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CHARACTERISTIC APPROACH TO PREDICTING ANALYSTS' FORECAST ERRORS IN THE FINNISH MARKET

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ABSTRACT

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Extensive literature shows that analysts' forecasts and recommendations are often biased. Thus, it is important for the financial market to be able to recognize this bias to be able to correctly valuate public companies.

This thesis uses characteristic approach, which was introduced by So (2013, pp. 615-640), to forecast analysts' forecast errors and tests if predictable forecast error is fully incorporated into share prices. Data is collected of listed Finnish companies. Thesis' timeframe spans over ten years from 2004 to 2013 consisting of 788 firm-years. Although there is earlier evidence that the characteristic approach is able to predict analysts' forecast errors, no support for this is found in the Finnish market. This thesis contributes to the current

knowledge by showing that the characteristic approach does not work universally as such but requires development to work especially in the smaller markets.

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Master's thesis requires work, no doubt in that. Sometimes it is easier and sometimes more challenging. In my case, especially countless hours spent with Excel without a single written page tested my patience from time to time. In the end I must give credit for myself for finishing the project and achieving M.Sc. as should everyone who reaches this milestone.

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In Helsinki on 21.2.2015

Kalle Kinnunen

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1. Introduction

1.1. Background and motivation of the research

Analysts play important part in financial markets. They operate as information intermediaries by conducting market and company research, and providing forecasts, recommendations and target prices regarding underlying securities. Investors use this information that analysts have provided to fill information gaps and make investment decisions. Analysts' research saves many investors from the trouble of conducting time consuming expertise requiring analysis themselves for every single stock and reduces information asymmetry. As So (2013, p. 618) says, market's assessment of firm value is significantly influenced by the information that analysts provide.

Analysts provide not only quantitative forecasts but also qualitative analysis of market and competitive situation. For many users of analysts' reports this might be just as useful as quantitative forecasts. Qualitative side of equity research can help the investors better to react on news regarding the company. The research conducted by analysts can also be seen affecting e.g. companies' cost of capital, valuation, the liquidity of their shares (e.g. (Kirk 2011, pp. 182-200; Irvine 2000, p. 224; Brennan & Subrahmanyam 1995, pp. 361-381). Even while some people argue that market and security analysis is not worth the effort because of the efficient markets one must remember that the research conducted by armies of analysts are significant part of the financial market structure that ensure this market efficiency.

Despite being professionals of security analysis, analysts tend to get it wrong. Analyst recommendations and forecasts may even be biased. As Malmendier & Shanthikumar (2007, p. 458) pointed out, compared to more optimistic recommendations, there are few pessimistic recommendations which shows signs of biased recommendations. Collective literature provides evidence that reliance on analysts' forecasts can lead to biased estimates of firm value. Concern and recent findings that analysts' forecasts and recommendations can be biased have increased interest on research in this field. Literature review section of this thesis covers these topics in more detail.

Incentive misalignment between analysts and the end users of their research can lead to biased reports. This has been noted as a significant problem even by the authorities. In the early 2000, US regulators, including SEC among others, investigated potential conflicts of interest among investment banks' security analysts. Regulators found that analysts' integrity had been compromised. Their objective had been to generate investment banking business. As a result, regulators and ten of the largest investment banks announced an agreement, Global Research Analyst Settlement. As a result of this agreement, in addition to over a billion dollar fines, investment banks had to separate their investment banking and research departments. They were also ordered to provide independent research to their retail clients. (Barber et al. 2007, p. 491)

Motivated by analysts' incentives to bias their forecasts and possible market anticipation of these biases this thesis studies analysts' earnings forecast errors. So (2013, pp. 615-640) developed a new method to predict analysts' forecast errors in his article "A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts?" In his article So demonstrates that prices do not fully reflect predictable components of analyst errors. Hence he argues that characteristic forecast, that solely focuses on firm fundamentals and dismisses qualitative analysis and subjective consideration, can provide better estimates of future earnings than analysts. He provides evidence that investors overweight analyst forecasts. I use this approach to forecast analyst forecast errors for Finnish companies.

Especially in Finnish market, which has low analyst coverage compared to the US market, characteristic forecast may provide more accurate forecast of future earnings than analysts' consensus forecast. These forecasts are then exploited in effort to find market inefficiencies and abnormal returns. Market characteristics can however also lower the usability of the characteristic method.

As said, the characteristic approach is not without problems. Past earnings are significant part of the characteristic approach (as is explained in the chapter 3.2). Earlier evidence shows that earnings management is found in Finnish firms and that lagged earnings management relates to the future profitability of the firm. Hence earnings information value is not as high as it may be assumed to be. (Kallunki & Martikainen 2003, pp. 311-325 & Sundgren 2007, pp. 35-63) Earnings management, however, is not Finland or IFRS specific matter but is conducted also in the US. Thus findings of earnings management in Finland do not alone mean that characteristic approach would not work in Finland as it does in the US. Characteristic approach still requires empirical testing in the Finnish setting.

Because So's (2013, pp. 615-640) approach to predict analyst forecast error is completely new and gives exciting results, it is interesting to test it with another data sample in another country. The Finnish stock market is tiny compared to the US market. The analyst coverage in Finland is much lower than in the United States. Hence, analysts may have more power to manipulate the market. Also, Finland as a small market does not often receive interest of academics which makes it interesting market to test the characteristic approach.

Compared to the United States, which has been most often the target market of analyst related research, Finland is a quite different market. In the end of November 2014 there were 124 individual companies with shares listed in main list of OMX Helsinki (including those whose home exchange is not Helsinki). Based on data in Thomson One Banker database 32 out of these 124 companies, i.e. 26 %, did not have any analysts following them. The number of covered companies creates a significant challenge for this thesis. On average 6,9 analysts followed one company. 59 companies had less than 10, 19 had ten to twenty and 14 more than 20 analysts following them. Analysts laid most interest in Nokia, Nordea and Fortum, with 51, 32 and 29 analysts following them correspondingly. Complete list of analyst coverage by company is presented in appendix 1.

Most significant equity research companies were ESN/Pohjola Markets, Evli Bank, Inderes and Carnegie Investment Bank, each of which followed 60 or more Finnish companies. Out of the ten companies with the widest firm coverage, only Inderes and FIM were without investment banking activities. All in all, out of the 77 research companies only 14 did not have investment banking activities. Most of these companies followed only one or two companies. List of companies covering Finnish firms can be found in appendix 2.

1.2. Research method and data

This thesis follows the methodology developed by (So 2013, pp. 615-640). I use the characteristic approach to forecast future earnings for cross-sectional samples in 2004-2013. The characteristic approach uses lagged company specific characteristics to forecast future earnings. Characteristic earnings forecasts and analyst forecasts are used to calculate new variable, characteristic optimism. This characteristic optimism serves as this thesis' prediction of analysts' forecast errors. Characteristic optimism is used to rank firms in the second section of empirical part of this thesis. In this second part, I examine returns by characteristic optimism quintiles. Also returns are calculated for a simple long-short strategy portfolio. This portfolio's returns are also compared to other quintiles. Data consists of company specific data spanning from 2002 to 2014. Data was collected using Thomson One Banker and Datastream databases. Methodology is covered in more detail in chapter four and data in chapter five.

1.3. Objectives and focus of the study

Theoretical background opens methodological concerns that are related to traditional approach in forecasting analysts' forecast errors has. It also familiarizes reader to the characteristic approach and explains its benefits compared to the traditional approach. Literature review is supposed to draw a comprehensive picture to the reader so that he or she can understand influences and especially incentives behind analysts' forecast errors.

The objective of this thesis is to test the characteristic approach on predicting analysts' earnings forecast errors. As this approach worked in the US (So 2013, pp. 615-640), I put it to a test in Finland which is significantly different market compared to the US measured by size, trading volumes and analyst coverage to give a few examples. In addition, Finnish companies use different accounting standards than their US counterparts. Finland is also a market, which rarely receives attention from foreign academics.

The different setting that Finland provides raises a whole new empirical question, is the characteristic approach applicable in such a different environment? As the characteristic approach primarily relies on financial statement fundamentals, differences in market structure may not influence too much. Thus, similar results with So's (2013, pp 615-640) can be expected.

The most influential structural factor affecting the usability of the characteristic model is the size of the market which limits sample size. This is likely to influence statistical significance of the results.

So (2013, p. 622), whose research this thesis exploits, gave two empirical predictions. These same empirical predictions work as research questions and hypotheses of this thesis.

Empirical prediction 1

Characteristic forecast in excess of analyst forecast predict realized earnings in excess of analyst forecast. Thus, characteristic forecast optimism, CO, positively predicts analyst forecast errors (actual earnings minus analyst forecast of earnings).

Empirical prediction 2

Characteristic forecast in excess of analyst forecasts correlate positively with earnings information not fully reflected in current prices. Thus, characteristic optimism, CO, positively predicts future abnormal returns.

Characteristic optimism equals characteristic forecast of earnings per share minus analyst forecast divided by total assets per share.

1.4. Structure of the thesis

This thesis consists of seven main chapters. After the introduction literature review focuses more on practical side of analysts' work and academic work concerning it. It covers analysts' role, their incentives to distort their forecasts. This chapter also discusses how the information provided by analysts is used by the market participants. The third chapter covers this thesis' theoretical background. It presents both traditional and characteristic approach.

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

2. Literature review

In this chapter, I cover the most significant theoretical frameworks and findings that are related to the thesis topic. I discuss of the role of analysts and of the ways they influence financial markets. After that I cover the range of sources of bias, were those intentional (result of incentives) or unintentional. This section provides reasons for why analysts' forecasts are not accurate. In the last section of the literature review I show how market uses the information provided by the analysts.

Equity research, financial analysis and forecasting have spanned a wide range of articles in the past which is no surprise considering how central part of finance these topics represent. Ramnath et al. (2008, pp. 34-75) went through financial analyst forecasting literature in effort to find out the roles that financial analysts play in allocation of economic resources. As a result of their article they categorized research into seven categories:

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

Of these seven topics, the literature review section of this thesis focuses most closely to the information content of analyst research and analysts' incentives and behavioral biases. The weight is more on later as this thesis also itself falls mostly under this category.

Also So (2013, p. 618) recognizes three primary streams of literature that relate to analysts' forecast errors. Firstly, he argues that market's assessment of the firm's value is significantly influenced by the information that analysts provide. Secondly, he states that the incentives of analysts and the end users differ, which results in biased forecasts of company performance. The third stream relates to the differing incentives and tests if investors rationally anticipate and undo the predictable bias in signals that the analysts give. Thus, So's literature background fits well with classification of Ramnath et al. (2008, pp. 34-75). So's first and second categories fall under Ramnath et al.'s third and fifth categories, correspondingly.

Influenced by these articles, the literature review section of this thesis is divided into three parts. First part discusses analysts' role and influence as information intermediary. Second part focuses on different incentives and potential sources of biases. Third part examines how investors take information provided by analysts and potential biases in this information into account in their own decision making process.

2.1 Role and influence of analysts

Analysts improve market efficiency by providing private information and interpreting public information to the market (Chen et al. 2010, p. 206). Their research also helps investors in their capital allocation decisions. (Barth, Hutton 2004, pp. 59-96; Healy, Palepu 2001, pp. 405-440; Kirk 2011, p. 184) Analyst coverage does not only benefit investors but also companies (Merton 1987, pp. 483-510; Brennan & Subrahmanyam 1995, pp. 361-381; Irvine

2000, p. 224; Kirk 2011, pp. 182-200). Furthermore, analysts help to reduce agency problem through monitoring (Moyer et al. 1989, p. 503). In the end, analysts influence companies' market value through information that helps market in its price discovery process (So 2013, p. 618; Chung, Jo 1996, p. 493). Analysts have many roles and many ways to influence financial market and its participants.

In this chapter, I first explain what research has found about analysts' coverage decisions. Then I present some findings of analysts' effects on companies. After that I describe the informational role of analysts.

Analyst coverage

Not all firms are covered. This raises a question whether only coverage itself tells us something about analyst or company in question. Chuang & Lee (2011, p. 489) state that financial analysts are less willing to cover stocks when these stocks have high information set-up costs. Analysts can be reluctant to issue negative information because they fear losing potential investment banking opportunities, access to management or trading commissions say McNichols & O'Brien (1997, pp. 167-169). While these factors are argued to be cause for upward bias in analysts' forecasts and recommendations, as is presented in this chapter, McNichols & O'Brien suggest that this may also lead to situation where analysts' are more likely to give forecasts and recommendations for companies that truly have more positive expectations. In addition, they find that analysts' forecasts are weighted toward strong buy recommendation and that analysts more often drop stocks with lower ratings from their coverage compared to stocks with higher ratings.

Information value of analyst research can vary. Branson et al. (1998, pp. 119-143) studied the impact of coverage initiation. They found that buy recommendation in coverage initiation causes larger positive stock price reaction when analyst coverage has been thin for the firm compared to cases when there has not been analyst coverage at all or if company had been already more heavily covered.

Especially in brokerage houses, sell-side analysis is partly a marketing function. Hence, analysts have incentives to follow high quality companies since these are easier to market. (Chung & Jo 1996, p. 493) Consequently not all companies are likely to receive analyst attention. In these cases, companies may rely on paid-for coverage. Kirk (2011, pp. 182-200) examined the determinants and impacts of paid-for coverage. He states that companies are more likely to buy coverage when they operate with greater uncertainty (e.g. of future earnings and cash flows), in weaker information environments and have low turnover. He also finds companies with harder to value assets and lower institutional ownership to be more likely to purchase analyst coverage. He recognizes that paid-for research has its conflicts of interests, but despite this, these paid-for reports have information content for investors. (Kirk 2011, pp. 182 & 197) Even if risk for conflicts of interest can be higher in case of paid-for research, it must be remembered that all research is paid in one way or another. Still, especially in cases where research company receives stock as part of compensation, incentives to bias can be seen especially high.

Agency problem

Analysts play a role in reducing agency costs by monitoring managerial performance (Moyer et al. 1989, p. 503). In a recent study Chen et al. 2014, p. 1) explored the causal effects of analyst coverage on mitigating expropriation of outside shareholders. They found that decrease in analyst coverage resulted lower internal cash holdings, higher excess compensation for the CEO, more value destroying acquisitions, and more earnings management activities. These findings highlight the importance of analysts' governing role in scrutinizing company management. Indeed, the market pricing reveals the increase in expected agency problems when analyst coverage is lost.

Lang et al. (2004) discuss about control and analysts. While analysts can play a key role in reducing agency costs, they notice that analysts tend not to follow companies with potential severe agency problems. Such problem can be e.g. management's incentives to withhold or manipulate information which might be case in presence of concentrated family or management control. So even when benefits for these companies would be the highest. These companies might even prefer to have wider analyst coverage, but are unable to attract it. (Lang et al. 2004, pp. 589 & 596) In these cases, companies might rely on paid-for research which, however, might have propensity to be biased.

Effects for companies

Analyst coverage gives companies more visibility which brings several economic benefits (Merton 1987, pp. 483-510). Kirk (2011, pp 182-200) points out that analyst coverage impacts valuation, liquidity, welfare and growth of companies. He found out that companies experience an increase in institutional ownership, sell-side analyst following and liquidity after the initiation of analyst coverage. Also Irvine (2000, p. 224) and Brennan & Subrahmanyam (1995, pp. 361-381) say that analyst coverage improves liquidity.

Informational role of analysts

Analysts make security markets informationally more efficient (Moyer et al. 1989, p. 503). They provide their expertise to the market by providing private information, also called information discovery, and interpreting public information. Chen et al. (2010, p. 224) showed that the discovery role of analysts dominate before earnings announcements but it turns to interpretation after.

A way to see and measure the informativeness of analyst research is through the changes in security prices after release of analyst reports (Frankel et al. 2006, p. 29). Chuang & Lee (2011, pp. 465-493) studied the informational role of institutional investors and financial analysts in the market. They made these five findings.

1. The price adjustment of stocks that are favored by institutions and analysts and associated with low information set-up costs helps better predict market-wide information
2. Firms that are primarily held by individuals and followed by fewer analysts tend to respond more sluggishly to market-wide information than do firms that are primarily held by institutions and followed by more analysts
3. High institutional-ownership portfolios and high analyst coverage portfolios play complementary role in predicting market returns
4. There is little systematic difference between high institutional-ownership portfolios and high analyst coverage portfolios in predicting the returns of stocks with different characteristics
5. Good market-wide news diffuses more slowly across securities than does bad market-wide news, and this finding primarily occurs in periods of NBER-dated expansions

Of these findings of Chuang & Lee, the most important from the point of view of this thesis are the first and second findings. These can be interpreted so that analysts provide valuable information to the market which helps prices faster to reflect current information.

Bradshaw (2004, p. 47) examined the relation between analysts' earnings forecasts and their stock recommendations. He argues that analysts do not use present value models as basis for their recommendations or if they do, their personal opinions bias the recommendations. As investors can use these present value models themselves the value of recommendations must lie somewhere else. Bradshaw suggests that it lies in the additional information that analysts incorporate into their recommendations. Such information can be e.g. analysts view on quality of the management or customer loyalty.

Casey (2013, pp. 36 & 48) studied the information value of independent research analysts versus investment bank analysts. He found that forecast revisions by independent research analysts have lower informativeness. This result implies that investment banks analysts' abilities and/or resources dominate conflicts that may occur due to investment banking relations. The disparity between informativeness of independent analysts versus investment bank analysts was however reduces when controlling analyst ability, portfolio complexity and brokerage firm resources.

Casey (2013, p. 36) formed portfolios based on analyst firm type (independent or investment bank). He calculated buy-and-hold abnormal returns daily for these portfolios. As a result investment bank analyst portfolios generally outperformed independent analyst portfolios. On contrast Barber et al. (2001, pp. 490-492) compared average returns for buy recommendations by investment banks and independent research firms and found out that later outperformed investment banks by 3,1 basis points (which is almost 8 percentage points annualized). Still, their results also show that investment banks' hold and sell recommendations outperformed independent firms by 1,8 basis points (4,5 percentage points annualized).

Kirk (2011, p. 183) studied abnormal returns two days after issuance of paid-for research report. He found out that cases of strong buys, buys, upgrades and reiterations are associated with significant abnormal returns in these days. He also found that hold and sell recommendations resulted negative abnormal returns. In case of sell recommendation, however, negative abnormal returns were statistically insignificant.

While research often focuses on analysts' earnings forecasts, as does this thesis, also other parts of analysts' research reports have been seen valuable. Market has been seen reacting to revenue and cost surprises (Ertimur et al. 2003, pp. 208-209). DeFond & Hung (2003, p. 73) focused their research efforts on analysts' cash flow forecasts. They say that with cash flow forecasts analysts are trying to provide market participants value-relevant information especially when cash flows are useful in interpreting earnings and assessing firm viability.

2.2 Analysts' intentional and unintentional biases

Multiple factors contribute to analysts forecast accuracy. Sometimes analysts may just have gotten it wrong, maybe because of under- or overreaction of uncertain information (Abarbanell & Lehavy 2003, p. 106). Also analyst and company characteristics, and forecast horizon has been suggested as determinants (García-Meca & Sánchez-Ballesta 2006, p. 29). Sometimes, however, there may be incentives to deliberately bias their forecasts. Biases can be seen in overly high or low forecasts and target prices or too optimistic or pessimistic recommendations. Also analysts' reluctance to change their recommendations can be seen as an sign of biasedness. Hence, analyst reports should not be considered naively as purely objective observations. The question, whether analysts' forecasts are biased, has spanned extensive literature. Failure to accurately incorporate new information in time or in unbiased way is called "forecast inefficiency" in financial analyst literature (Easterwood & Nutt 1999, p. 1777).

This chapter focuses on different incentives that may cause biases. Analysts' incentives have been studied since 1960s (Libby et al. 2008, p. 174) but even though much of the literature states that there are incentives that bias analysts forecasts there is also conflicting evidence to the question whether analysts are biased or not (Abarbanell & Lehavy 2003, p. 106). Hence definite answer to determinants of biased estimates remains still unanswered.

Ramnath et al. (2008, pp. 57-61) argue that earlier research has found that different incentives impact analysts' effort and decisions to follow firms and their systematic optimism or pessimism in their forecasts and recommendations. Research has also shown that economic incentives and behavioral biases can create underreactions in analysts' forecasts.

Investment banking relations

Investment banking relations have been one focus point of research studying incentives behind biased forecasts. Michaely & Womack (1999, p. 683) say that as underwriting company's analysts should have superior information about issuing company as a result of their due diligence process, they should also have more accurate forecasts compared to unaffiliated analysts. They also say that underwriter analysts have incentive to recommend stocks that their firms have taken public. Michaely & Womack found evidence of the later, but no empirical evidence for superior information was found in their study.

Malmendier & Shanthikumar (2007, pp. 457-458) argue that especially when analysts are affiliated with underwriter they tend to bias stock recommendations upward. Similarly Dugar & Nathan (1995, p. 131) show that both earnings forecasts and investment recommendations made by investment bank analysts are more optimistic than these of other analysts'. Malmendier & Shanthikumar also point out that stock recommendations generally exhibit strong upward bias with only 4,5 % of all the recommendations in the IBES database being sell or strong sell in December 2002.

Also Dechow et al. (2000, pp. 1-33) who studied analysts' long-term growth forecasts around equity offerings found that these forecasts tend to be overly optimistic. Furthermore, analysts', who were employed by the lead manager of the offering, were the most optimistic with their long-term growth forecasts. Lin & McNichols (1998, p. 101) received similar results with the studies mentioned above. They found growth forecasts and recommendations that were made by analysts in affiliated companies to be more favorable compared to ones made by unaffiliated analysts. However, they didn't find difference in earnings forecasts.

While many studies have stated that affiliation affects analysts' optimism, Bradshaw et al. (2003, pp. 1-42) argue that the key determinant of analysts' overoptimistic forecasts is the extent to which the target company in question is issuing new securities. They found analyst affiliation to be only second order importance. They say that unaffiliated analysts may have incentive to be overoptimistic so that they have a chance to win future investment banking deals or in order to receive side-payments from investment banking firms. As firms issuing new securities received most optimistic forecasts and recommendations, analysts were least optimistic for firms which were repurchasing securities. Bradshaw et al. also show evidence that analysts manipulate their investment advice in order to inflate stock prices around security issuances.

Also Ljungqvist et al. (2007, pp. 421 & 453-454) found greater optimism in analysts' recommendations when their companies had existing investment banking relations with the firm. Their article was made especially interesting by two influences that offset analysts' optimism. Firstly, they found negative relation between analysts' optimism and proxies for the loyalty of bank's corporate clients and bank's reputational capital. Secondly, large institutional investor presence related to less aggressive recommendations, more accurate forecasts and faster incorporation of bad news. This is in line with the expectation that cost of publishing biased and misleading information is higher when stocks are owned by highly visible institutional investors.

Access to management

Dialogue with the target company's management and investor relations is important part of analysts' job. Company's management is a crucial information source for them. Hence analysts have an incentive to maintain good relationship with the target company. This can lead to biased forecasts and recommendations. Libby et al. (2008, pp. 173-198) show evidence of this and even state that analysts are aware of their optimistic/pessimistic forecasts and that they believe that this benefits their future relationships with management. This optimistic/pessimistic pattern means that analysts tend to have more optimistic predictions at the beginning-of-period but predictions move to more pessimistic direction when end-of-period closes.

From the opposite point of view, company management can prefer beatable analyst forecasts to show that they are doing good job. On the other hand they may want forecasts to be favorable because those support higher market valuation of the company and higher compensation for them (Lim 2001, p. 370). In his paper he says that management can limit or eliminate flow of information to the analyst. Lim continues that this easily leads to biased forecasts by analysts', especially in case of analysts for whom management access is more crucial.

Trading

Many companies that provide security research also offer brokerage and trading services. For these companies, trading activity is one of the most important sources of revenue. Irvine (2004, pp. 125-149) studied the relationship between brokerage-firm trading and analysts' stock recommendations and earnings forecasts. He found that forecast that differs from consensus forecast causes significant trading activity for the stock in question for two weeks after the release of the forecast. He, however, did not find connection between forecast error and trading activity.

In another article by Irvine (2000, pp. 213-214) he says that while the compensation received by the analyst is not tied to trading volume of a stock, that the analyst follows, by a fixed percentage, trading volume of this stock affects analyst's compensation. Based on Irvine's findings it seems that analysts may have incentives to bias their recommendations and forecasts in order to generate trading (trading incentive). It also seems more likely that analysts bias their recommendations instead their earnings forecasts. In line with this, Ljungqvist et al. (2007, pp. 421 & 453-454) argue that analysts of banks that had large brokerage business issued more aggressive recommendations.

As Hayes (1998, p. 300) notes, when short selling is restricted, trading volume of a stock not performing well is limited to the investor’s current holding of that share. Hence, when analysts have incentive to boost trading volumes they also have incentive to give more optimistic forecasts and recommendations.

Analyst compensation

The compensation that analyst receives for his work is a powerful incentive. Thus compensation that is tied to forecasting accuracy could effectively limit incentives to bias forecasts. Groysberg et al. (2011, pp. 969-1000) studied factors that affected analysts’ compensation. They found that analysts’ forecasting accuracy did not affect their earnings. Still, it was related to analyst turnover in the investment banks studied. Groysberg et al. (2011, p. 970) argue that analysts’ compensation was designed to reward actions that increase brokerage and investment banking revenues.

Mikhail et al. (1999, pp. 185-186) had similar findings regarding analyst turnover. They argue that absolute forecasting accuracy is not that important factor for analyst compensation or turnover, but lower forecasting accuracy compared to analyst’s peers is associated with higher probability to turn over. In addition, Mikhail et al. (1999, p. 186) state that turnover followed by lower relative accuracy in earnings forecasts provides justification for investors and academics on reliance analyst forecasts.

Asymmetric response to negative and positive news

Easterwood & Nutt (1999, pp. 1795-1796) say that literature that has examined analysts' reactions to new information has given inconclusive results. Evidence for both underreaction and overreaction has been received. Their findings separate overreaction and underreaction from each other. Easterwood & Nutt argue that analysts underreact to negative information but overreact to positive information. Also Hugon & Muslu (2010, p. 42) say that analysts have incentives to emphasize good news and understate bad. Their findings give support for assumed analyst optimism.

Over extrapolation of past trends

Bradshaw (2004, pp. 47-48) studied on what analysts base their stock recommendations. He found that analysts' recommendations rely most on long-term growth forecasts. He found surprising that analysts recommend high-growth stocks even though growth expectations may already have been incorporated to share prices. Bradshaw states that analysts can have incentive to extrapolate past growth for several reasons which have already been discussed in this chapter. These reasons may be e.g. access to management and investment banking relations.

Overweighting of private information

Chen & Jiang (2006, p. 319) argue that analysts' incentives play a significant role on weighting their private and public information when they forecast earnings. When their forecasts were above consensus analysts overweighed their private information more and when below consensus, overweighting was less. Chen and Jiang say that in later case analysts may even underweight their private information. However, in their study Easterwood & Nutt (1999, p. 1796) did not find evidence for analysts under- or overweighting information.

Other sources

Sources of biases in analyst forecasts do not limit to the ones above. Selection bias results from analysts initiating and maintaining coverage only for companies for which they expect good prospercts (Bradshaw, Richardson et al. 2003, p. 24). Ramnath et al. (2008, p. 57) found that literature has recognized several incentives that analysts have. According to Ramnath et al. these incentives have primarily related to analysts' career concerns, the underwriting and trading incentives of their employers and how the incentives of, and communication with, company management influence analysts' behavior. Also Chen et al. (2005, p. 4) say that analysts care of their reputation and want to build it. In addition, Lim (2001, p. 370) says that companies with more uncertain environments are associated with more optimistic forecasts.

In the end, while there are several incentives to bias forecasts, incorrect forecasts are not always completely analysts' fault. Abarbanell & Lehavy (2003, pp. 107-108) highlighted that companies conduct earnings management and even manipulation which makes it problematic to benchmark analysts' forecasts against these earnings. Hence, results of biased earnings forecasts can be partly attributable to lack of motivation and/or ability of analysts to anticipate companies' earnings management in their forecasts.

This chapter has presented several incentives and reasons for biased analyst forecasts. I end this chapter with an idea by Lim (2001, p. 370). He argues that forecast's unbiasedness does not need to mean that it is the best or most accurate forecast. He states that statistically optimal forecast may be positively and predictably biased. This can be true especially in an uncertain environment where information gathering is difficult and access to management is hence particularly valuable.

Price manipulation

Bradshaw et al. (2003, pp. 1-43) studied sell-side analysts' and corporate financing activities. Also they found evidence of overoptimism that was systematically related to companies financing activities. This gives support for allegations that investment banking pressure leads to analysts manipulating their research conclusions in order to temporarily inflating stock prices around security issuance events. This inflation is also called pumping and dumping. Bradshaw et al. also give evidence for that investors are affected by this hype. Analysts' manipulation causes inefficiencies in the market and misallocation of capital.

Evidence of market manipulation was found also in the Pakistani market by Khwaja & Mian (2005, p. 204). Their study focused on broker activities. Still, especially in the emerging market where regulation, transparency and corporate governance are not on the same level as in more developed markets, this kind of manipulation may still be found. As it has been shown in this thesis, analysts can pump up the price by giving overly optimistic information and opinions. This strengthens concerns of analysts being biased especially in the emerging markets.

2.3 How investors use analyst information

The literature review chapter has already discussed about analysts' influences and incentives that affect and might bias them. This chapter of the literature review focuses on question "How investors use (biased) information provided by analysts?" This is especially interesting question as many empirical findings have shown that analysts' earnings forecasts are optimistic on average (e.g. Hayes & Levine 2000, p. 61 and Lim 2001, p. 369). This branch of financial research often focuses on value of analysts' forecasts and recommendations. Often different investment strategies are tested in search of abnormal returns and market reactions to analyst reports. In the focus of this thesis is question whether investors successfully take into account possible biases that analysts' recommendations contain. In the end, if predictable analyst biases are ignored, will this lead to significant valuation errors (So 2013, p. 616).

Malmendier & Shanthikumar (2007, p. 457) studied small and large investors and how these investors have taken possible biases into account by adjusting their trading responses. They found significant differences in the behavior of small and large investors. Their findings were that large investors "discount" analysts' recommendations when they are affiliated with underwriter. Buy recommendation causes no reaction in large investors and hold recommendation causes selling pressure. Buying pressure is experienced in relation with strong buy recommendations. Based on Malmendier's & Shanthikumar's (2007, p. 457-458) results, small investors, however, follow recommendations more literally. Small investors tend to buy when buy or strong buy recommendations were given and hold when holding was recommended. They argue that small investors take the informational content of the recommendation change or even only revision less into account.

Barber et al. (2007, pp. 490-517) studied market responses to stock recommendations by independent research companies and investment banks. The average abnormal return to independent firm’s buy recommendation beat that of investment bank’s by 3,1 basis points, which corresponds nearly 8 percentage point per annum. They point out that this outperformance was more pronounced after NASDAQ market peak in March 2000. However, performance turned when Barber et al. examined hold and sell recommendations. Hold and sell recommendations of investment banks’ outperformed those of independent research firms’ on average by 1,8 basis points daily (4,5 percentage points p.a.). Barber et al. argue that the underperformance of investment banks especially during bear markets of the early 2000 suggest that these companies were reluctant to downgrade stock recommendations even though prospects dimmed.

Investors’ reactions to analyst reports does not only depend on the incentives of the analysts but also of their conclusions, argue Hirst et al. (1995, p. 348). They say that investors found positive reports to be in line with their expectations of favorable reports. Unfavorable reports, however, were found unexpected. These reports were found even more unexpected when they originated from affiliated analyst. In line with this expectation that investment bank analysts are more optimistic, Dugar & Nathan (1995, p. 131) found evidence that while capital market participants rely less on investment bank analysts than other analysts when forming their earnings expectations. Still, they state that investment bank analysts’ and other analysts’ earnings forecasts are on average as accurate.

Similarly Lin & McNichols (1998, pp. 101-127) observed that market does not react to affiliated analysts’ strong buy and buy recommendations. They also found that hold recommendation causes negative market reaction. Also focusing on division to affiliated and unaffiliated analysts Michaely & Womack (1999, p. 653) found that returns to buy recommendations by affiliated companies’ analysts are lower than returns to buy recommendations by unaffiliated companies’ analysts. These findings imply that market takes analysts’ incentives into consideration.

In their paper Hayes & Levine (2000, pp. 61-83) tried to undo biases in analysts’ forecasts. Their adjusted earnings forecasts were more accurate and less biased. Still, those were not more correlated to returns than mean or median forecasts of original sample. Hayes & Levine suggest that this tells that market does not entirely adjust for analysts’ biases.

Battalio & Mendenhall (2005, pp. 289-290) identified two different subsets of investors who use significantly different information subsets to support their investment decisions. They showed that large traders (measured by deal size) respond to analysts’ earnings forecast errors. However, small traders react on less-sophisticated signal. They underestimate the implications of current earnings innovations for future earnings levels.

I have presented findings that tell how market responds to analyst forecasts. But do investors learn and correct their assumptions as time passes and more data of analysts earlier forecast errors becomes available? Chen et al. (2005, p. 3) studied just this and learnt that market’s reaction to analysts’ forecast revision is consistent with their expectation that investors learn about analysts’ past forecast accuracy and alter their response accordingly. Following Chen et al., also Hugon & Muslu (2010, pp. 42-57) found that the market reaction to more conservative analysts’ forecasts when their observation time was lengthened.

Based on the literature presented in this chapter, market is aware of analysts’ incentives and biases. Market also seems to take this into account, but not fully. This supports the expectation that there can still be a way to use analysts’ biases and find abnormal returns.

3. Theoretical background

The methodology and theory behind it in this thesis are based on work of So (2013, pp. 615-640). His new approach should overcome the methodological concerns that traditional method of forecasting analysts' forecast errors has.

Suppose that firm *j*'s realized earnings in year *t*, $E_{j,t}$ can be written in a function of observable firm characteristics. This function is presented in equation 3.1. (So 2013, p. 617)

$$E_{j,t} = \sum_{i=1}^{M} \beta_i \cdot X_{ij,t-1} + \epsilon_{j,t} \tag{3.1}$$

In this equation $X_{1j,t-1} \ldots X_{Mj,t-1}$ denote a comprehensive set of firm characteristics that are publicly observable at time *t-1* and that are associated with the firm's earnings. ϵ denotes the component of realized earnings that is not predicted by the set of firm characteristics. (So 2013, p. 617)

$$AF_{j,t-1} = \sum_{i=1}^{M} \gamma_i \cdot X_{ij,t-1} + \sum_{i=1}^{K} \delta_i \cdot Z_{ij,t-1} + \eta_{j,t-1} \tag{3.2}$$

Equation 3.2 presents analyst forecast in year *t-1* for year *t* earnings. $X_{1j,t-1} \ldots X_{Mj,t-1}$ is a set of publicly available signals. $Z_{1j,t-1} \ldots Z_{Kj,t-1}$ denote analysts' private information and incentives to bias forecasts. (So 2013, p. 617) Such incentives can be for example access to company's management or investment banking relationships that analyst's company has. Different incentives that affect analysts forecast accuracy were more comprehensively presented in chapter 2.2.

Realized forecast error, equation 3.3, is received by combining equations 3.1 and 3.2.

$$FE_{j,t} = E_{j,t} - AF_{j,t-1} = \sum_{i=1}^{M}(\beta_i - \gamma_i) \cdot X_{ij,t-1} + \epsilon_{j,t} - \sum_{i=1}^{K} \delta_i Z_{ij,t-1} - \eta_{j,t-1} \tag{3.3}$$

The theoretical background behind analysts' forecast errors is covered above. This provides basis for both traditional and characteristic approach which are discussed in the following chapters.

3.1 The traditional approach

Approach to predicting analysts' forecast errors has traditionally based on time-series model. This chapter covers the methodology of traditional approach and the problems related to this methodology.

When using the traditional approach the researcher first regresses realized forecast errors, $FE_{j,t}$, on lagged publicly available firm characteristics, $X_{1j,t-1} \dots X_{Mj,t-1}$. By examining equation 3.3 it can be seen, that the regression error equals equation 3.4.

$$\Omega_{j,t} = \epsilon_{j,t} - \sum_{i=1}^{K} \delta_i Z_{ij,t-1} - \eta_{j,t-1} \tag{3.4}$$

The methodological concerns that drove So (2013, pp. 615-640) to develop characteristic approach rises from the analysts' incentives to bias their forecasts. Because analysts' forecast is a function lagged firm characteristics, $X_{ij,t-1}$, and analysts' incentives, $Z_{ij,t-1}$, So argues that the estimated values of $(\beta_i - \gamma_i)$ in equation 3.3 are subject to bias.

The bias exists when analyst's incentives influence one or more control variable forecasts, $X_{ij,t-1}$. In this case the regression error term, $\Omega_{j,t}$, becomes correlated with the set of control variables, $X_{ij,t-1}$. These variables cause endogeneity problem to the model. This causes a reason to expect that $\Omega_{j,t}$ is also correlated with analyst forecast errors, $FE_{j,t}$. When this is the case, estimating equation 3.3 results biased coefficients. The direction of bias is however unclear ex ante and may vary across firm and time. (So 2013, p. 617)

In the second stage of traditional approach researcher uses historically estimated values for $(\beta_i–\gamma_i)$ on current firm characteristics, $X_{ij,t}$. The fitted value for $\widehat{FE}_{j,t+1}^{T}$ is the predicted analyst forecast error for year $t+1$. (So 2013, pp. 617-618) This is presented in equation 3.5, where T-superscript stands for traditional approach.

$$\widehat{FE}_{j,t+1}^{T} = \sum_{i=1}^{M}(\widehat{\beta_\iota - \gamma_\iota}) \cdot X_{ij,t} \tag{3.5}$$

So (2013, p. 618) explains that the use of biased regression coefficients leads to a situation where predicted analyst forecast error differs from the expected value of the realized forecast error. This is presented in equation 3.6, where $\mathbf{E}_t[\cdot]$ denotes the time t expectations operator conditional upon the correlations between $FE_{j,t+1}$, $X_{ij,t-1}$ and $Z_{ij,t-1}$. (So 2013, p. 618)

$$(\widehat{\beta_\iota - \gamma_\iota}) \neq \boldsymbol{E}_t[(\beta_i - \gamma_i)] \rightarrow \widehat{FE}_{j,t+1}^{T} \neq \boldsymbol{E}_t[FE_{j,t+1}] \tag{3.6}$$

This leads to a situation where $\widehat{FE}_{j,t+1}^{T}$ could be predictably different from realized forecast error depending on the bias in first stage estimated coefficients. Bias exists because inputs, $Z_{ij,t-1}$, in analyst’s forecast are unobservable. (So 2013, p. 618)

Idea that these biases can be avoided by controlling incentives and private information can be tempting. However, because observing all analysts’ incentives and private information is impossible. It is also impossible to create comprehensive set of proxies for these. And even if it would be possible to create this set of proxies, they would almost certainly measure inputs with error. Thus, attempts to control unobservable inputs could even increase the bias of the model. (So 2013, p. 618)

3.2 The characteristic approach

Due to problems of traditional approach of predicting analysts' forecast errors, So (2013, pp. 615-640) developed a new method: The characteristic approach. The characteristic approach estimates future earnings directly (equation 3.7), instead of regressing realized forecast errors on firm characteristics.

$$\hat{E}_{j,t+1} = \sum_{i=1}^{M} \hat{\beta}_i \cdot X_{ij,t} \tag{3.7}$$

So (2013, p. 618) states that the benefit of this approach, under mild distributional assumptions, is that it gives unbiased estimate of future earnings. The characteristic approach predicts analysts' forecast error by using characteristic estimate of future earnings and the observable analyst forecast error (equation 3.8). C-superscript in the equation stands for characteristic method.

$$\widehat{FE}^{C}_{j,t+1} = \hat{E}_{j,t+1} - AF_{j,t} = \boldsymbol{E}_t\left[E_{j,t+1} - AF_{j,t}\right] = \boldsymbol{E}_t[FE_{j,t+1}] \tag{3.8}$$

So (2013, p. 618) argues that this method will produces unbiased estimate of realized forecast error.

So (2013, p. 620-621) recognizes three benefits that using characteristic approach in forecasting analysts forecast errors has compared to traditional time-series approach. Firstly, time-series forecasts generally assume that earnings follow an autoregressive integrated moving average structure, also called as ARIMA structure. Cross-sectional characteristic approach only requires data for two years (t-1 and t) so that t+1 year's earnings can be forecasted. ARIMA structure, however, requires adequate historical data to estimate parameters. This restricts the available sample significantly. It is much easier to get larger sample to be used with characteristic approach. Secondly, he raises concern that time-series forecasts display lower levels of accuracy compared to analyst forecasts. Hence, this approach may not work best as a benchmark against which analysts' forecasts can be judged. Thirdly, he argues that cross-sectional characteristic approach allows additional variables, such as dividends and accruals, to be included into the model which helps to increase the explanatory power of the model. (So 2013, p. 620-621)

4. Methodology

Based on theoretical background (covered in chapter 3), motivated by the literature (covered in chapter 2) and following the methodology by So (2013, p. 615-640) this thesis focuses on earnings forecasts instead of analyst recommendations, target prices or long-term growth forecasts. The methodology in this thesis involves predicting earnings directly by using characteristic approach which is based on historical firm specific characteristics. These characteristic forecasts (CF) are compared to analysts' estimates of firms' future earnings to calculate expected analyst forecast errors.

In the second part of empirical section, predicted analyst forecast errors are used to form an investment strategy. By exploiting predicted analyst forecast errors I test if all earnings information is not yet fully reflected in current prices. If this holds true, investment strategy should be able to earn abnormal returns.

This chapter covers the methodology used in this thesis. Methodology chapter is followed by Data and Results.

4.1 Characteristic approach to predict analyst forecast error

The new characteristic forecast method introduced by So (2013, pp. 615-640) uses publicly observable firm characteristics in the prediction of firm's future earnings. His model relies on characteristics used by Fama & French (2006, pp. 491-518) but any set of publicly observable firm characteristics could be used as long as there is relevant economic justification behind this. Expanding the set of characteristics with relevant variables, the strength of the model could be still improved. In this thesis, however, to provide comparability I use the same set of characteristics as So (2013, pp. 615-640) in his article.

$$E_{j,t} = \beta_0 + \beta_1 E^+_{j,t-1} + \beta_2 NEGE_{j,t-1} + \beta_3 ACC^-_{j,t-1} + \beta_4 ACC^+_{j,t-1} + \beta_5 AG_{j,t-1} + \beta_6 DD_{j,t-1} + \beta_7 DIV_{j,t-1} + \beta_8 BTM_{j,t-1} + \beta_9 PRICE_{j,t-1} + \epsilon_{j,t-1} \tag{4.1}$$

In this thesis, the characteristic estimate of firm's year *t* earnings is estimated using cross-sectional regression (4.1) for all firms. Firm's earnings per share, $E_{j,t}$, is used as the dependent variable. The independent variables are lagged characteristics from year *t-1*. $E^+_{j,t-1}$ is the earnings per share when earnings are positive. $NEGE_{j,t-1}$ is a dummy variable in case when earnings are negative. $ACC^-_{j,t-1}$ and $ACC^+_{j,t-1}$ are the negative and positive accruals. Accruals equal the change in current assets, plus the change in debt in current liabilities, minus the change in cash-and short-term investments, minus the change in current liabilities. $AG_{j,t-1}$ is the percent change in total assets, $DD_{j,t-1}$ a dummy for zero dividends and $DIV_{j,t-1}$ dividends per share. $BTM_{j,t-1}$ is the book value of equity to market value of equity and $PRICE_{j,t-1}$ the fiscal year end share price. (So 2013, p. 620) All variables are in per share basis. For earnings forecasts in 2004-2013 data is needed from years 2002-2012. More detailed descriptions of the variables used are given in chapter 5.

By using the fitted coefficients of the previous year regression we can get the characteristic forecast ($CF_{j,t}$) at year *t*, for company *j*, for the following fiscal year earnings (4.2). In other words, *t-1* realized earnings are regressed on *t-2* characteristics. These coefficients are then used to *t-1* characteristics to receive earnings forecast for year *t*.

$$CF_{j,t} = \hat{\beta}_0 + \hat{\beta}_1 E^{+}_{j,t-1} + \hat{\beta}_2 NEGE_{j,t-1} + \hat{\beta}_3 ACC^{-}_{j,t-1} + \hat{\beta}_4 ACC^{+}_{j,t-1} + \hat{\beta}_5 AG_{j,t-1} + \hat{\beta}_6 DD_{j,t-1} + \hat{\beta}_7 DIV_{j,t-1} + \hat{\beta}_8 BTM_{j,t-1} + \hat{\beta}_9 PRICE_{j,t-1} \tag{4.2}$$

Following So's (2013, p. 622) the empirical prediction is that the forecast error equals the difference between the characteristic and consensus analyst forecasts. This is based on equations 3.7 and 3.8 (covered in chapter 3). After calculating the characteristic forecasts I calculate variable that So's (2013, p. 622) called characteristic forecast optimism (CO, equation 4.3). Characteristic optimism is received by dividing difference between per share CF and AF (analysts' consensus forecast) by company's total assets per share. Numerator of the equation is equivalent to $\widehat{FE}^{C}_{j,t+1}$ in equation 3.8 and so characteristic optimism corresponds to the predicted forecast error scaled by total assets per share. Characteristic optimism variable is used to rank firms in cross-sectional tests.

$$CO_{j,t} = \frac{CF_{j,t} - AF_{j,t}}{TA_{j,t-1}} \tag{4.3}$$

Characteristic estimate is assumed to be unbiased estimate of future earnings as explained in chapter 3.2. Characteristic optimism can be interpreted so that higher values mean that analysts are overly pessimistic and lower values mean excessive optimism. As CF is assumed to be unbiased estimate of realized earnings, prior case means that earnings are expected to be higher than analysts' forecast. In later case correspondingly realized earnings are expected to be below analysts' forecast (So 2013, p. 622).

As the methodology of this thesis follows methodology in So (2013, pp. 615-640) and as So's predictions were empirically supported, exactly the same predictions stand in this thesis. First empirical prediction focuses on first empirical part of the thesis while second relates to investment strategy part.

Empirical prediction 1
Characteristic forecast in excess of analyst forecast predict realized earnings in excess of analyst forecast. Thus, characteristic forecast optimism, CO, positively predicts analyst forecast errors (actual earnings minus analyst forecast of earnings).

Empirical prediction 2
Characteristic forecast in excess of analyst forecasts correlate positively with earnings information not fully reflected in current prices. Thus, characteristic optimism, CO, positively predicts future abnormal returns.

4.2 Investment strategy

Investment strategy section of the empirical part of this thesis covers the formation of investment portfolio and the performance follow up. Characteristic approach to analyst forecast errors and the derived characteristic optimism provide basis for portfolio formation.

High characteristic optimism can be interpreted so that analysts are being pessimistic compared to characteristic forecast. Low CO, in turn, means that analysts are being too optimistic. Based on So (2013, pp. 615-640) investors rely too much on analysts' forecasts. Thus, market prices do not completely take into account potential analyst errors and company fundamentals. This results undervaluation. Hence, higher CO values should forecast higher future returns. So put this in form of empirical prediction 2. Empirical prediction is tested by forming a simple long-short portfolio and calculating returns for one year starting from portfolio formation.

The methodology follows four steps:

1. Calculate CO as explained in chapter 4.1
2. Rank firms
3. Form portfolio using firm rankings
4. Calculate portfolio returns

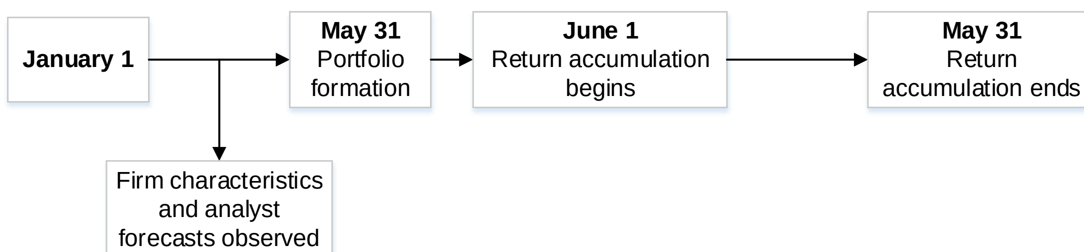

Figure 4.1 Timeline of analysis

Figure 4.1 presents the timeline of analysis in this thesis. This timeline is followed for all the companies in sample even though there are three companies which have differing fiscal years (Efore in 2002-2012, Rapala VMC in 2002 and Viking Line 2002-2009). To increase practicality of this thesis, all companies are treated the same way. Characteristic data and analysts forecasts are observed between fiscal year end and the next May 31st. It is assumed that this minimum five month separation between fiscal year end and observation of analyst forecast gives analysts enough time to include all available characteristic information into their earnings forecasts.

When previous financial year's characteristic data and realized earnings are available they are used to run a regression to get coefficients for all the characteristics. On May 31st previous year's fitted coefficients and latest characteristics are used to calculate characteristic forecast of earnings. Latest corresponding analyst forecasts are also observed on May 31st. Characteristic and analyst forecasts, and total assets per share are then used to calculate characteristic optimism (CO) for each firm in the sample. Process of obtaining CF and CO is explained in more detail in chapter 4.1.

After calculating CO, firms are ranked according to the characteristic optimism and divided into five quintiles. Portfolio is then formed by taking long position (buying) in the companies in the highest CO quintile and short position (selling) in the lowest CO quintile. Return for this portfolio is calculated starting from June 1st and ending May 31st in the following year. Process is repeated for each year from 2004 to 2013. Portfolio returns are calculated by using total return index that was obtained from Datastream. Also, monthly returns are calculated. Data chapter covers variables and the process how data was obtained in more detail.

5. Data

Timespan

Characteristic earnings were forecasted for years 2004-2013. This requires fundamental data from 2002 to 2013. Regressions were run for 2003-2012 and fitted coefficients then used to form characteristics forecasts for years 2004-2013. Year 2002 was selected as the first year for fundamental data as this is the first year in which companies reported their results in euros. This limits problems that currency translation could cause. Total return data spans from beginning of June 2003 to end of May 2014.

Companies

The sample consists of non-financial firms that have been primarily listed in OMX Helsinki during the sample period. Financial companies (banks, insurance and real estate) were excluded from the sample because of the incomparability of financial statements between financial and non-financial companies. Primary listing to OMX Helsinki rules out a few firms that are registered in Sweden and release their financial statements in Swedish krona. In some cases, companies have more than one class of shares listed.

In these cases the more liquid one was selected which is most often the share class for which analysts give recommendations. Fundamental data, analyst forecasts and total return data were obtained for the same share class. As this thesis doesn’t focus on forecasted share price or analyst recommendations, share class selection is not that significant of an issue as long as there is earnings per share forecast for that share class.

Because of data availability companies which have been public but now delisted had to be excluded from the sample. This could cause survivorship bias. Although So (2013, p. 623) excluded companies with share price below $5 from his sample, He states that using firms with low share prices may cause micro-structure related problems such as bid-ask bounce. I do not address such limitation to the data used in samples of this thesis because this would exclude too many companies from already small sample.

In order to be able to forecast earnings in year t+1, company must have fundamental data available for year t. Company however, does not need to be in sample in year t-1 which is used to calculate used variable coefficients. All companies in sample must have non-missing data. Also, companies with negative book value of equity are excluded from the sample as it causes negative book-to-market ratio.

The number of firms in sample is presented in figure 5.1. The graph shows for how many company earnings were forecasted by using the characteristic approach. Year 2003 is in the graph only to show how many companies were in sample that was used to get coefficients for year 2004 estimate (year 2004 estimate requires fundamental data from year 2003 and regression coefficients that were obtained by regressing year 2002 fundamentals to year 2003 realized earnings).

From year 2004 to year 2013 the sample size varies from low of 72 companies in 2004 to high of 88 companies in 2008. On average 78,8 companies were included in sample. In total sample consists of 788 firm-year observations of realized earnings, analyst forecasts and characteristic forecasts. In total 95 individual companies were part of the data. Complete list of companies in sample by year is presented in appendix 3.

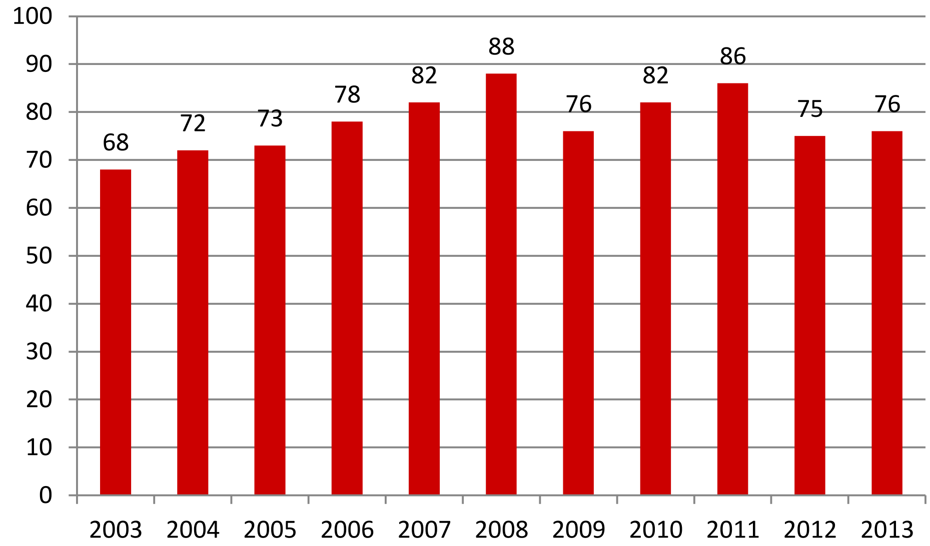

Figure 5.1 Number of firms in sample

The figure plots the total number of firms in sample by year.

Data collection and variables

Data used in empirical tests can be divided to three categories: fundamental data, market data and analyst data. Fundamental data consists of company specific financial statement data. Market data consists of company specific fundamental data such as historical book-to-market ratios and historical share prices and also of company specific total return series. Analyst data contains analysts' earnings estimates.

Because almost unlimited amount of publicly observable data is available and the number of variables that can be associated with future earnings is so high, there is practically unlimited amount of combinations for possible variables that can be used to forecast future earnings. To ensure economic justification and comparability of results, I follow the selection of variables used by So (2013, pp. 615-640), which was based on Fama & French (2006, pp. 491-518) and Hou et al. (2012, pp. 504-526).

Analyst data

Analyst consensus data was collected by using Thomson Reuters Spreadsheet Link add-in for Excel. The template used was called *Historical_Estimates*. Together with analyst data, comparable earnings data was collected. In a few cases where the comparable actual earnings were missing Reuters Fundamentals earnings from Thomson One Banker database were used. The analyst estimate of earnings was the latest available estimate at the end of May. Analyst estimates were called mean estimates. This differs from common method of using median analyst estimate as consensus estimate. More information about earnings is presented in the earnings paragraph of this chapter.

Market data

Market data, including Book-to-market ratio, historical share prices and total return data was collected using Datastream database. The variables mentioned can be considered as fundamental data, but those are separated from other fundamental data because of they are determined mostly by market.

As Datastream does not provide book-to-market data directly, market-to-book ratio was obtained and turned into book-to-market ratio

$$BTM = \frac{1}{MTB}$$

Fundamental data

Fundamental data was collected from Thomson One Banker database. To ensure comparability, I used standardized report format of Reuters Fundamentals. Also, I used the original reported figures as this is likely to be the information that the analysts have when making their forecasts. All financial statements were in euros (most often reported in millions of euros).

The summary chart of account codes (Sum COA) are presented for each variable in connection with variable description. The variable selection follows the models presented in chapter 3.2 and 4.1. The basis of the model is presented in equation 4.1.

$$E_{j,t} = \beta_0 + \beta_1 E^{+}_{j,t-1} + \beta_2 NEGE_{j,t-1} + \beta_3 ACC^{-}_{j,t-1} + \beta_4 ACC^{+}_{j,t-1} + \beta_5 AG_{j,t-1} + \beta_6 DD_{j,t-1} + \beta_7 DIV_{j,t-1} + \beta_8 BTM_{j,t-1} + \beta_9 PRICE_{j,t-1} + \epsilon_{j,t-1} \tag{4.1}$$

Earnings: $E_{j,t}$, $E^{+}_{j,t}$ and $NEGE_{j,t}$

As earnings, I primarily use Thomson One's valuation earnings per share (i.e. Adjusted EPS). This was collected together with analyst estimates by using Thomson Reuters Spreadsheet Link and *Historical_Estimates* template.

Thomson One definition for Earnings per Share (EPS):

"Valuation earnings per share, 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." (Thomson One Banker, 2014)

In a few cases realized valuation earnings per share is missing. In these cases, I use Thomson One Banker's basic EPS excluding extraordinary items

(Sum COA SBBF), which is the earnings best corresponding valuation earnings.

The definition of earnings differs from So (2013, p. 620) as he uses net income before extraordinary items after subtracting special items multiplied by 0.65, to take into account tax effect (assumed tax rate 35%). The corporate tax rate has varied during the timespan of the sample used in this study. Also, valuation earnings were directly available. Because of these facts, different approach was selected.

$E_{j,t}^{+}$ is earnings per share if positive earnings. $NEGE$ variable is created by coding all the negative earnings as 1, and all the positive earnings 0. $E_{j,t}$, is earnings per share as such.

Accruals: $ACC_{j,t}^{-}$ and $ACC_{j,t}^{+}$

For each firm-year, only $Acc+$ or $Acc-$ can have value, other one is coded as 0. Accruals consist of four elements and are calculated as follows: Change in current assets plus change in debt in current liabilities minus change in cash and short-term investments minus change in current liabilities. The Thomson One items used are presented in table 5.1 below.

Table 5.1 Accrual elements

Element	Sum COA	Item
Change in current assets	ATCA	Total Current Assets
Change in debt in current liabilities	LSTD	Notes Payable/Short Term Debt
Change in cash and short-term investments	SCSI	Cash and Short Term Investments
Change in current liabilities	LTCL	Total Current Liabilities

Asset growth: $AG_{j,t}$

Asset growth is calculated as percentage growth of total assets. Sum COA used for this is ATOT, Total Assets.

$$AG_{j,t} = \frac{TA_{j,t} - TA_{j,t-1}}{TA_{j,t-1}}$$

Dividends: $DIV_{j,t}$ and $DD_{j,t}$

For dividends per share, $DIV_{j,t}$, Thomson One Banker item DDPS1, DPS - Common Stock Primary Issue is used. $DD_{j,t}$ is a dummy variable which is coded 1 in case of zero dividends and 0 otherwise.

Book-to-market: $BTM_{j,t}$

$BTM_{j,t}$, that is book value of equity divided by market value of equity, was calculated by dividing one by Datastream item Market to book value (MTBV). Book-to-market ratio is calculated for the end of fiscal year.

Share price: $PRICE_{j,t}$

Historical fiscal year end share prices were collected from Datastream. The item used was Price (P).

Total assets: $TA_{j,t}$

Total assets per share was needed to calculate scaled characteristic optimism.

Number of shares

When figure was needed to transform into per share basis, Basic Weighted Average Shares (Sum COA SBAS) was used.

Total return:

Total returns are used in the Investment strategy section of this thesis' empirical part. To calculate total return for each of the companies I used Datastream's Total return index (RI). Total return takes into account both market price development and paid dividends.

Table 5.2 Table of variables

The table summarizes all the variables, and abbreviations used in the characteristic approach. It also lists the sources of data and item code used in these databases.

Variable	Description	Reuters Fundamentals Sum COA (R) or Datastream item (D)	
E+	Earnings (if positive).	Valuation earnings or SBBF	D/R
NEGE	Dummy for negative earnings.	Valuation earnings or SBBF	D/R
ACC+	Positive accruals. 0 otherwise.	ATCA, LSTD, SCSI, LTCL	R
ACC-	Negative accruals. 0 otherwise.	ATCA, LSTD, SCSI, LTCL	R
AG	Percentage growth of total assets.	ATOT	R
DD	Dummy for zero dividends.	DDPS1	R
DIV	Dividends per share.	DDPS1	R
BTM	Book-to-market ratio.	MTBV	D
P	Fiscal year end share price.	P	D
TA	Total assets per share	ATOT	R
	Number of shares	SBAS	R
	Total return	RI	D

Table 5.2 collects together all the variables described in this chapter.

Discussion and challenges with the data

Data availability limits the scope of this thesis. Finnish stock market is relatively small. On September 9th 2014 there were only 122 companies listed in OMX Helsinki compared to 259 in Stockholm and 145 in Copenhagen. In Finland only 27 of these were large cap companies. 37 were mid cap and 58 small cap. (Nasdaq OMX Nordic, 2014).

Small number of companies and the small size of many of these companies result in that there is even smaller number of firms that were followed by analysts. This sets limits to the sample size. The yearly sample size is presented in figure 5.1.

So (2013, p. 623) excluded firms with share price below $5 but because of already limited sample size all the non-financial companies for which all data is found are included in the sample. He states that this may cause microstructure-related problems such as bid-ask bounce.

Unlike in So's (2013, pp. 615-640) article, analyst forecast used in this thesis is not the consensus estimate defined as median estimate of the analysts forecasts but the analysts' mean estimate. So also defines earnings as net income before extraordinary items after subtracting special items multiplied by 0,65. This multiplier reflects assumed tax rate of 35 %. In this thesis, however, adjusted EPS/valuation EPS which is collected directly from Thomson Reuters database is used.

The differing decisions concerning data were made mainly because of data availability. Lack of access to the same databases forced several adjustments to be made. All the adjustments were however made so that the validity is as little compromised as possible.

6. Results

This chapter presents the empirical findings of this thesis. The results are divided into two parts. First focuses on analysts' forecast error forecasts and second on realized investment returns and investment strategy that was based on the predicted forecasted errors. Because the only article using characteristic approach is published by So (2013, pp. 615-640) the results of this thesis are greatly reflected to his results. The first part tries to find whether the empirical prediction 1 holds and the second part focuses on the empirical prediction 2.

6.1 Characteristic forecast and predicted forecast errors

Table 6.1 presents simple descriptive statistics of variables used in the regressions. Values were calculated using data from years 2004-2013.

Table 6.1 Descriptive statistics of firm characteristics

The table presents descriptive statistics for variables used in the characteristic approach. Variable definitions are presented in table 5.2.

	E+	NEGE	ACC-	ACC+	AG	DD	DIV	BTM	P
Average	0,630	0,169	-0,303	0,335	0,099	0,183	0,394	0,649	9,444
Min	0,000	0,000	-8,691	0,000	-0,644	0,000	0,000	-0,719	0,050
Median	0,430	0,000	0,000	0,002	0,034	0,000	0,250	0,529	6,985
Max	8,305	1,000	0,000	13,717	9,548	1,000	3,000	5,882	67,860
Std. Dev.	0,769	0,375	0,846	0,939	0,500	0,387	0,434	0,476	8,672

Table 6.2 presents the regression statistics for earnings that were regressed to lagged company characteristics. Adjusted R^2 is 0,548 which mean that the

model explains a significant portion of variation in year t+1 earnings. Even though the sample in this thesis was significantly lower than the one used by So (2013, pp. 615-640), Adjusted R^2 is in line with his finding (So's Adjusted R^2 0,561). Still, Adjusted R^2 did not remain stable. It varied from minimum 0,20 in 2005 to maximum 0,89 in 2007. Adjusted R^2 is relatively high taken into account that individual variables were not statistically significant as shown in table 6.3. Statistical insignificance is most likely result of too small yearly sample size.

Table 6.2 Average regression statistics

Table 6.2 presents average regression statistics from 2004-2013.Firms' earnings per share were regressed on respective lagged firm characteristics.

Regression Statistics	
Multiple R	0,765
R Square	0,602
Adjusted R Square	0,548
Standard Error	0,626

Table 6.3 Average results of earnings regressions

Realized earnings were regresses on firm characteristics. The table presents regression coefficients, standard errors and statistical significance for the independent variables.

	Description	***Coefficients***	***Standard Error***	***P-value***
Intercept		0,267	0,193	0,298
E+	Positive earnings per share	0,711	0,250	0,104
NEGE	Loss dummy	-0,099	0,291	0,472
ACC-	Negative accruals per share	0,050	0,132	0,164
ACC+	Positive accruals per share	-0,041	0,128	0,415
AG	Asset growth	-0,162	0,293	0,573
DD	Zero dividend dummy	-0,260	0,269	0,403
DIV	Dividend per share	0,142	0,418	0,402
BTM	Book-to-market	-0,127	0,212	0,458
P	Share price	-0,002	0,021	0,281

Table 6.3 presents the coefficients of the characteristic model. Coefficient signs indicate that companies with higher positive earnings and dividends, and lower accruals have higher earnings in the next year. On the other hand, companies making loss, with positive accruals and asset growth, zero dividends, higher book-to-market ratio and higher share price tend to have lower earnings in FY1. Still, especially in case of negative accruals and share price it must be noted that the coefficient is really close to zero. Positive earnings per share was the only variable that was close to 10 % risk level. Statistical significance of the other variables was lower. Signs of the coefficients were in line with So (2013, p. 621) but with this data, coefficient for *NEGE* is lower than for So (-0,099 vs. -0,631).

Table 6.4 Correlations and average forecast errors

The table presents correlations between realized earnings (RE), characteristic forecast (CF) and analyst forecast (AF). Table also shows mean error defined as realized earnings minus forecast. Mean error shows that both forecasts are too optimistic.

	Correlation Forecast, RE	Correlation AF, CF	Mean Error	T-statistic (two-sided)	P value
CF	0,453	0,740	-0,013	-1,717	0,086
AF	0,741	0,740	-0,121	-6,784	0,000

In table 6.4 we can observe the correlations between realized earnings (RE), characteristic forecast (CF) and analyst mean forecast (AF) calculated based on the whole 10-year sample. Based on the sample of our study, it seems clear that analysts' forecasts are superior in forecasting future earnings compared to characteristic model forecasts. Correlation between analyst forecast and realized earnings is substantially high, over 0,74. Compared to this, correlation between realized earnings and characteristic forecast is modest, only 0,45. Still even 0,45 correlation is significantly high which can be interpreted so that characteristic model has predictive power.

Table 6.4 also contains mean errors calculated as realized earnings minus forecast. Also, it presents the two-sided t-statistic and p values for errors. Mean errors are negative for both AF and CF which suggests that on average, both give too optimistic forecasts. CF error, however is only slightly negative while mean error for AF is higher. P value shows statistical significance for both CF and AF, on 10 percent risk level for CF and 1 percent risk level for AF.

Table 6.5 Regressions on realized earnings

Realized earnings were regressed on characteristic (CF) and analyst forecasts (AF) separately and to the two forecasts together. Table 6.5 presents the regression coefficients. T-statistics are presented in brackets. Asterisks *, ** and *** reflect the statistical significance on 10 %, 5 % and 1 % risk levels, respectively.

	CF	AF	CF & AF
Intercept	0,250***	-0,066**	-0,058*
	(6,375)	(-2,082)	(-1,852)
CF	0,529***		-0,247***
	(14,247)		(-6,079)
AF	-	0,918***	1,113***
	-	(30,959)	(25,785)
Adj. R2	0,204	0,549	0,569
p < 0,10 *			
p < 0,05 **			
p < 0,01 ***			

Table 6.5 contains regression results from pooled estimations where realized earnings were regressed on CF and AF. Numbers in brackets represent standard error of the coefficient. Coefficient for CF in regression, where CF was the only independent variable, is only 0,529 which is far lower than regression using AF as independent variable. In AF regression the AF coefficient is 0,918. Based on this AF seems far better estimate of realized earnings than CF. Adjusted R^2 is only 0,204 for CF alone. This is far below

the explanatory power of AF alone. The adjusted R^2 for AF alone is 0,549. Using both CF and AF adds only model's predicative power only by a little.

Compared to previous results by So (2013, p. 621) the coefficient of CF in regression of RE on CF alone is much lower. In his research So got coefficient of 1,001 (p-value < 0,01). This is significant difference in the results. Also, the AF coefficient of the second regression is below the one that So received (0,918 in this thesis and 1,054 in So's article). This difference however is not that large. Like in So's article, the intercept in the second regression is statistically significant and negative, which means that analyst forecasts tend to be overly optimistic.

Another significant difference to So's (2013, p. 621) results is that when fitting both CF and AF to realized earnings, the coefficient of CF is negative. Still, both CF and AF are highly statistically significant, which speaks for the usefulness of both forecasts. In the third regression intercept is negative, but statistically significant only on 10 % risk level.

Figures 6.1 and 6.2 present averages and median values of realized earnings, analyst forecasts and characteristic forecasts for each year in the sample period. When examining average values on figure 6.1 one can notice that realized earnings have been below analyst forecasts in all years but in 2004. Even in 2004 average values were 0,53 and 0,52 eur per share for realized earnings and analyst forecasts respectively. This result gives support for prediction that analysts tend to give generally overly optimistic forecasts of future earnings.

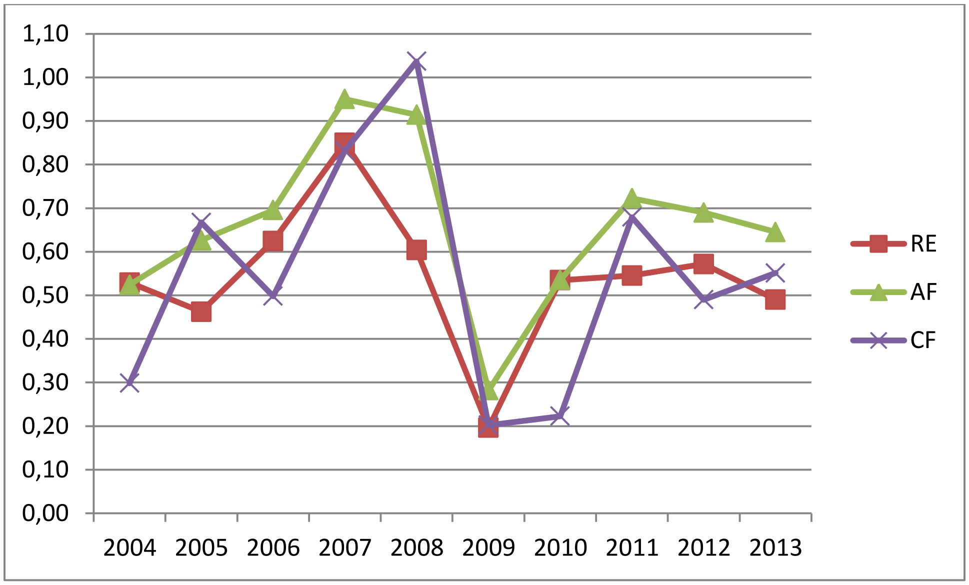

Figure 6.1 Average values for RE, AF and CF

The figure plots average values of realized earnings per share, analyst forecast and characteristic forecast throughout the sample period.

Examination of median values of RE, AF and CF does not give as clear results. Order of the forecasts and realized earnings varies from year to year. In general median values are below average values. This also tells about long tail of the distribution. Still, the graph of median values resembles the one of average values.

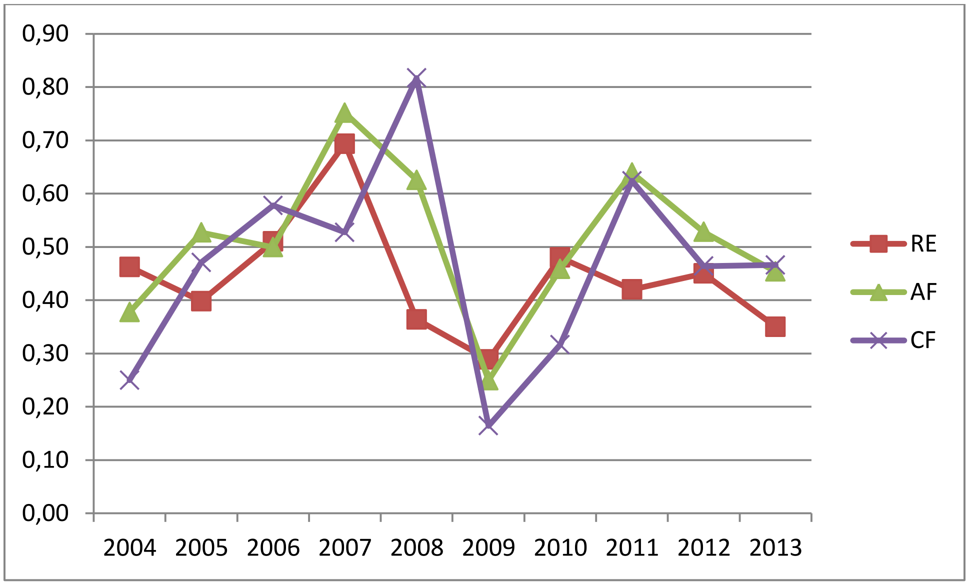

Figure 6.2 Median values for RE, AF and CF

The figure plots median values of realized earnings per share, analyst forecast and characteristic forecast throughout the sample period.

In both figures 6.1 and 6.2 it is clear that results of the Finnish companies dropped dramatically in 2008 and 2009. In year 2008 both analysts and characteristic model were poor in forecasting earnings. Notable is however, that both were much more accurate immediately in 2009. Big errors in CF are of course expected in cases of drastic shocks, such as global financial crisis in 2007-2008 and the sovereign-debt crisis after it. Despite economic difficulties, both average and median realized earnings were positive in every year in the sample.

In relation to realized earnings characteristic forecast fluctuated more. Of the ten years in the sample period characteristic forecast was below realized earnings in five, above in four and equal to in one year. On average AF was 23,77 % and CF 1,74 % higher than realized earnings. CF is above AF only in 2005 and 2008. While CF is on average closer to RE the standard deviation of both CF value and its percentage difference to RE is higher than in AF's case.

Characteristic optimism

This section of empirical part of the thesis uses characteristic optimism ($CO_{j,t} = \frac{CF_{j,t} - AF_{j,t}}{TA_{j,t}}$) to sort companies into five quintiles. Because number of firms in sample varies over time, the division of companies is collected to table 6.6. Companies were divided into quintiles as equally as possible.

Table 6.6 Quintile division

The table presents division of the sample firms to five characteristic optimism quintiles. Characteristic optimism (CO) is defined as the difference between characteristic forecast and analyst forecast divided by the firm's total assets by share. The firms were distributed to the five quintiles as evenly as possible.

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Sample size	72	73	78	82	88	76	82	86	75	76
1 (Low CO)	15	15	16	17	18	16	17	18	15	16
2	14	14	15	16	17	15	16	17	15	15
3	14	15	16	16	18	14	16	16	15	14
4	14	14	15	16	17	15	16	17	15	15
5 (High CO)	15	15	16	17	18	16	17	18	15	16

Average and median values and standard errors for CF, AF and RE are presented in table 6.7. CF-% and AF-% show relation of forecast to realized earnings. On average, CF is 9 % lower and AF 12,1 % higher than RE. This gives support for optimism of analysts. Average CF is close to average RE. CF has a bit higher standard deviation than AF. Still realized earnings vary more than either of the forecasts.

Table 6.7 Descriptive statistics

The table presents descriptive statistics for characteristic forecast, analyst forecast, realized earnings and characteristic optimism. Characteristic optimism (CO) is defined as the difference between characteristic forecast and analyst forecast divided by the firm's total assets by share. CF-% and AF-% were calculated as corresponding forecast minus realized earnings divided by realized earnings.

	CF	AF	RE	CO	CF-%	AF-%
Average	0,557	0,665	0,545	-0,014	-0,090	0,121
Min	-2,253	-3,920	-11,464	-6,065	-118,818	-88,676
Median	0,436	0,491	0,435	-0,004	-0,043	-0,021
Max	8,895	9,797	8,305	3,432	82,679	83,745
Std. Dev.	0,897	0,845	1,047	0,381	8,210	6,631

Quintiles average values for CF, AF, RE and CO as well as standard deviation of CO are presented in table 6.8. Averages have been calculated using the whole sample from year 2004 to 2013. P-values were calculated for all variables using two-sample t-test. CF was significantly lower in the lowest CO quintile than in highest the CO quintile. For lowest quintile characteristic forecast was only 0,054 where it was 0,686 for highest CO quintile. All other quintiles had higher CF than the first quintile. Highest values were found in quintiles four and three.

Table 6.8 Average values by quintile

The table presents average values for characteristic forecast, analyst forecast, realized earnings and characteristic optimism by quintile. The table also shows the standard deviation of CO by quintile. Characteristic optimism (CO) is defined as the difference between characteristic forecast and analyst forecast divided by the firm's total assets by share.

	CF	AF	RE	CO	Std. dev. (CO)
1 (Low CO)	0,054	0,624	0,518	-0,232	0,676
2	0,530	1,017	0,913	-0,027	0,020
3	0,762	0,861	0,723	-0,005	0,012
4	0,776	0,590	0,462	0,016	0,017
5 (High CO)	0,686	0,261	0,132	0,177	0,402
High-Low	0,632	-0,363	-0,386	0,409	-0,274
p-value for H0: High-Low = 0	0,000	0,000	0,000	0,000	

AF, however, was significantly higher in the first quintile compared to the fifth quintile. This is expected taken the way how CO is calculated. Highest analyst forecasts can be found in second and third quintile. Also realized earnings are significantly higher in the first quintile than in the fifth one. The highest realized earnings were found in quintile two followed by quintile three. The lowest value of realized earnings on fifth quintile is also noteworthy observation. On average, analyst forecast was closer to the realized earnings in four quintiles of five. Only in the middle quintile characteristic forecast was on average closer to realized earnings than analysts' mean forecast.

Table 6.8 also contains average characteristic optimism for all quintiles. CO ranges from high of 0,177 to low of -0,232. The two highest quintiles were above zero where in remaining three cases AF was on average higher than CF. Also standard deviations of CO are presented in table 6.8. In quintiles two to four standard deviation is much lower than in the two extremes. This indicates that the CO's distribution has long tails.

Average and median errors for CF and AF were calculated by subtracting forecast from realized earnings and scaling the difference by total assets per share. The calculated errors are presented in table 6.9. For all quintiles AF error was negative which tells that analysts have given too optimistic forecasts. CF values decrease from quintile one to five. Characteristic forecast were too pessimistic in quintiles one and two, and optimistic in remaining three quintiles. Results of median values are similar. The smallest errors were found in the middle quintile. According to the empirical prediction one, analyst forecast error should increase across CO quintiles. This however does not seem to hold and thus CO does not seem to be able to predict analyst forecast errors.

Table 6.9 Average and median forecast errors by quintile

The table presents average and median errors for characteristic and analyst forecasts. These were calculated by subtracting forecast from realized earnings and scaling the difference by total assets per share. Characteristic optimism (CO) is defined as the difference between characteristic forecast and analyst forecast divided by the firm's total assets by share.

	Average		**Median**	
	CF error	**AF error**	**CF error**	**AF error**
1 (Low CO)	0,181	-0,051	0,075	-0,008
2	0,023	-0,004	0,020	-0,003
3	-0,001	-0,006	0,002	-0,003
4	-0,026	-0,010	-0,017	-0,005
5 (High CO)	-0,197	-0,020	-0,081	-0,009

The number of firms receiving positive and negative characteristic optimism values is collected to table 6.10. When CO is positive, it means that characteristic forecast is more optimistic than analysts. In this case analysts are assumed to be too pessimistic. In turn negative CO means that analysts are more optimistic than CO.

Table 6.10 shows that analysts are generally more optimistic than the characteristic forecast. Out of 10 years of the sample, analysts were more optimistic in seven years while characteristic approach was more optimistic only in two years. In total, analysts are more optimistic 453 times out of 788 and characteristic approach 353 times. General analyst optimism is in line with the existing literature that shows that analysts tend to be optimistic and bias their forecasts upwards. Year 2008 is a fine example of characteristic approach inability to adjust to dramatic events in the market.

Table 6.10 Number of positive and negative CO

The table presents the number of companies with positive and negative characteristic optimism value by year. Characteristic optimism (CO) is defined as the difference between characteristic forecast and analyst forecast divided by the firm's total assets by share.

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Total
Positive	32	35	39	39	63	24	24	48	20	29	353
Negative	40	38	39	43	25	52	58	38	55	47	435

Table 6.11 examines forecast optimism against realized earnings. Realized earnings per share and both forecasts were rounded to two decimal places so that correct number of accurate forecasts could be calculated. Compared to characteristic forecast analyst forecasts have been more often optimistic (i.e. RE < Forecast). Also CF has been more often optimistic than pessimistic but not by as much as analysts. Out of the 788 observations CF was correct only eight times and analysts 24 times. When examining optimism by quintile, as presented in table 6.11 we observe in case of analyst forecast, both optimism and pessimism were distributed quite evenly. Based on the distribution of CF in CO quintiles, we can say that it is likely that characteristic forecast of company in high CO quintile is optimistic and in turn low CO can be associated with pessimistic forecast. For empirical prediction 1 to hold true,

analysts should be more optimistic when CO is high and more pessimistic when CO is low. The findings in table 6.11 do not support this.

Table 6.11 Forecast optimism and pessimism by quintile

The table presents the optimism (realized earnings < forecast) and pessimism (realized earnings > forecast) of characteristic and analyst forecasts by quintile of characteristic optimism. Characteristic optimism (CO) is defined as the difference between characteristic forecast and analyst forecast divided by the firm's total assets by share. Forecasts were rounded to two decimal places so that correct number of accurate forecasts could be calculated.

	CF			AF		
	Optimistic	**Pessimistic**	**Equal**	**Optimistic**	**Pessimistic**	**Equal**
1 (Low CO)	9% (15)	90% (147)	1% (1)	61% (99)	36% (58)	4% (6)
2	25% (39)	75% (115)	0% (0)	58% (89)	41% (63)	1% (2)
3	44% (68)	54% (83)	2% (3)	54% (83)	45% (69)	1% (2)
4	82% (127)	15% (23)	3% (4)	61% (94)	36% (56)	3% (4)
5 (High CO)	95% (155)	5% (8)	0% (0)	59% (96)	35% (57)	6% (10)
Total	404	376	8	461	303	24

Finally, AF error, which equals realized earnings minus analyst forecast divided by total assets per share, was regressed on characteristic optimism. CO is positive and statistically significant variable but Adjusted R^2 is only 0,125. CO has predicative power but alone it is inadequate independent variable.

Table 6.12 CO Regression on AF error

The table presents the results of analyst forecast error being regressed on characteristic optimism. Analyst forecast error equals realized earnings minus analyst forecast divided by firm's total assets per share. Characteristic optimism (CO) is defined as the difference between characteristic forecast and analyst forecast divided by the firm's total assets by share.

	Coefficients	***Standard Error***	***t Stat***	***P-value***
Intercept	-0,016	0,007	-2,130	0,033
CO	0,204	0,019	10,634	0,000
Adjusted R^2	0,125			

In the end, based on the evidence in this chapter analyst forecasts seem to be superior compared to the characteristic approach. This result is conflicting with the findings of So (2013, pp. 615-640) who shows that overreliance on analyst forecast is likely to result valuation errors and affect the information content of market prices. The results of this chapter do not provide support for empirical prediction 1 which states that characteristic optimism would positively predict analyst forecasts errors.

6.2. Investment strategy

The second part of the empirical section of this thesis presents the results of an investment strategy that is based on predicted analyst forecast errors, i.e. characteristic optimism. In this investment strategy, companies are divided into five quintiles based on their CO value (Characteristic optimism: $CO_{j,t} = \frac{CF_{j,t} - AF_{j,t}}{TA_{j,t}}$, see chapter 4.1 for details). Following a simple long-short strategy where long position is taken on high CO value firms and short position on low CO value firms I calculated annual returns for my sample period 1.6.2004-

31.5.2014 which corresponds to forecasted earnings for years 2004-2013. Methodology is presented in more detail in chapter 4.2.

Table 6.13 and table 6.14 contain yearly and monthly average returns per CO quintile as well as yearly returns for sample portfolio and long-short strategy portfolio. Years correspond to the portfolio formation year. E.g. return accumulation period for year 2013 is 1.6.2013-31.5.2014. For monthly returns, June (6th month) is the first month of return accumulation after portfolio formation.

Returns are inconsistent with empirical prediction that high CO firms earn higher returns and others lower in order from higher to lower which can be seen in table 6.13 which presents the return by year and CO quintile. The average returns that are presented in this table were calculated using the whole sample. Returns do not increase across quintiles from lowest to highest as expected. Average returns of high CO quintile are higher than the one of low CO quintile in half of the years: 2007, 2008, 2010, 2012 and 2013. In 2007 and 2008 all quintiles and the sample as whole generated negative return. High CO quintile beat every other quintile only in 2007 and 2008 when its return was least negative and in 2012 when it was able to generate highest positive return of all quintiles. On average high CO quintile earned 0,68 % higher return than the low CO quintile. Clear pattern of return by quintile is not clearly to be seen in table 6.13. Still, extremes, i.e. high and low quintiles, generated on average below 10 % return while three middle quintiles performed better.

During the ten year period, on average, the yearly return for the long-short strategy is only 0,34 %. During the same period, sample as whole generated on average 10,93 % return. The long-short strategy also loses to all the quintiles alone. The return for the long-short strategy was negative in five out of ten years and it only beat whole sample in years 2007, 2008 and 2011.

This is because of short portion in the investment strategy portfolio. These were years when returns were negative both as whole and in every quintile of the strategy. In 2007 and 2008 the return for low CO quintile was more negative than for high CO quintile. Thus the short position in the low quintile was able to pull portfolio return to positive. There was no substantial size difference in the returns of positive and negative years. The long-short strategy generated on average 4,59 % on positive years and -4,28 % on negative years.

Examination of monthly returns tells similar story as the yearly returns as can be seen in table 6.14 which presents average monthly returns. There is no support for expected higher return for high CO quintile firms and lower for low CO quintile firms. Examination of monthly returns however reveals that on average May, June and October were bad for investors although long-short strategy was able to generate 0,3 % monthly return in both May and June. Beginning of the year, from January to April, however, generated generally higher return than other months. One possible explanation for the highest returns in January can be the January anomaly. Proving this is however out of the scope of this thesis. The long-short strategy generated on average 0,37 % on positive months and -0,72 %, almost double, on negative months. The eight positive months however were enough to results slightly positive average strategy return.

In addition to five quintile division, the sample portfolio was divided into two parts: CO higher and CO lower than median. In cases when there were odd number of firms in the portfolio, the median firm was left out. Long-short strategy return was also calculated to this two category division. High CO firms were bought and low CO firms sold short. Return accumulation followed the same procedure as in quintile division case. Return accumulation started at the beginning of June each year and lasted one year until end of May.

Low CO firms generate higher returns on positive years than high CO firms. However, those also generate larger losses on negative years. Year 2012 makes an exeption to this rule. In this year high CO portfolio generated higher return than low CO portfolio.

The long-short strategy generated positive returns only on years 2007, 2008 (loss years) and 2012. On average investor would have received highest returns by investing in low CO portfolio. Investing in diversified portfolio of all the companies would have resulted the second best return. High CO portfolio is on third place leaving the long-short strategy with negative return on the last place.

These findings of the second part of the empirical section do not support the empirical prediction 2 that the characteristic optimism predicts future abnormal returns is not supported. Based on the examination of investment returns, the characteristic approach does not seem to help predict analysts' forecast errors or future returns. I find no evidence that investors overweight analysts' forecasts. Investor seems to receive highest returns by investing in stocks for which analyst forecast and characteristic forecast are in line. These results conflict with the findings of So (2013, p. 636).

Table 6.13 Average yearly returns

The table presents the portfolio returns during one year return accumulation period by characteristic optimism quintile. Sample firms were divided yearly into five quintiles based on their characteristic optimism on that year. Return accumulation period started on June first on the year in quastion and lasted to the end of May on the following year. The average return for the whole observation period was calculated by using the whole sample data. Characteristic optimism (CO) is defined as the difference between characteristic forecast and analyst forecast divided by the firm's total assets by share. The long-short strategy return was calculated by buying high CO portfolio and selling short low CO portfolio.

	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**Average**
1 (Low CO)	0,3248	0,3537	0,2902	-0,1616	-0,2780	0,3625	0,1125	-0,2911	0,1320	0,1930	0,0896
2	0,4220	0,4424	0,4779	-0,2562	-0,3916	0,4536	0,2439	-0,2866	0,1843	0,1187	0,1227
3	0,2884	0,2008	0,3845	-0,2422	-0,2651	0,4394	0,2511	-0,2419	0,2587	0,4560	0,1371
4	0,3066	0,2735	0,4522	-0,1900	-0,2693	0,3946	0,0781	-0,1422	0,1576	0,0912	0,1024
5 (High CO)	0,1017	0,1946	0,2557	-0,1246	-0,1644	0,3560	0,2263	-0,2963	0,2761	0,2439	0,0964
All	0,2866	0,2912	0,3697	-0,1936	-0,2724	0,3996	0,1821	-0,2527	0,2017	0,2174	0,1093
Long-Short	-0,1116	-0,0796	-0,0172	0,0185	0,0568	-0,0032	0,0569	-0,0026	0,0720	0,0254	0,0034

Table 6.14 Average monthly returns

The table presents the average monthly portfolio returns by characteristic optimism quintile for sample period 2004-2013. Portfolios were formed in the end of May each year and return accumulation began in the beginning of each month. Characteristic optimism (CO) is defined as the difference between characteristic forecast and analyst forecast divided by the firm's total assets by share. The long-short strategy return was calculated by buying high CO portfolio and selling short low CO portfolio.

	6	**7**	**8**	**9**	**10**	**11**	**12**	**1**	**2**	**3**	**4**	**5**
1 (Low CO)	-0,0235	0,0040	-0,0042	0,0031	-0,0187	-0,0002	0,0088	0,0583	0,0135	0,0066	0,0498	-0,0130
2	-0,0105	0,0101	0,0042	-0,0026	-0,0034	-0,0069	0,0042	0,0407	0,0249	0,0121	0,0362	-0,0101
3	-0,0160	0,0012	0,0125	0,0165	-0,0149	0,0028	0,0090	0,0451	0,0113	0,0074	0,0394	-0,0114
4	-0,0237	0,0059	0,0031	0,0069	-0,0133	-0,0115	0,0122	0,0282	0,0162	0,0239	0,0336	-0,0054
5 (High CO)	-0,0174	0,0255	-0,0026	0,0043	-0,0214	0,0079	-0,0058	0,0487	0,0149	0,0202	0,0190	-0,0070
All	-0,0183	0,0095	0,0025	0,0056	-0,0145	-0,0015	0,0056	0,0444	0,0161	0,0140	0,0356	-0,0094
Long-Short	0,0030	0,0108	0,0008	0,0006	-0,0014	0,0040	-0,0073	-0,0048	0,0007	0,0068	-0,0154	0,0030

Table 6.15 Yearly average returns for low and high CO portfolios

The sample data was divided into two categories by characteristic optimism. Both categories have the same amount of firms. Table presents the average yearly returns for low and high characteristic optimism portfolios. Portfolios were formed in the end of May each year. The return accumulation period lasted from the beginning of June to the end of May next year. Characteristic optimism (CO) is defined as the difference between characteristic forecast and analyst forecast divided by the firm's total assets by share. The long-short strategy return was calculated by buying high CO portfolio and selling short low CO portfolio.

	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**Average**
Low CO	0,3630	0,3363	0,3987	-0,2175	-0,3228	0,4293	0,2107	-0,2902	0,1668	0,2363	0,1151
High CO	0,2102	0,2510	0,3407	-0,1698	-0,2220	0,3700	0,1535	-0,2152	0,2328	0,1985	0,1028
All	0,2866	0,2912	0,3697	-0,1936	-0,2979	0,3996	0,1821	-0,2527	0,2017	0,2174	0,1093
Long-Short	-0,0764	-0,0426	-0,0290	0,0238	0,0504	-0,0296	-0,0286	0,0375	0,0330	-0,0189	-0,0061

7. Conclusions

This thesis examines analyst forecasts and applies characteristic approach to predict analysts' forecast errors. Data consists of 788 firm-years spanning from 2002 to 2014. Sample was collected of listed Finnish companies. The methodology followed the one by So (2013, pp. 615-640). This thesis' objective was to test his empirical predictions that he was able to verify with data from the US. These predictions are:

Empirical prediction 1

Characteristic forecast in excess of analyst forecast predict realized earnings in excess of analyst forecast. Thus, characteristic forecast optimism, CO, positively predicts analyst forecast errors (actual earnings minus analyst forecast of earnings).

Empirical prediction 2

Characteristic forecast in excess of analyst forecasts correlate positively with earnings information not fully reflected in current prices. Thus, characteristic optimism, CO, positively predicts future abnormal returns.

Based on the empirical findings of this thesis I find no support for the empirical predictions. Despite general optimism, analysts' forecasts provide better estimate of companies' future earnings than the characteristic approach. Also, characteristic optimism had no power in predicting future abnormal returns. These results are conflicting with findings of So (2013, pp. 615-640).

So's (2013, pp. 615-640) methodology was followed as closely as possible, but some adjustments had to be made mostly due to data availability. Still, my belief is that the differences in results do not result from methodology, but data and focus of the study. As explained in the introduction, the Finnish market differs from its US counterpart especially in size and analyst coverage. So was able to obtain data for total sample of 51 591 firm-years spanning from 1980 to 2009. At worst, his sample consisted of more than 500 companies in one year climbing up to over 3000 at best. The sample of this thesis was collected from only 10 years and consisted at best of 88 companies. In total 788 firm-years were used.

Still, in addition to the data, the methodology is not without problems. As the characteristic approach utilizes accounting information, the differing accounting standards may lead to differing results. Companies in the US and in Finland may have differing incentives to manage their accounting figures and the true informativeness of those. Also, only companies with certain type of characteristics are able to obtain analyst coverage. Size, trading volume and potential investment banking relations are examples of such characteristics. (Kirk 2011, p. 184) This can result selectivity in sample that is studied. Still, even companies that do not meet characteristic requirements can be subject of paid-for analysis.

When conducting the kind of research as in this thesis, it is important to have access to proper databases. Access to IBES database could at least partly solve this problem. Another weakness of the characteristic approach is that it is unable to take into account new information in the market. The characteristic forecast, that is obtained using the methodology of this thesis, is always based on two year old coefficients and one year old characteristics. A lot can happen in the fast moving financial market, as the drop in earnings in 2009 shows. Analysts on the other hand revise their forecasts according to new information.

To conclude, in Finland analysts provide superior forecasts for earnings compared to characteristic approach. In addition, analysts are able to revise their prediction during time. Still also in Finland, analysts' forecasts tend to be optimistic. Investors should take this into account when using analyst forecasts to support their valuations and investment decisions. The evidence by (So 2013, pp. 615-640) shows that characteristic approach can be useful. To work, however, it requires larger data than Finnish market can alone provide.

Although similar results as in the US were not found, this thesis contributes to the current knowledge by showing that investors in the Finnish market do not overweight analysts' forecasts as much as they do in the US. Also this thesis provides evidence, that analysts are overly optimistic also in Finland. Characteristic approach can provide additional support for analyst forecasts when these two forecasts are in line. When there is significant difference in the two forecasts investor should be extra cautious.

Future research could develop the characteristic approach from where it is. In the future one could look for an answer for the question whether different results between this thesis and So (2013, pp. 615-640) are caused by internal factors of companies or the environment. Different sets of characteristics should be tested to find the best relevant variables to use in the model. By doing so, the explanatory power of the model could be improved and perhaps then, it would work also in smaller markets and samples such as Finland. Academics should also continue to test the characteristic approach in different markets. Focus could be shifted to all Nordic countries, the Eurozone or at least to a larger market than Finland. In markets where the approach works, it would be interesting to focus research on the development of characteristic optimism over time. As it is easier for analyst to provide more accurate forecasts as financial year is coming to an end and more information of the current fiscal year is available, it would be interesting to see how characteristic approach performs in predicting both earnings and forecast errors. In addition, characteristic approach could be utilized using quarterly data instead of using full fiscal year figures. As Finland has thin analyst coverage, future research could be conducted of analyst coverage's impact on consensus estimate's accuracy. Also, it would be interesting to focus on the investment strategies that are based on characteristic optimism. Is there an optimal time to form a portfolio? For how long it is possible to generate abnormal return and when should the portfolio be rebalanced? Analysts are still an interesting research focus, especially from the behavioral finance's perspective.

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Appendices

Appendix 1 Analyst coverage

Company	Analysts	Company	Analysts	Company	Analysts	Company	Analysts
Afarak Group	2	Finnair	7	Norvestia	0	SRV Yhtiöt	3
Affecto	3	Finnlines	0	Nurminen Logistics	0	SSAB	24
Ahlstrom	8	Fiskars	6	Okmetic	2	SSH Comm. Security	0
Aktia Pankki	2	Fortum	29	Olvi	5	SSK Suomen Säästäjien Kiinteistöt	0
Alma Media	5	F-Secure	7	Oral Hammaslääkärit	1	Stockmann	11
Amer Sports	15	Glaston	3	Orava Asuinkiinteistörahasto	1	Stora Enso	22
Apetit	3	HKScan	5	Oriola-KD	9	Suominen	2
Aspo	4	Honkarakenne	2	Orion	14	Takoma	0
Aspocomp Group	0	Huhtamäki	10	Outokumpu	22	Talentum	4
Atria	5	Ilkka-Yhtymä	3	Outotec	17	Talvivaara	7
Basware	5	Incap	0	Panostaja	2	Technopolis	0
Biohit	0	Innofactor	2	PKC Group	6	Tecnotree	2
Biotie Therapies	2	Ixonos	0	Pohjois-Karjalan Kirjapaino	0	Teleste	3
CapMan	3	Kemira	14	Ponsse	6	TeliaSonera	28
Cargotec	14	Keskisuomalainen	0	Pöyry	6	Tieto	14
Caverion	8	Kesko	10	QPR Software	1	Tikkurila	8
Cencorp	0	Kesla	0	Raisio	5	Trainers' House	0
Citycon	16	Kone	25	Ramirent	10	Tulikivi	0
Componenta	3	Konecranes	15	Rapala VMC	4	Turvatiimi	0
Comptel	5	Lassila & Tikanoja	7	Raute	3	UPM-Kymmene	21
Cramo	8	Lemminkäinen	5	Restamax	1	Uponor	10
Digia	4	Marimekko	5	Revenio Group	2	Vaahto Group	0
Dovre Group	0	Martela A	0	Saga Furs	0	Vacon	7
Efore	3	Metso	25	Sampo	23	Vaisala	3
Elecster	0	Metsä Board	11	Sanoma	12	Valmet	12
Elektrobit	4	Munksjö	3	Scanfil	0	Viking Line	0
Elisa	27	Neo Industrial	0	Sievi Capital	0	Wulff	0
Endomines	2	Neste Oil	18	Solteq	1	Wärtsilä	21
eQ	0	Nokia	51	Soprano	1	YIT	11
Etteplan	4	Nokian Renkaat	24	Sotkamo Silver	0	Yleiselektroniikka	0
Exel Composites	3	Nordea Bank	32	Sponda	14	Ålandsbanken	0

Appendix 2 Research companies

#	Broker name	Companies followed	#	Broker name	Companies followed
1	ESN/POHJOLA BANK MARKETS	79	40	CANACCORD GENUITY	2
2	EVLI BANK	66	41	COMMERZBANK CORPORATES & MKTS	2
3	**INDERES**	63	42	EDISON INVESTMENT RESEARCH	2
4	CARNEGIE INVESTMENT BANK AB	60	43	ERIK PENSER	2
5	NORDEA MARKETS	57	44	INVESTEC BANK (UK) PLC	2
6	DANSKE MARKETS	51	45	**JYSKE BANK**	2
7	SEB EQUITIES	47	46	KEEFE, BRUYETTE & WOODS EUROPE	2
8	**FIM**	38	47	KEMPEN & CO	2
9	HANDELSBANKEN CAPITAL MARKETS	38	48	MIRABAUD SECURITIES	2
10	KEPLER CHEUVREUX	24	49	RABOBANK EQUITY RESEARCH	2
11	GOLDMAN SACHS & CO.	23	50	RBC CAPITAL MARKETS	2
12	DNB MARKETS	20	51	REMIUM SECURITIES	2
13	UBS	20	52	**SANFORD C. BERNSTEIN & CO., LLC**	2
14	BOFA MERRILL LYNCH	17	53	SANTANDER GBM	2
15	**ALPHAVALUE**	16	54	ANALISIS BANCO SABADELL	1
16	JPMORGAN	16	55	ARCTIC SECURITIES	1
17	CREDIT SUISSE - EUROPE	15	56	**ARETE RESEARCH**	1
18	SWEDBANK MARKETS	15	57	ATON LLC	1
19	BERENBERG	11	58	AXIA FINANCIAL RESEARCH	1
20	CITI	11	59	BBVA GLOBAL MARKETS RESEARCH	1
21	DEUTSCHE BANK RESEARCH	11	60	BRYAN GARNIER & CO	1
22	EXANE BNP PARIBAS	11	61	CENKOS SECURITES	1
23	HSBC GLOBAL RESEARCH	11	62	**DAY BY DAY**	1
24	MORGAN STANLEY	9	63	**DEXIA BANK BELGIUM**	1
25	PARETO SECURITIES AS	9	64	EQUITA SIM	1
26	NOMURA	8	65	**EUROLAND FINANCE**	1
27	BARCLAYS	7	66	**FIRST GLOBAL STOCKBROKING LTD.**	1
28	DAVY	6	67	LIBERUM	1
29	ESPIRITO SANTO INVESTMENT BANK	6	68	**NEW STREET RESEARCH LLP**	1
30	JEFFERIES & CO.	6	69	NORD LANDESBANK	1
31	**MORNINGSTAR, INC.**	6	70	PORTZAMPARC	1
32	SOCIETE GENERALE	6	71	**PRIME PREDICTIONS**	1
33	NATIXIS	4	72	RAYMOND JAMES EURO EQUITIES	1
34	ODDO SECURITIES	4	73	RBS	1
35	ABN AMRO BANK	3	74	REDEYE AB	1
36	LANDESBANK BADEN-WUERTTEMBERG	3	75	STEUBING AG	1
37	LANDSBANKI SECURITIES	3	76	THEODOOR GILISSEN	1
38	**MACQUARIE RESEARCH**	3	77	WESTEND BROKERS AG	1
39	MAINFIRST BANK AG	3			

Bolded companies do not have investment banking activities.

Appendix 3 Sample companies

In the table X marks the year in which the company is included in the sample.

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Afarak Group			X	X	X	X			X	X	X
Affecto				X	X	X	X	X	X	X	X
Ahlstrom					X	X	X	X	X	X	X
Alma Media				X	X	X	X	X	X	X	X
Amer Sports A	X	X	X	X	X	X	X	X	X	X	X
Apetit	X	X	X	X	X	X	X	X	X	X	X
Aspo	X	X	X	X	X	X	X	X	X	X	X
Aspocomp Group	X	X	X	X	X	X					
Atria	X	X	X	X	X	X	X	X	X	X	X
Basware	X	X	X	X	X	X	X	X	X	X	X
Biohit	X	X	X	X	X	X					
Biotie Therapies	X	X	X	X		X	X	X	X	X	X
Cargotec				X	X	X	X	X	X	X	X
Cencorp	X	X	X	X	X	X	X	X	X		
Componenta	X	X	X	X	X	X	X	X	X	X	X
Comptel	X	X	X	X	X	X	X	X	X	X	X
Cramo	X	X	X	X	X	X	X	X	X	X	X
Digia	X	X	X	X	X	X	X	X	X	X	X
Dovre Group	X	X	X	X	X	X		X	X	X	
Efore			X	X	X	X	X	X	X		X
Elecster		X	X		X	X	X	X	X		
Elektrobit	X	X	X	X	X	X	X	X	X	X	X
Elisa	X	X	X	X	X	X	X	X	X	X	X
Etteplan	X	X	X	X	X	X	X	X	X	X	X
Exel Composites	X	X	X	X	X	X	X	X	X	X	X
Finnair	X	X	X	X	X	X	X	X	X	X	X
Finnlines	X	X	X	X	X	X	X	X	X		
Fiskars								X	X	X	X
Fortum	X	X	X	X	X	X	X	X	X	X	X
F-Secure	X	X	X	X	X	X	X	X	X	X	X
Glaston	X	X	X	X	X	X	X	X	X	X	X
HKScan	X	X	X	X	X	X	X	X	X	X	X
Honkarakenne B	X	X		X	X	X	X	X	X	X	X
Huhtamäki	X	X	X	X	X	X	X	X	X	X	X
Ilkka-Yhtymä II		X	X	X	X	X	X	X	X		X
Incap	X	X	X	X	X	X					
Innofactor								X		X	X

Ixonos	X	X	X	X	X	X	X	X	X		
Kemira	X	X	X	X	X	X	X	X	X	X	X
Keskisuomalainen				X	X	X	X	X	X		X
Kesko B	X	X	X	X	X	X	X	X	X	X	X
Kesla A								X	X	X	
Kone				X	X	X	X	X	X	X	X
Konecranes	X	X	X	X	X	X	X	X	X	X	X
Lassila & Tikanoja	X	X	X	X	X	X	X	X	X	X	X
Lemminkäinen	X	X	X	X	X	X	X	X	X	X	X
Marimekko	X	X	X	X	X	X	X	X	X	X	X
Martela A				X	X	X		X	X	X	
Metso	X	X	X	X	X	X	X	X	X	X	X
Metsä Board B	X	X	X	X	X	X	X	X	X	X	X
Neste Oil				X	X	X	X	X	X	X	X
Nokia	X	X	X	X	X	X	X	X	X	X	X
Nokian Renkaat	X	X	X	X	X	X	X	X	X	X	X
Okmetic	X	X	X	X	X	X	X	X	X	X	X
Olvi A	X	X	X	X	X	X	X	X	X	X	X
Oral Hammaslääkärit	X	X	X	X	X	X		X	X	X	X
Oriola-KD B					X	X	X	X	X	X	X
Orion B					X	X	X	X	X	X	X
Outokumpu	X	X	X	X	X	X	X	X	X	X	X
Outotec					X	X	X	X	X	X	X
PKC Group	X	X	X	X	X	X	X	X	X	X	X
Ponsse	X	X	X	X	X	X	X	X	X	X	X
Pöyry	X	X	X	X	X	X	X	X	X	X	X
QPR Software		X	X	X		X					
Raisio V	X	X	X	X	X	X	X	X	X	X	X
Ramirent	X	X	X	X	X	X	X	X	X	X	X
Rapala VMC	X	X	X	X	X	X	X	X	X	X	X
Rautaruukki	X	X	X	X	X	X	X	X	X	X	X
Raute	X	X	X	X	X	X	X	X	X	X	X
Revenio Group	X	X	X			X			X	X	X
Sanoma						X	X	X	X	X	X
Solteq	X	X	X	X	X	X			X		
SRV Yhtiöt						X	X	X	X	X	X
SSH Comm. Security	X	X	X	X	X	X	X				
Stockmann B	X	X	X	X	X	X	X	X	X	X	X
Stora Enso R	X	X	X	X	X	X	X	X	X	X	X
Suominen	X	X	X	X	X	X	X	X	X		X
Talentum	X	X	X	X	X	X	X	X	X	X	X
Talvivaara											

Tecnotree	X	X	X	X	X	X	X	X	X		X
Teleste	X	X	X	X	X	X	X	X	X	X	X
Tieto	X	X	X	X	X	X	X	X	X	X	X
Tikkurila									X	X	X
Trainers' House	X	X	X	X	X	X	X	X	X	X	
Tulikivi A	X	X	X	X	X	X	X	X	X		
Turvatiimi						X					
UPM-Kymmene	X	X	X	X	X	X	X	X	X	X	X
Uponor	X	X	X	X	X	X	X	X	X	X	X
Vacon	X	X	X	X	X	X	X	X	X	X	X
Vaisala A	X	X	X	X	X	X	X	X	X	X	X
Viking Line		X	X		X	X		X	X		
Wulff	X	X	X	X	X	X				X	X
Wärtsilä							X	X	X	X	X
YIT	X	X	X	X	X	X	X	X	X	X	X
Yleiselektroniikka E									X		
Total number of companies	**68**	**72**	**73**	**78**	**82**	**88**	**76**	**82**	**86**	**75**	**76**