.013	0.009	0.007	0.053

Notes: The table shows the minimum, mean, median, maximum and the standard deviation of the characteristic forecast optimism (CO) in each quintile. The characteristic forecast (CF) is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast (AF) is the latest available mean consensus forecast on May 31st each year. CO equals CF subtracted by AF, divided by firms' total assets per share in the previous year. CO1 is the portfolio for the stocks with lowest CO and CO5 for the stocks with highest CO.

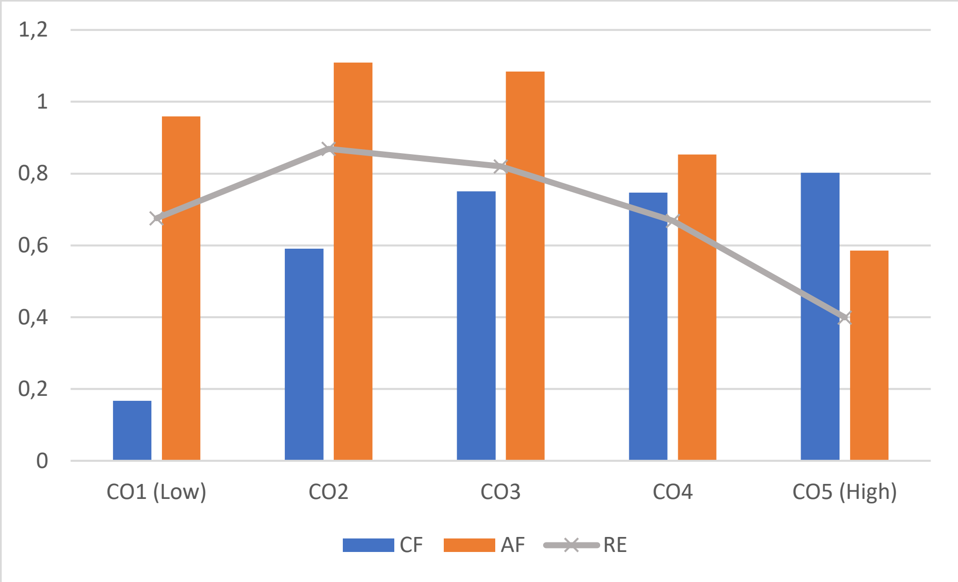


Figure 4 Characteristic forecast (CF), analysts' forecast (AF) and realized earnings (RE) averages by characteristic forecasts optimism (CO) quintiles.

Notes: The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available mean consensus forecast on May 31st each year. CO equals CF subtracted by AF, divided by firms' total assets per share in the previous year. CO1 is the portfolio for the stocks with lowest CO and CO5 for the stocks with highest CO.

Table 10 once again shows averages for CF, AF, RE, but each in quintiles of CO. The actual mean value of CO is presented in the next column, and by definition it is increasing towards the highest quintile. Also, the difference between realized earnings and the forecasts, defined as mean error (ME) earlier is presented for both forecasts in each quintile. Judging by the table, the analysts' forecast error does not increase across quintiles, therefore, the answer to the first research question is that characteristic forecast optimism, CO, does not positively predict analysts' forecast error. This can be easily observer in Figure 5 below, which presents the mean error for both forecasts across the quintiles. However, these results indicate that CF offers greater forecast accuracy compared to AF. The AF is higher than RE in every portfolio, whereas CF lower in the first three portfolios while higher in the last two portfolios.

Table 10 Mean values of characteristic forecast (CF), analysts' forecast (AF), realized earnings (RE), characteristic forecasts optimism (CO) and the mean error (ME) of the two forecasts for each characteristic forecast optimism quintile.

	CF	AF	RE	CO	CF ME	AF ME
CO1 (Low)	0.167	0.959	0.676	-0.154	0.509	-0.283
CO2	0.591	1.109	0.869	-0.037	0.278	-0.241
CO3	0.750	1.084	0.820	-0.019	0.070	-0.264
CO4	0.747	0.853	0.669	-0.006	-0.078	-0.184
CO5 (High)	0.802	0.585	0.399	0.036	-0.402	-0.186

Notes: The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available mean consensus forecast on May 31st each year. CO equals CF subtracted by AF, divided by firms' total assets per share in the previous year. CO1 is the portfolio for the stocks with lowest CO and CO5 for the stocks with highest CO.

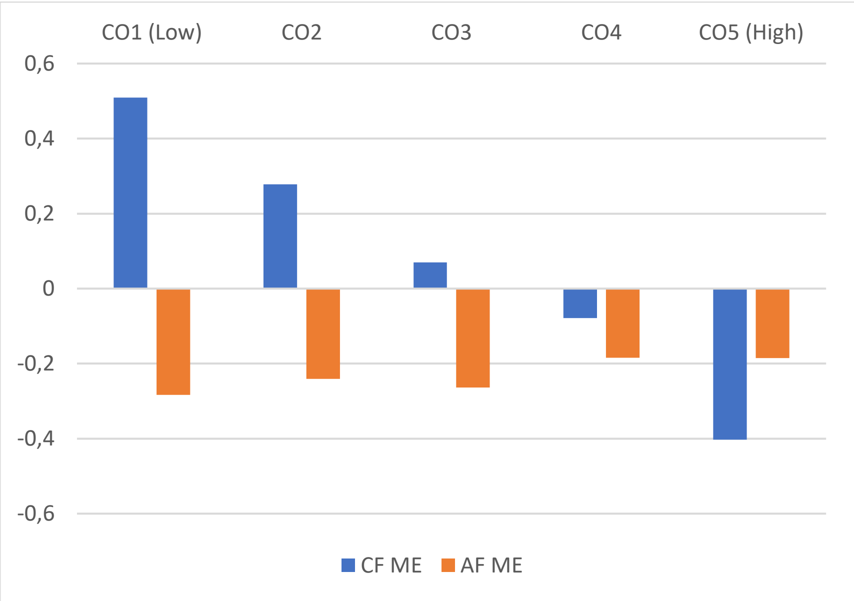


Figure 5 Mean errors of characteristic forecast (CF ME) and analysts' forecast (AF ME) for each characteristic forecast optimism (CO) quintile.

Notes: The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available mean consensus forecast on May 31st each year. CO equals CF subtracted by AF, divided by firms' total assets per share in the previous year. CO1 is the portfolio for the stocks with lowest CO and CO5 for the stocks with highest CO.

4.2.1 Forecast results by exchanges

While the Nordic markets are similar in many aspects, there seems to be differences between the exchanges in the forecast accuracy, as can be seen in Table 11. The forecast error is measured as an absolute value, because in this sub-section the research is only interested in the magnitude of the forecast error. For the sample in this study there is a clear negative linear relationship between the sample size on behalf of each exchange and the mean absolute analysts' forecast error, as the error is most severe for Copenhagen Stock Exchange, the smallest contributor to the sample and the lowest for Stockholm Stock Exchange, by far the biggest contributor. The sample size itself should not be the cause for analysts' forecast inaccuracy. However, the inaccuracy of the forecasts in the market may be an output of a more uncertain information environment, which bounds from the small number of firms in the market. Less information about peer companies and the industry under observation is available, thus less data on which to perform any kind of analysis is attainable.

The results for characteristic forecast do not seem to follow the same pattern. While Copenhagen is still the exchange that receives the most inaccurate forecasts and Oslo the very next, the companies with most predictable earnings by their characteristics seem to reside in Finland, with the absolute CF mean error of only 0.070 for Helsinki Stock Exchange. The second most accurate forecasts were for companies in Stockholm Stock Exchange with 0.103 absolute mean error.

Table 11 Absolute mean errors (ME abs) of characteristic forecast (CF) and analysts' forecast (AF) by exchanges.

	CF ME abs	AF ME abs
Copenhagen	0.415	0.425
Helsinki	0.070	0.193
Oslo	0.130	0.417
Stockholm	0.103	0.145

Notes: The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available mean consensus forecast on May 31st each year.

The differing accuracy in the analysts' and characteristic forecasts between the markets can also be the consequence of differing accounting disclosure requirements in the countries. A more transparent disclosure and a higher degree of enforcements of accounting standards reduces the informational uncertainty and hence increase the forecast accuracy (Hope 2003). The credibility of the accounting figures directly affects the accuracy of the characteristic forecast, as it does not consider the trustworthy of individual figures or companies, as analysts may do. Also, the characteristic approach is much slower in incorporating any news and ongoing trends into the forecasts; a weakness of the approach that will be discussed in more detail in the following sub-chapter.

4.3 Investment strategy

The investment strategy in this study is based on the characteristic forecast optimism (CO). Long position is taken on firms in the high CO quintile and short position on those in the low CO quintile. The strategy returns are calculated from June until May each year. The year in the table indicates the year in which the strategy returns calculation ends, so for example the returns for the last column in Table 12 below, indicating 2017, are calculated from June 2016 until May 2017. The returns are calculated as compounded daily returns and the dividends are included, using the dividend reinvested total returns methodology. The returns are presented as raw returns; thus, they have not been market-adjusted. Table 12 shows the average annual returns for each CO quintile, as well as the yearly averages for all firms and the returns for the long-short strategy. Even though, the returns do not increase across quintiles as the third quintile (CO3) generates the highest annual returns with 19.126% and the high quintile (CO5) generates only the second-best returns with 18.896%, the long-short still managed to generate 2.371% annual return on average throughout the seven-year time period. Therefore, the answer to the second research questions is that the characteristic forecast optimism does positively predict future abnormal returns. The transaction costs for the strategy are not very high as the portfolio needs only a single rebalance each year, but still for a small investor the returns would not be very significant after transaction costs are considered. For a large-scale institutional investor, the returns are still attractive.

Table 12 Average annual returns percentages for characteristic forecast optimism (CO) quintiles, annual average returns percentages for all firms and for the long-short investment strategy.

	2011	2012	2013	2014	2015	2016	2017	Total
CO1 (Low)	19.572	-26.065	20.625	42.240	29.890	9.627	19.791	16.526
CO2	27.981	-18.952	26.010	33.049	17.831	14.190	25.178	17.898
CO3	25.028	-5.240	27.216	33.212	25.723	5.918	22.024	19.126
CO4	17.789	-20.433	28.156	30.519	15.536	6.347	30.710	15.518
CO5 (High)	19.984	-15.231	34.467	43.634	18.031	-2.462	33.851	18.896
Avg	22.071	-17.184	27.295	36.531	21.402	6.724	26.311	17.593
High-Low	0.413	10.834	13.842	1.394	-11.858	-12.089	14.060	2.371

Notes: The returns include the price change from June 1st previous year until May 31st the current year plus any relevant dividends during the period. The returns are calculated as compounded daily returns using the dividend reinvested total return methodology. The characteristic forecast (CF) is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast (AF) is the latest available mean consensus forecast on May 31st each year. CO equals CF subtracted by AF, divided by firms' total assets per share in the previous year. CO1 is the portfolio for the stocks with lowest CO and CO5 for the stocks with highest CO.

The average annual returns for the full sample are 17.593%. There are noticeable differences in the sample in annual returns between observation years, the average returns ranging from a high of 36.531 for 2014 to a low of -17.184 for 2012. The 2011 – 2012 returns period was bad for the entire sample as all the quintiles generated negative returns during the period. Interestingly, only one quintile apart from 2012 generates negative returns in the whole sample, and this is the highest quintile for 2016. Because of the weak performance of the CO5 quintile, the long-short strategy returns for 2016 are the worst across the sample with -12.089% annual return. Digging deeper into the data on this particular quintile, I discovered that the two worst performing companies, which both suffered substantial losses during the period, were Archer Ltd and Petroleum Geo-Services ASA. Both are Norwegian oil industry companies with annual returns for the given period of -76.751% and -50.515%, respectively. The most probable cause for this is the price drop in crude oil prices during 2014 and 2015. For example, from June 1st, 2015 to May 31st, 2016, the period for which the 2016 strategy returns are calculated, the Brent Crude index decreased by over 20 (Thomson Reuters Eikon). This finding shows the weakness of the characteristic approach, as it cannot incorporate news and market trends into the forecasts as quickly as most analysts' can, as it uses coefficients based on two-year old characteristics applied on characteristics of the preceding year. Also, due to the relatively small sample size, the effect of such returns on the strategy performance can be drastic.

Inferences of the weight's investors assign on these forecasts can be drawn from the fact that the highest quintile is consistently beating the lowest quintile in this sample. This indicates that the market puts more than optimal weight on the analysts' forecast and less than optimal on characteristic forecast. Looking at the CO quintile returns in Table 12, we can see that the middle portfolio generated the highest returns. For this portfolio realized earnings lie in between the two forecasts in Figure 4. This suggest that by incorporating complementary information into analysts' forecast with the help of characteristic approach, more accurate and trustworthy forecasts can be achieved.

The yearly results are robust to using different division to portfolios. Division into eight groups shows very similar results with average annual returns of 2.168%. When divided only into two groups the returns for the investment strategy reduces mildly to 1.771%. The results of the investment strategy using the differing divisions can be accessed through Appendices 5 and 6.

Table 13 shows the average returns for each month starting from June and the returns for the long-short strategy on monthly basis. The returns for the monthly strategy are calculated as compounded daily returns and they do not include dividends. When calculated monthly, the long-short strategy generates average monthly returns of 0.098%, with 8/12 months generating positive returns. This again suggest a profitable investment strategy for institutional investors.

Looking at the monthly averages for the full sample, the most profitable months are February and July, with monthly return averages of 3.882% and 3.114%, respectively. Even though, dividends are not included in the returns, the relatively high returns for February could be caused by the stock price behaviour around the ex-dividend date. Investors interested in the dividend yield will buy the stock leading up to the ex-dividend day. Financial theory suggest that the price drop of a stock should approximately equal the amount of the dividend on the ex-dividend date, and this could again cause the relatively low returns in March. (Campbell & Beranek 1955)

Table 13 Average monthly returns percentages for characteristic forecast optimism (CO) quintiles each month and the returns of each month for the long-short investment strategy.

	June	July	August	September	October	November	December	January	February	March	April	May	Total
CO1 (Low)	-3.381	3.230	-2.193	1.183	2.608	2.173	2.132	2.102	3.625	1.026	1.506	1.871	1.324
CO2	-2.930	2.968	-1.094	0.056	2.403	1.200	2.265	1.869	3.967	1.360	3.098	0.699	1.322
CO3	-2.674	3.214	-1.411	0.991	2.390	2.669	3.110	0.961	4.573	1.220	2.652	1.411	1.592
CO4	-3.235	3.277	-1.771	1.131	2.805	1.781	2.352	1.455	4.327	0.881	1.416	0.035	1.204
CO5 (High)	-2.331	2.882	-1.734	2.416	2.868	2.503	1.471	2.410	2.916	1.288	2.149	0.220	1.421
Avg	-2.910	3.114	-1.641	1.155	2.615	2.065	2.266	1.759	3.882	1.155	2.164	0.847	1.373
High-Low	1.050	-0.349	0.459	1.233	0.260	0.330	-0.661	0.308	-0.709	0.262	0.643	-1.652	0.098

Notes: The returns include the price change during the month and the returns are calculated as compounded daily returns. The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available mean consensus forecast on May 31st each year. Characteristic forecast optimism equals the characteristic forecast subtracted by analysts' forecast, divided by firms' total assets per share in the previous year. CO1 is the portfolio for the stocks with lowest CO and CO5 for the stocks with highest CO.

4.4 Informational quality of the firm

Table 14 shows the results of a time-wise fixed effects panel regression where absolute analysts' forecast error is explained by lagged firm size and analysts' coverage. As the table indicates, both independent variables are statistically significant, SIZE at 10% and COV at 5%, while the intercept of the model at 1%. The SIZE variable receives a negative coefficient as expected. This means that for larger firms the absolute analysts' forecast error is smaller, thus, reinforcing the prediction that for larger firms, earnings are more easily forecasted by analysts. However, the positive sign of COV is unexpected and needs to be considered in more detail.

Table 14 Results of a time-wise fixed effects panel regression where absolute analysts' forecast error is explained by lagged firm size (SIZE) and analysts' coverage (COV).

	Coefficient	Standard Error	t-statistic	p-value
Intercept	0.318	0.088	3.630	0.000***
SIZE	-0.030	0.016	-1.930	0.054*
COV	0.063	0.027	2.330	0.020**
R^2	0.014			

Notes: SIZE is the log of firm's market capitalization at previous year-end and COV is the log of average analyst following the firm during previous fiscal year. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

The positive sign implies that for firms with less coverage, the analysts' consensus forecasts are more accurate. This is opposite to the prediction set, that for firms with wider coverage the information uncertainty should be smaller, and hence the forecasts more accurate. The positive sign could be an outcome of "herding", meaning that analysts tend to adjust their forecasts towards the consensus, rather than solely forecasting on basis of their valuations, a phenomenon that for example was found with regards to forecast revisions by Gleason and Lee (2003). If this behaviour exists in the sample, most likely such behaviour would be found for firms with relatively wide coverage. This could bias analysts' forecast and the errors would increase with the "width" of the coverage of the firms, which could explain the positive sign. Also, for companies that have more coverage, there might exist more incentives for analysts to report biased estimates. For example, in order to increase the probability of winning a deal for the analyst's company for an upcoming SEO issued by the firm under observation, the analyst can bias the forecast upwards (Michaely & Womack 1999). This sort of behavioural explanation could again cause the positive sign on the coefficient of COV. Whatever the cause of sign, the answer to first part of the research question based on these results is that the informational quality of the firm does not affect the degree of analysts' forecast error.

The same analysis was also ran for characteristic forecast, to find out the effects of firms' size and coverage on characteristic forecast error. The results are presented in Table 15 below. The coefficients of the explanatory variables and the intercept are similar to those in the regressions explaining analysts' forecast error. SIZE again receives a negative coefficient, while COV a positive one. However, only the intercept of the model is statistically significant. The R^2 for the regression explaining CF error is one percentage point higher than for AF error with 1.5%.

Table 15 Results of a time-wise fixed effects panel regression where absolute characteristic forecast error is explained by lagged firm size (SIZE) and analysts' coverage (COV).

	Coefficient	Standard Error	t-statistic	p-value
Intercept	0.351	0.093	3.780	0.000***
SIZE	-0.005	0.017	-0.320	0.751
COV	0.045	0.029	1.570	0.117
R^2	0.015			

Notes: SIZE is the log of firm's market capitalization at previous year-end and COV is the log of average analyst following the firm during previous fiscal year. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

Similarly, the positive coefficient for COV is unexpected, as it suggests that the CF error increases with the coverage. Although, the relationship between the variables is not as clear, as it is for AF error, as the CF exploits characteristics of the firm from year *t-1*, while the CF error is not observed until *t+1* and yet again the proxies for informational quality are observed at year ending *t*. The positive coefficient for COV and already the statistical insignificance of the two variables, allows me to conclude that the informational quality of the firm does not affect the degree of characteristic forecast error.

5 Conclusions

This research studied the analysts' forecast error in the Nordic capital markets. The methodology, firstly introduced by So (2013), was implemented to avoid biases most often emerging from the traditional approaches on predicting analysts' forecast error. The methodology involves forecasting companies' earnings directly from the characteristics of the companies obtained from financial statements, and comparing them to analysts' earnings forecasts, thus creating an unbiased estimate of the analysts' forecast error. Through the approach the objective was not only to predict earnings and analysts' forecast error, but also to recognize if investors are systematically overweighting analysts' forecasts. For the latter objective, an investment strategy was implemented based on the differences between the two forecasts.

There exist many incentives for analysts to bias their earnings forecasts, and for the Nordic markets the analysts' forecasts seems to exhibit bias, as the forecasts are constantly above realized earnings. Same pattern has been found in numerous previous studies, including the reference paper by So (2013), and many others discussed in the literature review of this research. In a sample that consisted of companies from four different Nordic counties' stock exchanges, the bias in analysts' forecasts was found to be the most severe in Copenhagen Stock Exchange and Oslo Stock Exchange.

The results of the earnings regressions using nine characteristics, derived from the work of Fama and French (2006), provided proof on cross-sectional earnings forecast performance. The regression coefficients indicated that negative earnings, book-to-market ratio, accruals, not paying dividends and asset growth negatively affect future returns, while lagged earnings, dividends and stock price had a positive effect. The annual regression coefficients were fitted to the current characteristics of the firms, thus achieving an unbiased measure of future earnings, the characteristic forecast. Also, prevailing analysts' mean consensus forecasts for current year's earnings were observed at the same point in time. Comparing the two forecasts with realized earnings, the characteristic forecasts was more accurate.

The research investigated deeper into these forecasts and a division into quintiles was performed on basis of the difference of these two. Specifically, the companies were divided into quintiles of characteristic forecast optimism, a measure that scales the difference with total assets of the company. As the analysts' forecast error do not increase across the quintiles, the answer to the first research question is that the characteristic forecast optimism does not positively predict analysts' forecast error. The forecast error was found to be highest in the first quintile and only second lowest in the fifth quintile. As unexpected as this was, judging by the mean errors of the two forecasts, the characteristic forecast was still able to produce more accurate forecasts. Therefore, the implementation of the investment strategy was supported.

The second research question was also based on the characteristic forecast optimism. The objective was to reveal whether characteristic forecast optimism convey information about the prospects of the companies, and to access the degree of investors' overweighting of analysts' forecasts, by answering if characteristic forecast optimism positively predicts future abnormal returns. Similarly, there is no linear positive relationship between the characteristic forecast optimism and the strategy returns, as the highest quintile generated only the second-best returns. However, the strategy still managed to generate noticeable annual raw returns averaging an annual return of 2.371% for the full sample with five out of seven sample years generating positive returns. The same strategy was able to produce abnormal returns also on a monthly basis. Therefore, an answer to the second research question is that the characteristic forecast optimism does positively predict future abnormal returns.

The highest quintile was consistently beating the lowest quintile in the sample; hence I can reason that investors do place more than optimal weight on analysts' forecasts, and less than optimal on characteristic forecast. This suggests that when making investment decisions investors should incorporate additional information into their decision-making in order to make well-advised investment decisions, instead of using analysts' forecasts directly. Especially small investors, who are found not to consider the possibility of biases in analysts' forecasts. In line with So's (2013) conclusion I will also make a notion that, due the effects of inaccurate analysts' forecasts on small investors, regulators should take measures in trying to improve analysts' forecasts.

Additionally, to the two main research questions, the companies' informational quality was accessed, and a third research question based on it was developed. Informational quality was measured with two proxies, the log of firm size and the log of analyst coverage. The proxies were utilized in regressions explaining the analysts' and the characteristic forecast error, and contradictory evidence were found. While the size positively affected the accuracy of both forecasts the same was not found for coverage, and an answer to the third research question concludes that the informational quality of the firm does not affect the analysts' nor the characteristic forecast error. The unexpected sign of the coefficient for the coverage variable can be due to unobservable biases in analysts' forecast or other such factors ignored by the model. Measuring the effect on the forecast errors using more proxies for informational quality could reveal more and would be an interesting subject for a later study.

The research was carried out following the methodology by So (2013) for the first two research questions. So (2013) found that the characteristic forecast optimism predicts analysts' forecast error and future abnormal returns. Both the analysts' forecast error, and the returns for the long-short strategy in So's (2013) sample increased across quintiles, and the long-short strategy managed to generate abnormal returns with a one and a half-year investment horizon. The results are comparable to the results of this research, even though this research did not find the characteristic forecast optimism predicting the analysts' forecast error, the long-short strategy was still successful in this study. There were obviously differences in the samples between the studies, as So (2013) concentrated on the U.S. market while this study focused on the Nordic markets. Also, the sample size already was significantly larger for So's (2013) study. However, in both markets, analysts tend to be overly optimistic and this enabled the abnormal returns for the long-short strategy in both studies, regardless of the differences in the markets.

Based on these findings, the implementation of the characteristic approach is supported for the Nordic markets. However, further specification on the selection of the characteristics could be examined, and perhaps a set of even more suitable characteristics for the market could be found. This would require a thorough research of the effects of supplementary characteristics desired for the model, but this would surely be an interesting subject for a further study.

Other further research topics on the area of analysts' forecast error could be the information content of an individual analyst's reports (for example, Frankel et al. 2006). There is also a wide range of studies focusing on the analysts forecast accuracy, based on either past performance of the analyst (for example, Brown 2001) or the characteristics of the analyst (for example, Clement & Tse 2003; Keskek 2017), which could be interesting topics. Also, one possible topic for further research could be a study focusing on paid-for equity research, which in the wake of Mifid II regulation has become more popular, as financial institutions are finding new earnings opportunities. Study focusing on the credibility of such research compared to a traditional research would surely be needed.

References

ABARBANELL, J. and LEHAVY, R., 2003. Biased forecasts or biased earnings? The role of reported earnings in explaining apparent bias and over/underreaction in analysts' earnings forecasts. Journal of Accounting and Economics, 36(1), pp. 105-146.

ALFORD, A. and BERGER, P., 1999. A simultaneous equations analysis of forecast accuracy, analyst following, and trading volume. Journal of Accounting, Auditing & Finance, 14(3), pp. 219-240.

ALI, A., KLEIN, A. and ROSENFELD, C., 1992. Analysts' Use of Information about Permanent and Transitory Earnings Components in Forecasting Annual EPS. Accounting Review, 67(1), pp. 183-198.

BALTAGI, B.H., 2005. Econometric analysis of panel data. 3rd ed edn. Chichester: Wiley.

BARNIV, R.A.N. and MYRING, M., 2006. An international analysis of historical and forecast earnings in accounting-based valuation models. Journal of Business Finance and Accounting, 33(7-8), pp. 1087-1109.

BARRON, O.E., BYARD, D., KILE, C. and RIEDL, E.J., 2002. High-technology intangibles and analysts' forecasts. Journal of Accounting Research, 40(2), pp. 289-312.

BROOKS, C., 2014. Introductory econometrics for finance. 3rd ed edn. Cambridge: Cambridge University Press.

BROWN, L., 2001. How important is past analyst forecast accuracy? Financial Analysts Journal, 57(6), pp. 44-49.

CAMPBELL, J.A. and BERANEK, W., 1955. STOCK PRICE BEHAVIOR ON EX-DIVIDEND DATES. The Journal of Finance, 10(4), pp. 425-429.

CLEMENT, M.B. and TSE, S.V., 2003. Do Investors Respond to Analysts' Forecast Revisions as if Forecast Accuracy Is All That Matters? Accounting Review, 78(1), pp. 227.

COËN, A., DESFLEURS, A. and L'HER, J., 2009. International evidence on the relative importance of the determinants of earnings forecast accuracy. Journal of economics and business, 61(6), pp. 453-471.

DAS, S., LEVINE, C.B. and SIVARAMAKRISHNAN, K., 1998. Earnings predictability and bias in analysts' earnings forecasts. Accounting Review, 73(2), pp. 277.

EASTERWOOD, J.C. and NUTT S.R., 1999. Inefficiency in Analysts' Earnings Forecasts: Systematic Misreaction or Systematic Optimism? Journal of Finance, 54(5), pp. 1777-1797.

ELGERS, P. and MURRAY D., 1992. The relative and complementary performance of analyst and security-price-based measures of expected earnings. Journal of Accounting and Economics, 15(2), pp. 303-316.

FAMA, E.F. and FRENCH, K.R., 1992. The Cross-Section of Expected Stock Returns. Journal of Finance, 47(2), pp. 427-465.

FAMA, E.F. and FRENCH, K.R., 1995. Size and Book-to-Market Factors in Earnings and Returns. The Journal of Finance, 50(1), pp. 131-155.

FAMA, E.F. and FRENCH, K.R., 2001. Disappearing dividends: changing firm characteristics or lower propensity to pay? Journal of Financial Economics, 60(1), pp. 3-43.

FAMA, E.F. and FRENCH, K.R., 2006. Profitability, investment and average returns. Journal of Financial Economics, 82(3), pp. 491-518.

FRANKEL, R., KOTHARI, S.P. and WEBER, J., 2006. Determinants of the informativeness of analyst research. Journal of Accounting and Economics, 41(1), pp. 29-54.

FRANKEL, R. and LEE, C.M., 1998. Accounting valuation, market expectation, and cross-sectional stock returns. Journal of Accounting and Economics, 25(3), pp. 283-319.

GINTSCHEL, A. and MARKOV, S., 2004. The effectiveness of Regulation FD. Journal of Accounting and Economics, 37(3), pp. 293-314.

GLEASON, C.A. and LEE, C., 2003. Analyst Forecast Revisions and Market Price Discovery. The Accounting Review, 78(1), pp. 193-225.

GU, F. and WANG, W., 2005. Intangible Assets, Information Complexity, and Analysts' Earnings Forecasts. Journal of Business Finance & Accounting, 32(9), pp. 1673-1702.

HODGDON, C., TONDKAR, R.H., HARLESS, D.W. and ADHIKARI, A., 2008. Compliance with IFRS disclosure requirements and individual analysts' forecast errors. Journal of International Accounting, Auditing and Taxation, 17(1), pp. 1-13.

HOPE, O., 2003. Disclosure Practices, Enforcement of Accounting Standards, and Analysts' Forecast Accuracy: An International Study. Journal of Accounting Research, 41(2), pp. 235-272.

HOU, K., VAN DIJK, M.A. and ZHANG, Y., 2012. The implied cost of capital: A new approach. Journal of Accounting and Economics, 53(3), pp. 504-526.

HUGHES, J., LIU, J. and SU, W., 2008. On the relation between predictable market returns and predictable analyst forecast errors. Review of Accounting Studies, 13(2), pp. 266-291.

IRVINE, P.J., 2004. Analysts' Forecasts and Brokerage-Firm Trading. Accounting Review, 79(1), pp. 125-149.

IVKOVIĆ, Z. and JEGADEESH, N., 2004. The timing and value of forecast and recommendation revisions. Journal of Financial Economics, 73(3), pp. 433-463.

JOHNSON, T.C., 2004. Forecast Dispersion and the Cross Section of Expected Returns. Journal of Finance, 59(5), pp. 1957-1978.

KESKEK, S., 2017. The Effects of Disclosure and Analyst Regulations on the Relevance of Analyst Characteristics for Explaining Analyst Forecast Accuracy. Journal of Business Finance & Accounting, 44(5-6), pp. 780-811.

KIM, J.-., LI, L. and ZHANG, H., 2017. Analyst Forecast Accuracy and Media Independence. Financial Management, 46(4), pp. 1023-1051.

KOTHARI, S.P., 2001. Capital markets research in accounting. Journal of Accounting and Economics, 31(1), pp. 105-231.

LANG, M.H., 2004. Concentrated Control, Analyst Following, and Valuation: Do Analysts Matter Most When Investors Are Protected Least? Journal of Accounting Research, 42(3), pp. 589-623.

LIN, H. and MCNICHOLS, M.F., 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. Journal of Accounting and Economics, 25(1), pp. 101-127.

LO, M.H. and ELGERS, P.T., 1998. Alternative adjustments to analysts' earnings forecasts: Relative and complementary performance. Financial Review, 33(2), pp. 99.

LONG, J.S. and ERVIN L.H., 2000. Using Heteroscedasticity Consistent Standard Errors in the Linear Regression Model. The American Statistician, 54(3), pp. 217-224.

LOPEZ, T.J. and REES, L., 2002. The Effect of Beating and Missing Analysts’ Forecasts on the Information Content of Unexpected Earnings. Journal of Accounting, Auditing & Finance, 17(2), pp. 155-184.

MACKINNON, J.G. and WHITE, H., 1985. Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. Journal of Econometrics, 29(3), pp. 305-325.

MALMENDIER, U. and SHANTHIKUMAR, D., 2007. Are small investors naive about incentives? Journal of Financial Economics, 85(2), pp. 457-489.

MARTIKAINEN, M. 2003. Earnings management as a predictor of future profitability of Finnish firms. European Accounting Review, 12(2), pp. 311-325.

MICHAELY, R. and WOMACK, K.L., 1999. Conflict of interest and the credibility of underwriter analyst recommendations. The Review of Financial Studies, 12(4), pp. 653-686.

MIKHAIL, M., WALTHER, B. and WILLIS, R., 2007. When Security Analysts Talk, Who Listens? The Accounting Review, 82(5), pp. 1227-1253.

MONTE-MOR, D.S., GALDI, F.C. and COSTA, C.M., 2018. The role of accounting fundamentals and other information in analyst forecast errors. International Finance, 21(2), pp. 175-194.

PAYNE, J.L., 2008. The influence of audit firm specialization on analysts' forecast errors. Auditing, 27(2), pp. 109-136.

PAYNE, J.L. and THOMAS, W.B., 2003. The Implications of Using Stock-Split Adjusted I/B/E/S Data in Empirical Research. Accounting Review, 78(4), pp. 1049-1067.

PAYNE, J.L. and ROBB, S.W.G., 2000. Earnings Management: The Effect of Ex Ante Earnings Expectations. Journal of Accounting, Auditing & Finance, 15(4), pp. 371-392.

RAGHAVAN, A., 1997. Jack of all trades: How one top analyst vaults 'Chinese wall' to do deals for firm. Wall Street Journal, p. A.

SLOAN, R.G., 1996. Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? The Accounting Review, 71(3), pp. 289-315.

SO, E., 2013. A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts? Journal of Financial Economics, 108(3), pp. 615.

VERBEEK, M., 2008. A guide to modern econometrics. 3rd ed edn. Chichester: Wiley.

WALLACE, T.D. and HUSSAIN A., 1969. The Use of Error Components Models in Combining Cross Section with Time Series Data. Econometrica, 37(1), pp. 55.

WHITE, H., 1980. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. Econometrica, 48(4), pp. 817-838.

ZHANG, X.F., 2006A. Information Uncertainty and Analyst Forecast Behavior. *Contemporary Accounting Research,* **23**(2), pp. 565-590.

ZHANG, X.F., 2006B. Information Uncertainty and Stock Returns. *Journal of Finance,* **61**(1), pp. 105-137.

Appendices

Appendix 1 Descriptions of the items used from Eikon.

Item	Description
EPS actual	Earnings Per Share is defined as the EPS that the contributing analyst considers to be that with which to value a security. This figure may include or exclude certain items depending on the contributing analyst’s specific model.
Total current assets	Is the sum of: Cash and Short-Term Investments; Total Receivables, Net; Total Inventory; Prepaid Expenses and Other Current Assets, Total.
Notes payable/short-term debt	Represents short-term bank borrowings. It also represents notes payable that are issued to suppliers, reported outside of Trade/Accounts Payable
Cash and short-term investment	Is the sum of: Cash, Cash & Equivalents and Short-Term Investments.
Total current liabilities	Represents current liabilities for industrial and utility companies.
Total assets reported	Represents the total assets of a company.
Dividend per share actual	Dividend Per Share are a corporation’s common stock dividends on an annualized basis, divided by the weighted average number of common shares outstanding for the year. In the US dividend per share is calculated before withholding taxes (though for some non-US companies DPS is calculated after withholding taxes).
Price / book value per share	A security's price divided by its Book Value Per Share Actual. Book Value Per Share is a company's common stock equity as it appears on a balance sheet equal to total assets minus liabilities, preferred stock, and intangible assets such as goodwill, divided by the weighted average number of total shares outstanding for the year.
Hist fscl period price close (fin cur)	This item represents Historic Price Close as of the fiscal period end date converted into financial currency. If fiscal period end date is holiday or weekend then the closest price will be used.
Earnings per share - Mean	The statistical average of all broker estimates. Earnings Per Share is defined as the EPS that the contributing analyst considers to be that with which to value a security. This figure may include or exclude certain items depending on the contributing analyst’s specific model.

Total return	The total return incorporates the price change and any relevant dividends for the specified period. Compounded daily return for the specified period is used to calculate Total Return and it's effectively the dividend reinvested Total Return methodology. The most recently completed trading day is set as the default period. The Dividend type used is the most widely reported Dividend for a market and it is either Gross or Net.
Basic weighted average shares	Represents the weighted average common shares outstanding less the dilution of stock options for a given period. These shares are used to calculate Basic EPS.
Analyst coverage	Average analysts following the firm during the fiscal year rounded to nearest integer.

Appendix 2 Person correlation matrix of characteristic forecast, analysts' forecast and realized earnings, using median analysts' consensus forecasts.

	CF	AF	RE
CF	1		
AF	0.806	1	
RE	0.733	0.826	1

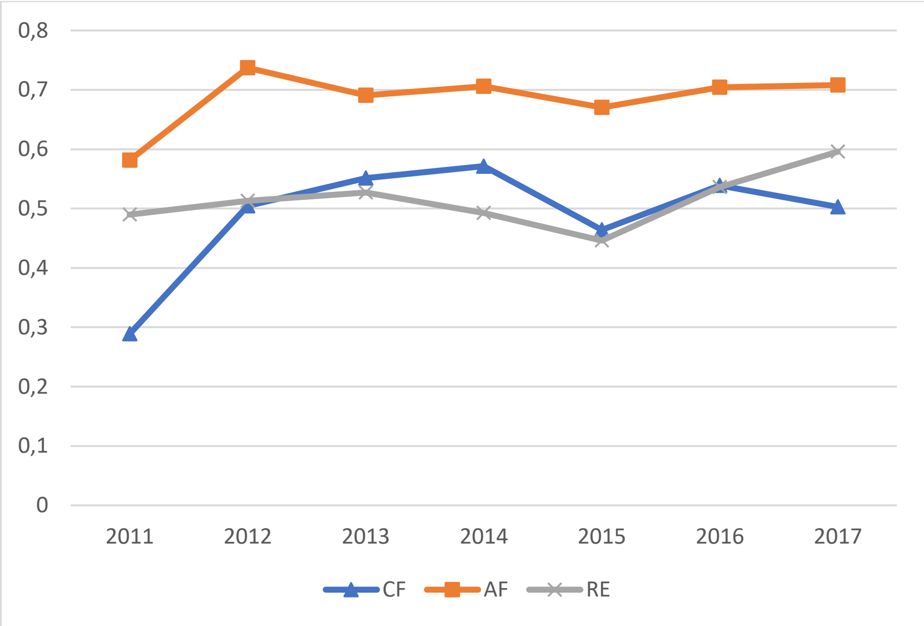
Notes: The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available median consensus forecast on May 31st each year.

Appendix 3 Yearly mean errors of characteristic forecast and analysts' forecast, using median analysts' consensus forecasts.

	2011	2012	2013	2014	2015	2016	2017	Avg
CF	0.186	0.056	-0.01	0.019	0.022	0.132	0.093	0.071
AF	-0.156	-0.284	-0.286	-0.275	-0.291	-0.186	-0.113	-0.227

Notes: The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available median consensus forecast on May 31st each year.

Appendix 4 Characteristic forecast, analysts' forecast and realized earnings yearly medians.



Notes: The characteristic forecast is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast is the latest available mean consensus forecast on May 31st each year.

Appendix 5 Average annual returns for high and low CO portfolios, annual average returns for all firms and returns for the long-short investment strategy.

	2011	2012	2013	2014	2015	2016	2017	Total
CO1 (Low)	19.051	-15.828	29.243	35.157	17.893	1.696	29.782	16.713
CO2 (High)	25.217	-18.559	25.372	37.769	24.616	12.246	22.729	18.484
High-Low	6.166	-2.731	-3.872	2.612	6.724	10.550	-7.053	1.771

Notes: The returns include the price change from June 1st previous year until May 31st the current year plus any relevant dividends during the period and the returns are calculated as compounded daily returns using the dividend reinvested total return methodology. The characteristic forecast (CF) is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast (AF) is the latest available mean consensus forecast on May 31st each year. CO equals CF subtracted by AF, divided by firms' total assets per share in the previous year. CO1 is the portfolio for the stocks with lowest CO and CO2 for the stocks with highest CO.

Appendix 6 Average annual returns for eight portfolios formed based on CO, annual average returns for all firms and returns for the long-short investment strategy.

	2011	2012	2013	2014	2015	2016	2017	Total
CO1 (Low)	17.449	-29.344	24.459	53.131	23.227	4.573	27.491	17.284
CO2	19.284	-21.662	22.784	26.527	26.770	16.109	18.715	15.504
CO3	35.859	-22.279	22.258	35.149	20.649	18.206	21.448	18.756
CO4	27.437	-0.790	32.081	36.799	27.613	10.026	23.394	22.366
CO5	18.163	-11.074	22.886	26.723	23.137	2.609	28.194	15.805
CO6	13.831	-20.039	24.674	31.674	10.144	5.624	27.875	13.397
CO7	24.259	-14.800	30.007	36.831	22.745	-0.864	29.103	18.183
CO8 (High)	19.754	-17.606	39.649	45.694	15.141	-0.516	34.046	19.452
High-Low	2.304	11.738	15.190	-7.438	-8.086	-5.089	6.555	2.168

Notes: The returns include the price change from June 1st previous year until May 31st the current year plus any relevant dividends during the period and the returns are calculated as compounded daily returns using the dividend reinvested total return methodology. The characteristic forecast (CF) is obtained by regressing firm-level characteristics each year of the sample on a cross-section earnings regression and applying the coefficients on the subsequent years' characteristics. Analysts' forecast (AF) is the latest available mean consensus forecast on May 31st each year. CO equals CF subtracted by AF, divided by firms' total assets per share in the previous year. CO1 is the portfolio for the stocks with lowest CO and CO8 for the stocks with highest CO.