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ANCHORING AND ADJUSTMENT IN ESTONIAN SELL-SIDE EQUITY ANALYSTS’ FORECASTS

Master’s Thesis

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INTRODUCTION

Every day thousands of participants in the investment profession around the world carry out their day-to-day duties to find profitable investment opportunities. Determining the value of different investment choices is a crucial task in many investment companies’ work routine, as well as for retail investors who seek for higher profits in trade for the costs assigned with investment analysis. Forecasting is an important part in this specific work routine: accurately determining the future of a company’s financial performance is a confident way of distinguishing lucrative investment choices from unprofitable ones. Therefore it is important to know which factors and at what degree influence forecasting performance in the investment valuation process.

In the last few decades, the field of behavioural economics and finance has strongly taken part in conventional economics and finance research. This development was strongly confirmed in 2002 when Daniel Kahneman, a well known psychologist was awarded the Nobel Memorial Prize in Economics for his work in studying prospect theory. Coincidentally, Kahneman is also the leading researcher in the field of cognitive biases, a sub-chapter of scientific psychology that has lately been closely connected to behavioural economics and finance, amongst others.

Cognitive biases are a specific type of judgmental error observable in human decision-making processes, of which one example is forecasting. Although most economists would like to implement the rationally thinking *homo oeconomicus* approach whenever possible, in reality this rarely fits the case. Human judgement is prone to errors and some of these errors occur systematically, these are called cognitive biases. This thesis is more focused on the particular cognitive bias which is most often associated with forecasting, i.e. anchoring and adjustment bias, or simply anchoring in its short form.
Anchoring and adjustment bias is most often associated with decision-making processes which involve numerical judgments, such as forecasting tasks. It involves individual disposition to overly rely on a specific piece of information and then adjust from that information when giving their judgmental assessment. In case of insufficient adjustment, the estimated value is prone to systematic errors.

The aim of this thesis is to determine whether evidence of anchoring and adjustment exists in Estonian sell-side equity analysts’ forecasts. As there is lack of research which discusses the characteristics of Estonian sell-side equity analysts’ forecasts, this thesis concentrates on the main findings in the research reports that the analysts publicly disclose. Retail investors, as well as institutional investment houses often rely on third-party research and it is therefore extremely important to know the main factors which influence the analysts’ judgment in giving forecasts on the financial results of publicly listed companies. Knowing if and how much the forecasters might be anchored to previous period financial results might give a significant advantage in certain situations. Although the empirical part of this thesis focuses only on Estonian sell-side equity analysts, the overall aim is also to give a more general approach to the current research carried out on financial results’ forecasting.

There are four distinctive research tasks in this thesis:

1) To identify the importance of forecasting in the investment valuation process by showing step-by-step the detailed work routine of sell-side equity analysts and how forecasting output is inserted into the investment process and how much value it carries within.

2) To give an outline of the main findings in the present academic literature on the different factors which influence forecasting accuracy, as well as the intentional biases that are important in forecasting.

3) To examine how anchoring and adjustment bias affects forecasting performance in theory and in the current academic research.

4) To present evidence if anchoring and adjustment bias is present in Estonian sell-side equity analysts’ forecasts.
On completing these research tasks, this thesis gathers conclusively all available theoretical findings on different factors which influence forecasting performance as well as how different cognitive biases, including anchoring and adjustment bias, are related to the effectiveness of forecasting tasks.

The first part of this thesis focuses on the forecasting process of sell-side equity analysts. The role of investment analysts in the financial markets is discussed, while also outlining the main tasks of their everyday work routines. In addition, a brief synopsis on the theoretical background of financial forecasting and investment valuation is given, to better explain the structure of financial forecasting, as well as the importance of forecasting in the investment decision-making process.

The second part of this thesis examines more closely forecasting accuracy. Main findings on different factors which influence forecasting accuracy are given, while showing how and why these factors have an impact on the forecasting performance. Furthermore, this part of the thesis discusses the different intentional biases that influence forecasting accuracy and examines more closely the effect of anchoring and adjustment, this bias being the main theme of this thesis.

The third part of this thesis creates an overall model for measuring anchoring and adjustment in Estonian sell-side equity analysts’ forecasts. The sample data used in this thesis comprises of 757 quarterly forecasts of 12 Baltic companies listed on the OMX stock exchange. These forecasts are made by 15 analysts from 4 research firms in 5 years from 2005 to 2009. Main data characteristics of these forecasts are given, as well as their overall forecast accuracy. In the final chapter of this thesis, evidence of possible anchoring effect in analysts’ forecasts is provided.

The research presented here would have not been possible without the investment professionals at the respective research firms who were willing to gather the equity analysts’ research reports which found the basis of the empirical work presented in this thesis. I would also like to thank my supervisor Assoc. Prof. Priit Sander for the constructive criticism, good advice and encouragement given during my thesis writing.
1. FORECASTING PROCESS OF SELL-SIDE EQUITY ANALYSTS’

1.1. The Role of Investment Analysts in Financial Markets

Since 1970s when Fama (1970: 384) first published his well-know paper on efficient markets, practitioners and theorists have endlessly argued if and at what degree markets are efficient. Efficient market by the Fama definition of market efficiency is a market where all prices fully reflect all available information and therefore it is impossible to earn abnormally large profits in an efficient market which would exceed the overall market return. At any given point in time, investors know all information and make their decisions rationally based on that information.

Different markets always act on different levels of market efficiency, depending on transaction costs and information availability. Large transaction costs somewhat limits market efficiency, as it influences prices by inhibiting transaction flow, meaning that when transactions take place, the prices will not fully reflect all available information (Fama 1970: 388). Information availability is necessary for market efficiency as higher information costs or information asymmetry means that some market participants are able to buy excess information or have access to more information, again influencing the prices and whether these incorporate all available information.

Now in 2010, after the worst stock market crash since the 1929 collapse, it is clear that markets are not always efficient, even the most developed ones. Largely as a result of the emergence of behavioural finance in the 1990s, it is explained that in addition to information asymmetry, the market inefficiency is caused by market participants’ behavioural factors. All individual investors, be that small retail investors or large
institutional investment houses, have built-in psychological biases and misperceptions that can push prices away from fundamental values. Advocates of behavioural finance suggest that these systematic errors, caused by human psychology, are the main reason why markets are not always efficient. (Brealey et al. 2008: 369-371)

Although the controversy over the efficiency of securities markets is unlikely to end soon, there are some lessons that are accepted by most researchers. Most important in the view of this thesis’ subject is that securities markets not only reflect publicly available information but also anticipate much of it before it is released. This is where the importance of forecasting becomes obvious for both supporters and non-supporters of the efficient market hypothesis: as the securities markets anticipate future information, in case one creates superiorly accurate forecasts which are inconsistent with the market expectations then it provides significantly more profitable investment opportunities. (Palepu et al. 2004: 9-4)

In light of that it is crucial to understand which behavioural and emotional factors may influence forecasting accuracy and how large is the possible effect on forecasters’ performance. This chapter gives an outline on the investment analyst work process, the forecasting methods used in projecting future financial results and how these are translated into investment decisions.

Investment analysts collect and evaluate information from different sources, generate financial forecasts, predict future prospects and give recommendations which then influence the decision of investors whether to sell or buy certain companies’ securities (Cheng et al. 2004: 3). Stock selection is the main task of investment analysts, which means evaluating one company at a time and deciding if it would be a profitable investment opportunity at the current market price. Market prices reflect the expectations of investors about the future prospect of companies and the analyst has to find out which expectations about a company’s future performance are consistent with the current market price and which are not. (Stowe et al. 2002: 2-3)

Two types of investment analysts exist: sell-side and buy-side analysts. The tasks they perform for assessing investment opportunities are similar: evaluating firms’ business
models, forecasting future financial results and building financial models of stock prices. Both write reports to communicate their analysis and investment recommendations. However, the difference between different analysts’ is in their target audience, the scale and scope of coverage, the sources of used information, and different ways in which analyst performance is measured and analysts are compensated. (Groysberg et al. 2008: 25)

Sell-side analysts work for brokerage firms and provide research for the firms’ brokers and their clients, their earnings forecasts and stock recommendations are also made available to the public. Sell-side analysts’ research usually concludes with a price target and a specific recommendation which suggests to buy, sell or hold the specific stock, in order to guide the investors in their action. (Cheng et al. 2004: 3)

Sell-side analysis’ target audience includes retail investors, as well as buy-side analysts and portfolio managers. Clients reward sell-side firms for providing this research by directing trading activities through their firms, allowing the costs of research to be covered through commissions. Sell-side analysts also provide value for companies which are issuing stock by lowering the information costs for investors who are considering the stocks and by helping create a liquid market for stocks. The cost of providing these services is recovered indirectly through investment banking fees. (Groysberg et al. 2008: 26)

Buy-side analysts on the contrary make internal recommendations and forecasts exclusively for fund managers and are hired by asset management firms which create their revenues from managing investment funds or their clients’ investment portfolios (Cheng et al. 2004: 3). Buy-side analysts add value for portfolio managers in two ways. First, they filter the large amount of sell-side research and company news and data into shorter reports which can be easily used by portfolio managers and the investment committee. Secondly, buy-side analysts provide the portfolio managers with a perspective on companies that is different from the perspective they receive from sell-side analysts. Buy-side analysts are expected to reach their own conclusions independently on how profitable a particular investment might be and how it would fit with the fund’s or investment portfolio’s overall structure and investment strategy. Buy-
side analysts are mostly considered as prospective fund managers, meaning that with time, more and more of their work competence revolves around investment decision making and portfolio management. (Groysberg et al. 2008: 26)

As stated previously, buy-side analysts are often users of sell-side analysts’ reports, using these as an input in own decision process (Schipper 1991: 106). Analysts at buy-side firms are often responsible for covering companies in an entire industry or region while sell-side analysts usually cover one segment of an industry, meaning that they have more expertise in the companies they cover and therefore make more meaningful forecasts. It seems then quite rational that buy-side analysts often use sell-side analysts’ forecasts as a basis for own forecasts (or use these directly in case they have less knowledge about the specific company).

This is also confirmed by empirical studies. Groysberg et al. (2008: 27) carried out research on US asset management and brokerages industries and in addition studied more extensively 37 buy-side and ca 3100 sell-side analysts covering the same 337 companies in 1997 to 2004. On average, the research department of a buy-side firm comprises of 20-30 analysts compared to 186 analysts employed by an average brokerage department in an investment bank. Consequently, this means that buy-side analysts follow up to 100 companies and write reports on roughly 15 of them at any given time. Sell-side analysts also write 10-15 reports at a given time but this represents a much larger fraction of the total companies followed. As a result, buy-side analysts’ reports are shorter in length, up to 2 pages while sell-side analysts also include detailed industry analysis and bottom-up firm-level analysis. (Ibid.: 34)

Researching different analysts’ quality of analysis, Groysberg et al. (2008: 30-33) noted that buy-side analysts underperform their sell-side counterparts. Depending on the forecast horizon, mean absolute forecast error for buy-side analysts is 11-15 per cent higher compared to sell-side analysts. One of the possible reasons is that sell-side firms are less likely to retain analysts with low forecast accuracy compared to buy-side firms; sell-side analysts are continuously compared to each other in terms of forecast accuracy while buy-side firms evaluate by and reward their analysts for investment performance relative to an absolute index (e.g. S&P 500). This means that the difference in the
quality of analysis is at least in part driven by a more competitive environment in sell-side firms. This was proven correct by Groysberg et al. (2008: 32) who found out that the average annual retention rate for buy-side analysts in their study was 71 per cent which was significantly higher than the 64 per cent retention rate for the sell-side analysts.

In addition, sell-side analysts’ accuracy may be increased due to information advantage. They get feedback and market information from clients, sales representatives, traders and other analysts, whereas buy-side analysts’ main communication is limited with the portfolio managers at their own firm (Groysberg et al. 2008: 27, 33).

Groysberg et al. (2008: 37) also analyzed closely the switching of analysts from sell-side firms to buy-side firms and found that same analysts’ forecasting performance lowered significantly after switching, implying that buy-side firms don’t hire lower quality analysts in the first place but the work process and environment, professional tasks and information inputs influence the forecasting accuracy.

In addition to being used as an input by buy-side analysts, sell-side analysts’ forecasts are also used to evaluate market expectations. The so-called consensus forecasts are the average of all sell-side analysts’ forecasts in the market. These can be used to measure overall market expectation of sales, earnings etc. and are used ex-post to measure the unanticipated portion of results, which affects investors’ behaviour and market reaction to the results. (Schipper 1991: 106)

As companies’ stock prices incorporate the view the overall market has on company’s future performance, the deviation of actual results from consensus forecasts, i.e. earnings surprises, usually has the largest influence on sudden stock price movements. According to a thorough study on a sample of nearly 130,000 earnings forecasts between 1983 and 1997 in the U.S., Bartov et al. (2002: 175) found that average return over quarters ending with a positive earnings surprises is significantly higher, by about 3.2 per cent, than the return over quarters that have the same overall quarterly earnings forecast error but end with a negative surprise.
Womack concludes (1996: 138) the discussion on the value of analysts’ recommendations for investors by showing evidence of analysts’ market timing and stock picking evidence. Investors should be willing to pay for brokerage investment advice only if the expected benefit is at least as great as the cost of the advice. A logical source of benefits for an investor would be excess stock returns following changes in broker recommendations. According to Womack’s research (1996: 137) on 14 major U.S. brokerages, significant and systematic discrepancies exist between pre-recommendation prices and eventual values, enabling stock analysts’ recommendations provide excess stock returns over the market average after all transaction costs. This has been confirmed by several later studies on that effect (Kasznik and McNichols 2002: 27-28).

As identified in the previously mentioned studies, sell-side analysts’ work output carries significant value to investors. Their research is used by numerous different market participants, from small private investors, to large investment houses, and overall market expectations are developed around their forecasts and investment recommendations. In addition to sell-side analysts’ work being important and value adding for the investors, the researching and forecasting process of sell-side analysts in particular is examined in this thesis due to the reason of significant restrictions in collecting data reported by buy-side analysts. Buy-side analysts’ research is private and mostly considered a trade secret. Also, as mentioned beforehand, sell-side analysts’ research is used as a research input by buy-side analysts and their forecasts have proven to be more accurate due to significantly higher knowledge in the companies they cover. From here on, if not stated otherwise the term “analyst” is used in this paper instead of the longer and more specific term “sell-side analyst”.
1.2. Theoretical Approach to Financial Forecasting

In any field requiring forecasts, not only financial forecasting, the performance of forecaster depends jointly on the environment about which forecasts are made, the information system that brings data about the environment to the forecaster and the cognitive system of the forecaster (Stewart, Lusk 1994: 579).

In financial results forecasting the environment includes the overall economy, industry sector, legal environment and other features that affect the company performance. The information system includes financial reporting standards, public disclosures by the company, meetings with the managements, statistical data and other sources of information used by the forecaster. The cognitive system consists of perceptual and judgmental processes that the forecaster uses to acquire information, analyze it and produce the forecast. These three main components which influence the forecasting process are summarized on figure 1.1.

![Diagram](image)

**Figure 1.1.** Factors influencing the forecasting process (by the author, based on Stewart and Lusk 1994: 579).

This chapter mainly observes the first two factors: forecasting environment and information system, giving an outline how different aspects are considered in forecasting process, as well as their effect on the end result.

There are numerous different techniques in most finance textbooks about how to forecast efficiently (Brealey and Myers 2003, Brealey et al. 2001, Copeland et al. 2000). Financial forecasting is carried out by investment analysts in a similar way as financial planning is executed in corporate finance. However, a more simplified
approach is used, considering the limited availability of information, limited time resources and the goal of forecasting. The process is an extension of historical patterns and relationships, based on assumptions about future economic conditions, market behaviour and managerial actions (Fridson, Alvarez 2002: 211). It takes steps from business strategy, accounting and financial analysis and creates assumptions and projections conditional on what becomes evident from these three areas (Palepu et al. 2004: 6-1). A few main outlines of the theory of financial forecasting are brought here to better understand the role of judgement in forecasting process.

It is important to understand that financial forecasting is always a simplification of real future results as it is impossible to consider all influential factors. Unforeseeable events may invalidate the assumptions underlying the forecasts: economic shocks or unexpected changes in company’s or its competitors’ strategies may change financial projections useless. Therefore there is always a share of uncertainty in the forecasts and analysts’ should not aim for absolute precision rather for a sound financial model of the future which logically incorporates all significant and available evidence about the company’s operations development. (Fridson, Alvarez 2002: 265)

Although sometimes, the analyst might be interested in only one certain output of forecasting, e.g. earnings or cash flow, it is important to carry out forecasting comprehensively, producing not only the particular needed forecast but a forecast for income statement, cash flows, as well as the balance sheet. This helps avoid unrealistic implicit assumptions, as this way not only the primary performance indicator but all the associated financing characteristics are also forecasted. (Palepu et al. 2004: 6-2)

Forecasting starts with sales forecast, which is based on pro-forma financial statements from annual reports, qualitative data on market share development, competition, product development and other relevant information (Copeland et al. 2000: 233-235). Past sales performance is closely analyzed for one-off impacts and the quality of sales growth, to better estimate the factors which could be influencing sales development in the future. Sales projections depend largely on the assumptions made about growth of the whole economy and of the specific sector where the company operates, it is therefore crucial to
judge if these assumptions are realistic (Fridson, Alvarez 2002: 215). The sales forecast will be the basis of all other forecasts, including earnings and dividends forecasts.

It is crucial to develop a strategic perspective on future company performance, considering both the company-specific competitive advantages or disadvantages and industry characteristics. This means the analyst will create a plausible story about company’s future performance, based on the knowledge on industry structure, company’s competitive position, strategy and execution. The understanding of the business model and the industry is important as this understanding enables the analyst to interpret new information as it arrives and to infer its implications (Palepu et al. 2004: 9-9). It is also important to understand if the strategy is sustainable, otherwise the positive results for next few financial years would be achieved at the cost of future earnings. The forecast is usually done for a 3-5 years time horizon. (Copeland et al. 2000: 235)

Next step is to forecast operating and financial expenses for the time period. These are forecasted in a similar way as sales forecast is done but with different factors taken into consideration this time. Operating expenses development depends on past expenses as well as information about company’s strategy: new investments, expansion, material costs, efficiency measures etc. Financial expenses depend on interest rates, planned debt levels, currency movements, tax burden etc. (Copeland et al. 2000: 254). After expenses, a simplified balance sheet is forecasted, in particular the relevant components of balance sheet is more precisely projected, e.g. equity, capital structure, cash and cash equivalents. The balance sheet forecast depends on past structure of the balance sheet, the necessary investments, needed working capital and future projected capital structure, primarily the relationship between debt and equity (Palepu et al. 2004: 6-6).

Based on these forecasts we get the main output of the forecasting process for the investment analysis: EBITDA, EBIT, net profit and free cash flow. The fifth important output is dividend forecast, which is based on known dividend policy, past cash flows and projected net profit and cash flow (Copeland et al. 2000: 255-256). Balance sheet forecast is relevant at this point as it shows clearly if the projected income statement and
cash flows are sustainable in the long run. The forecasting process is briefly summarized on figure 1.2.

![Figure 1.2. The forecasting process (by the author).](image)

Two forecasting approaches are distinguished: top-down and bottom-up forecasting (Alexander 2001: 354-355). In case of the top-down approach, the analyst is first involved in making forecast for the economy, then forecasts for industries and then for the companies. Each next level is based on the previous level forecast. Bottom-up forecasting considers the estimates for each specific company to build estimates for industries and then the economy (if necessary). In reality, a combination of those two approaches is often used, which means that top-down forecasts provide a setting for bottom-up forecasts. For example, when considering certain company’s future sales growth, an assumption for the growth of the whole economy is used.

In practice, analysts use information from multiple sources and they mentally give different importance ratios for different types of information. It is by definition extremely difficult to gather all available data on how specifically analysts use different information and what are the major influences behind their decisions and choices under one overall theory. As much as there are different analysts, there are different ways on how they conduct their research and generate their forecasts. The main challenge according to Ramnath et al. (2008: 10) is that analysts have a context-specific task that is very difficult to model. Still, some generalized overview can still be given on analysts’ forecasting process.
Previts et al. (1994: 55) carried out a content analysis of analysts’ reports, using a sample of 479 reports comprising over 3500 pages of research. Amongst other findings their paper states that the forecasts are primarily based on a subjective evaluation of company’s financial figures, the analysts emphasize company’s core earnings while analysing the variability and quality of earnings and they also extensively consider nonfinancial information, such as company risks and concerns, competition, management, strategy etc. Another content analysis carried out by Rogers and Grant (1997: 17-20) on a sample of 187 reports states that only about 52 per cent of information in financial analyst reports comes from financial reports, rest is divided equally between operating data from the firm and descriptive information.

Bouwman et al.’s (1994: 35) protocol-based analysis of the analysis process by a sample of 20 analysts observed that by average 38 per cent of information used is financial information from or based on financial statements (i.e. financial data or different performance ratios). Rest is mostly general company and segment information (35 per cent), information from management and employees (7 per cent), management projections (4 per cent) and other (16 per cent). This particular research employs different methods, as it does not involve analysing the content of the reports the analysts disclose but instead it uses verbal protocols collected by financial analysts as they went through the analysis process. This way, the part of information which is left out of the final research report is also considered.

In many cases, the management itself discloses their forecasts to the public or gives a rough outline what their expectations are for the next period results. It is up to the analyst to decide if and how to use this information. Management forecasts may be more accurate than those by financial analysts as the management possesses information regarding up-to-date market and industry studies, they are better aware of the current strategy execution in the company and have access to more detailed past financial information (Ruland 1978: 439-440). The management may also commit considerable resources to develop better financial forecasts in order to plan their actions ahead more efficiently.
Financial analysts, on the other hand, are able to exercise greater objectivity in evaluating the available information and can filter the information accordingly, e.g. in the case of an overly optimistic management. In reality, there has been no statistically significant difference in accuracy of management and analysts found so far.

However, there is greater incentive for managers to give out lower forecasts in order to exceed market expectations and be rewarded accordingly. At the same time, if this would happen consistently, the market would adjust their forecasts proportionately, as analysts can always use the subsequent earnings report to assess whether the management has misrepresented their information (Rogers and Stocken 2005: 1233).

The latter view is supported by Williams (1996: 113) who on empirical results suggests that managements appear to acquire forecasting reputations among analysts. As there are practically no formal sanctions to prevent management from issuing a misleading forecast, the analysts themselves start to adjust their announcements accordingly if persistent over- or underestimating occurs.

Also, it has been observed by several studies that managements avoid reporting earnings lower than analyst forecasts. Managements can manage earnings with valuation allowances, the choice of the accounting method (for example, through the choice of inventory cost flow methods or depreciation methods), accounting estimates (for example the useful life of depreciable assets) and real economic decisions (for example through cost control or sale of assets) (Guenther 2005: 488-489).

Consistently with previous research, Burgstahler and Eames (2006: 634) found from a sample of 25 000 US company earnings reports in the period from 1986 to 2000 that distributions of annual earnings surprises contain an unusually high frequency of zero and small positive surprises and an unusually low frequency of small negative surprises. They also provided evidence that in order to meet or slightly beat analyst forecasts, the managements pushed earnings upward or announced lower forecasts. Managements’ actions to drive earnings upward were confirmed by a link between zero and small positive earnings surprises and unusually positive changes in operating cash flows and discretionary accruals. Managements’ intentional lowering of forecasts was confirmed.
by evidence of unusually negative changes in forecasts associating with zero and small positive earnings surprises. (Burgstahler and Eames 2006: 634-638)

Abarbanell and Lehavy (2002: 23-28) noted similarly that company managements are prone to manipulating with company earnings but in addition they pointed out that this also depends on the current investment recommendation given to the company’s stock. In companies which are rated a sell recommendation, managements are more frequently engaged in extreme, income-decreasing earnings management to create accounting reserves while in companies which are rated a buy recommendation, managements are more likely to engage in earnings management to leave reported earnings equal to or slightly higher than analysts’ forecasts. The difference in the behaviour possible derives from the fact that sell-rated company stock was less volatile from a deviation in actual earnings from the consensus forecast and there was less pressure for the management to meet the consensus forecasts as the stock price fell less in case of missing the forecast.

As stated previously, in case managements are consistently manipulating with either the financial results or their forecasts in order to meet or exceed market expectations, this would only succeed for a short time. Analysts collect management forecasts and therefore they can adjust management bias accordingly. Also, the manipulation of financial results through discretionary accounts, irregular cash flows or one-off economic influences, is always identified by analysts afterwards through detailed financial reports and company meetings. In the long run, all of this counterbalances the effects of management actions in order to meet expectations, and the market adjusts accordingly.

Based on the given findings on which information analysts mostly used in producing their forecasts, it can be said that most of the information used in the investment decision making process is left to be evaluated by the analyst, increasing the importance of judgement. The decisions on which information to consider important and use as a basis of forecasting and the decision on which information to present to investors are all part of analysts’ competence. This way, forecasting is a mix of using quantitative data and predicting the figures oneself based on all known information, while neither of those two is prevailing.
As we identified that a large part of forecasting is based on analysts’ own judgement and decision-making competence, the question arises why not use statistical methods instead. There are numerous of different statistical methods available to predict company’s financial results based on historical data and it is certain there are some which are suitable for the task. This would save the costs for brokerages to employ a vast department of equity analysts and would limit the possibility of human error.

In the present forecasting paradigm, the forecasting approach used by equity analysts is identified as expert opinions, an alternative to conjoint analysis, econometric models and other forecasting methods (Armstrong 2001: 57). Expert opinions method is suitable in cases requiring many forecasts, to model complex problems and to handle unstructured problems. In contrast, for problems that are well-structured, statistical techniques (such as regression) can provide good forecasts, while problems that are unstructured (such as forecasting sales and profitability for a company in a consistently changing economic environment) cannot be translated into statistical rules. In these cases, research has shown the superiority of expert opinions method over other forecasting approaches, especially econometric methods (Collopy et al. 2001: 285). The same is valid for forecasting financial results. Research has shown more accuracy in analysts’ ability to predict abnormal results (compared to statistical methods) which after being reported result in a more sudden change in the stock price and are therefore more important (Schipper 1991: 107).

Although several studies have shown analysts’ forecast errors to be too large to outperform econometric models, Brown (1996: 40) argued that when measuring forecast surprises (actual minus predicted forecast), stock price to earnings per share ratio is more relevant as it shows a constant approximate average over long time periods for specific companies, more stable measure than the actual earnings per share. Brown also concluded (1996: 44) on numerous studies on financial results forecasting that earnings forecasts by analysts achieved very high accuracy based on the average ratio of stock price to earnings per share, i.e. within 3 per cent of actual result, which is significantly more accurate than statistical models could predict.
There are two main reasons or sources for the analysts’ superior forecasting accuracy compared to statistical methods. First, they possess better information which may explain a considerable portion of the non-modelled component of the results variance. Analysts have access to far more information than only the financial data stated in the annual report and this qualitative data is difficult to use as an input for the statistical models. Secondly, the analysts possess more timely information, i.e. information that has come to light after the last history point in the time series has been recorded and made available. Thus, their forecasts are based on up-to-date data. At the time of release of the latest data, statistical forecasts do considerably well but the forecasts become progressively less accurate as time passes. (Lawrence et al. 2006: 499)

This chapter outlined the main steps of forecasting process and gave a notion what kind of data analysts gather and how it is used in the forecasting process. As identified, a large part of forecasting involves human judgment, making forecasting prone to judgmental errors. The next chapter explains shortly the process how forecasts are translated into investment recommendations, to demonstrate the importance of forecasting in the investment decision making process.

1.3. From Forecasting to Investment Recommendations

Forecasting gives an input to the ultimate analyst judgement, i.e. what recommendation to give for a specific stock (Schipper 1991: 106). In other words, a stock recommendation is the final product of a company analysis but its characteristics as well as the value for investors depend on the forecasts. Although this thesis focuses on analysts’ forecasts not stock valuation, a brief insight into how equity investment choices are made is given to show the importance of forecasting in this process.

Equity research uses mainly fundamental analysis. Fundamental analysis entails searching for a security in which case the estimates (forecasts) of future company growth, earnings and dividends are not reflected in the security’s market price, i.e. the stock is undervalued in analyst’s view (Alexander et al. 2001: 340-341).
Therefore, fundamental analysis operates on the broad premise that some securities may be mispriced in the marketplace at any given point in time; it is assumed that by undertaking a careful analysis of the inherent characteristics of each company, it is possible to distinguish those securities that are correctly priced from those that are not (Gitman, Joehnk 2001: 274). Fundamentals are characteristics of a company related to profitability, financial strength, risk and growth opportunities (Stowe et al. 2002: 3).

There are five steps in the process of valuation which lead to the investment recommendation according to Stowe et al. (2002: 6):

- understanding the business model;
- forecasting company performance;
- selecting the appropriate valuation model;
- converting forecasts to a valuation;
- making the investment decision.

As the previous chapter in this thesis covered the first two steps, the valuation model and the use of forecasts in valuation are described here. There are two main approaches to fundamental analysis which are applied most often: multiples-based valuation and discounted cash flow (DCF) method; the analyst may decide to use either one of them or a combination of the two. Both of these methods use financial forecasts as a main input and both methods include numerous different valuation models.

The discounted cash flow (DCF) valuation relates the value of the company to the present value of expected future cash flows of the company (Damodaran 2002: 16). DCF discounts expected total free cash flows of the company to the present value using opportunity cost of capital. Free cash flows are calculated based on the forecasts of income statement and investments of the company and are found for the detailed forecasting period (up to 10 years). The company value after the detailed forecasting period is given with a terminal value which is based for example on the value of company’s assets on the terminal year or the discounted perpetual cash flows after the forecasting period (Palepu et al 2004: 8-7-8-11).
The cost of capital, i.e. the discount rate at which the cash flows are discounted, is found using the weighted average cost of capital (WACC) and Capital Assets Pricing Model (CAPM) approaches. An alternative possibility is to examine the returns that can be earned from investments of comparable risk. (Brealey, Myers 2003: 75-76)

The DCF method can also be used for discounting expected future dividends from the company and expected future stock price to present value and comparing the result to current stock price, this is called dividend discount model (DDM). In case the present value is higher than the current stock price, this would be a profitable investment case as it is an opportunity for excess return. The used discount rate is the return that can be earned in the capital market on securities of comparable risk. (Brealey, Meyers 2003: 60-61)

The DDM is most suitable for evaluating stable dividend-paying stocks where the particular company has a discernible dividend policy and the investor has a non-control perspective (minority ownership). The analyst has to evaluate the sustainability of the dividend policy and the risks associated with it. Stable dividend-paying companies are companies which are less prone to changes in the economic cycle, i.e. non-cyclical or defensive companies, such as telecom operators, utilities, pharmaceutical producers etc. (Stowe et al. 2002: 91)

There are numerous other DCF method adjustments which use free cash flows to equity or to the firm, capital cash flows, economic value added or other inputs and consider the capital structure, tax shields and other effects. Considering the focus of this thesis, those DCF adjustments are not reviewed here.

The second widely used method in fundamental analysis is multiples-based valuation, also called relative valuation or ratio-analysis. Relative valuation finds the company’s fair value based upon how other similar companies are currently priced in the market. It uses ratios which incorporate past financial information, financial forecasts and market values (i.e. stock prices). Ratio analysis may be very sophisticated or it can be overly simplistic, suiting the specific investor’s or analyst’s needs. (Alexander et al. 2001: 356)
Multiples-based valuation is a popular method for analysis of listed companies as it does not require multi-year forecasts or a calculation of discount rate, therefore making the end value less sensitive to analyst choices. On the other hand, the identification of comparable companies is a difficult challenge as rarely two very similar companies exist. Also, explaining why multiples vary across firms requires a sound understanding of the determinants of each multiple. (Palepu et al. 2004: 7-2)

There are two main steps in multiples-based valuation (Damodaran 2002: 637). The first is to convert stock prices into multiples of earnings, book values, sales etc. The second step is to find similar firms for comparison. These ratios are then compared with ratios of other companies in the industry or an industry average ratio; the peer group may consist of companies from the same country or comprehend a wider region. (Alexander et al. 2001: 356)

According to Damodaran (2002: 638-640), there are four types of different ratios used. Firstly, earnings multiples are ratios which look at the stock price as a multiple of earnings per share generated by that company. Different ratios include P/E (price-to-earnings per share, i.e. net income per share), P/EBIT (price-to-earnings before interests and taxes per share), P/EBITDA (price-to-earnings before interest taxes and depreciation & amortization per share) and EV/EBITDA (enterprise value-to-EBITDA). These are most widely used multiples as they are easiest to use and most comparable between companies. Problems may occur when firms generate a loss in a particular profit level as then it becomes impossible to compare companies based on that multiple.

Secondly, book value or replacement value multiples look at the relationship between the stock price and the book value of equity per share or the replacement cost of assets. Different ratios include P/B (price-to-book value per share), P/TBV (price-to-tangible book value per share, excluding intangible assets) and replacement cost per share. While the first two are used to compare companies, the replacement cost shows if the company's stock price is undervalued or not compared to replacing these assets. Although P/B and P/TBV are heavily influenced by the original price paid for assets and by any accounting adjustments, these are widely used to value banks or asset-dependant companies, e.g. hotels. Usually the ratio is above 1 as book value does not
take future profits into account, but market value also reflects the company’s ability to create future earnings.

Thirdly, revenue multiples measure the value of an asset to the revenues it generates, giving a P/S (price-to-sales per share) ratio. Depending on the situation, it might be more reasonable to compare firms in different markets and different accounting systems with revenue multiples than with earnings multiples as revenues are less prone to different accounting standards. At the same time revenue multiples do not consider company’s profitability.

Last, sector-specific multiples are used to compare companies within one sector. These are different for any given industry and may include ratios such as P/net premiums (price-to-net premiums per share) for insurance companies, P/clients (price-to-clients per share) for Internet companies etc. These multiples cannot be used to compare companies in different sectors but are more precise due to using industry-specific measures. (Damodaran 2002: 40)

All of these ratios can be estimated using current financial results (current ratio), financial results over the past 4 quarters (otherwise known as trailing twelve months ratio), and future expected financial results in the next year (1-year forward looking ratio) or in the year after that (2-year forward looking ratio). All of these ratios use current stock price, while the importance of forecasting is more apparent in the 1-year and 2-year forward looking ratios. Although fundamental analysis based on current ratios also considers the outlook of company performance on the future, the forecasts are directly inserted into valuation process in 1-year and 2-year forward looking ratios. These ratios are then compared to the ratios of other similar companies in the particular industry.

As mentioned previously, finding comparable companies is one of the key difficulties in multiples-based valuation. Firms within the same industry are the most obvious candidates but then again, many firms operate in multiple industries. In addition, even firms within the same industry have different strategies, growth opportunities and profitability, creating comparability problems. One approach is to average across all
firms in the industry, implicitly hoping that the various sources of non-comparability cancel each other out so the company is being valued to a “typical “ industry member. Another approach is to focus only on those firms within the industry which are the most similar. (Palepu et al. 2004: 7-6)

To conclude, an overview of different methods which are used in fundamental analysis is given here:

![Diagram of Fundamental Analysis](image)

**Figure 1.3.** Different methods used in fundamental analysis (by the author).

In terms of multiples-based valuation, the investment decision is based on whether the company’s stock multiples are currently at a lower level than the industry or peer group average. In terms of discounted cash flow method, the investment decision compares the present value of the cash flows to the current market value of the company.

Analysts justify their recommendations by means of a target price, relative to current trading price. The target price reflects the analysts’ view on the fair or intrinsic value of the company, considering all available information and company’s growth prospects and based on either one of the previously mentioned methods or a combination of those (Alexander et al. 2001: 341).

There may be a number of specific reasons to why a company is undervalued compared to its peers, such as higher country risk, non-transparent management, illiquidity of the stock, preferred stocks (non-voting shares), small capitalization etc. These reasons
should be taken into account when calculating the target price with the use of discounts. In case the investor or the analyst decides the company has a positive outlook and it would be a solid investment, then the final investment decision is based on the assumption that the positive outlook has not been priced in yet and the stock price should rise, offering a profitable investment opportunity.

In case the target price is lower than the current stock price (i.e. the stock is overvalued), the analyst gives a recommendation to sell the specific stock. Vice versa, in case the stock is undervalued, the analyst gives a recommendation to buy the stock. In some research firms, the analysts also give out stronger or weaker buy/sell recommendation, depending on how much the target price differs from the current stock price. In case the target price is the same or close to current stock price, the analyst gives a recommendation to hold the stock, meaning that the investor should refrain from buying it but hold the stock in case it is already in the portfolio, as the price will probably move in line with the overall market, i.e. it is market neutral. (Schipper 1991: 106)

This part of the thesis gave an outline of analysts’ work process, how forecasting is performed, what is the importance of forecasting and how investment decisions are based on forecasts. As mentioned, a large part of forecasting involves human judgment. Therefore it is important to identify and discuss different aspects which influence both human judgment as well as the end result of forecasting. The next part of the thesis deals with different factors which influence forecasting accuracy, one of which, anchoring and adjustment being the main theme of this thesis.
2. FORECASTING ACCURACY – FACTORS AND BIASES

2.1. Factors which Influence Forecasting Accuracy

Studying forecast accuracy of analysts’ is important for a number of different reasons. Investors benefit from identifying more accurate forecasts (and forecasters), as investment recommendations based on more accurate forecasts are more profitable. Characteristics that are associated with analyst forecasting superiority should also be of interest to brokerage houses as employers who try to enhance the quality of their output. Analysts themselves benefit from knowing the reasons of their accuracy or inaccuracy as they can improve to do better forecasts and perform their duties more efficiently. From a scientific perspective, studying forecast accuracy helps understand better how and why market expectations reflect the current information at any given moment. (Ramnath et al. 2008: 18-22)

Looking at the connection between analysts’ career development and work performance, it has been found (Hong, Kubik 2003: 313) that relatively accurate forecasters are more likely to experience favourable career outcomes like moving up to a high-status brokerage house or receiving better salary. According to their results, being in the top 10 per cent of analysts based on forecasting accuracy (compared to the average) increases analysts’ chances of moving up the career ladder about 41 per cent while being in the lowest 10 per cent of analysts decreases these chances by about 52 per cent (Ibid.: 324). Also, Mikhail et al. (1999: 185) found that analyst turnover is likely to be higher if their forecast accuracy is relatively lower compared to other
analysts. According to their results, a decrease of one standard deviation in relative accuracy increased the probability of turnover by 7 per cent.

In theory, higher forecasting accuracy should also mean that the analyst is able to give a more justified fair value for the company and a better target price for the company’s stock, leading to more profitable investment recommendations. A study by Loh and Mian (2006: 457-482) on a sample of 3800 analysts from 1994 to 2000 reveals that there is a positive relation between the accuracy of analysts’ forecasts and the profitability of their stock recommendations. On average, the recommendations of the most accurate analysts generate profits that exceed those of the least accurate analysts by 1.27 per cent per month, i.e. 16.35 per cent p.a. However, even recommendations of inferior analysts proved to be profitable, albeit less.

Past forecasting accuracy is a strong determinant in future forecasting performance, implying a constant difference in different analysts’ forecasting performance (Brown 2001: 47-48) and also providing means to evaluate analysts’ performance on the basis of forecast accuracy, an approach which is widely used in practice. This is supported by findings of Mikhail et al. (1999: 199) who point out that relative lower accuracy of the analyst, i.e. the accuracy compared to other analysts following the same company is associated with higher probability of employee turnover, implying that forecast accuracy is important for both analysts and brokerages.

There are numerous different factors which affect forecasting accuracy. As cognitive biases which also affect forecasting accuracy are more closely discussed in the next chapter, other measurable analyst- and firm-specific characteristics are outlined here. The first part of this subchapter outlines the main influence factors and the second part gives an overview of the intentional biases in the forecasts and how these are addressed in known theoretical standings.

Although most of the research discussed here which focuses on forecast accuracy are related only to net profit forecasts, the results can still be generalized over all financial forecasts. The reason behind this is that net profit forecasts incorporate almost all other forecasts as well, as shown in chapter 1.2 of this thesis.
The factors which influence forecast accuracy can be divided into two main groups: analysis’ content related factors and analyst-related factors. Analysis’ content related factors are associated with the analyzed company, market data, available information and forecast characteristics. Analyst-related factors are associated with the work routine of the analyst and employer- or analyst-specific factors. The next graph takes together all different analysis’ content related and analyst-related factors which affect forecasting accuracy and states the direction of the influence:

<table>
<thead>
<tr>
<th>Content-related factors</th>
<th>Analyst-related factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality of information</td>
<td>+</td>
</tr>
<tr>
<td>Forecast frequency</td>
<td>+</td>
</tr>
<tr>
<td>Forecast time</td>
<td>−</td>
</tr>
<tr>
<td>Forecast horizon</td>
<td>−</td>
</tr>
<tr>
<td>Complexity of information</td>
<td>−</td>
</tr>
<tr>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>+</td>
<td>+</td>
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<td>+</td>
<td>−</td>
</tr>
</tbody>
</table>

**Figure 2.1.** Factors which influence forecasting accuracy (by the author).

One of the most observed relationship is between the accuracy of the forecast and the time before results announcement. It is fairly well established in related literature that recent forecasts are more accurate (Rammath *et al.* 2008: 19). Analysts may have revised their forecasts in order to bring it closer to consensus forecasts or after taking into account information that has been disclosed by the company. As the time period before the results announcement decreases, analysts also have the advantage of observing the assumptions and predictions of other analysts. Thus there is a possible study design problem with studies that evaluate analyst forecast accuracy using *ex post* data, as analysts that are identified as superior in terms of forecast accuracy, may actually not bring any new information to the market (*Ibid.*: 20). Still, most studies control the effect of forecast age to avoid this.

As stated, there is a relationship between forecast time and accuracy. At the same time, from the investor viewpoint, analysts’ overall decision process is a loss function of time
which in turn transfers into inaccuracy of the forecasts. There is an obvious trade-off between timeliness and accuracy of forecasting. To some extent having the forecast sooner (even at the cost of inaccuracy) implies greater investing profits to clients (investors reading the analysis) than the loss implied from inaccurate forecasts. Alternatively, in case the clients prefer forecast accuracy to analysis timeliness, this effect will be vice versa, creating a preference for accuracy at the expense of timeliness. (Schipper 1991: 113)

Cooper et al. (2001: 415) found evidence in support of the former hypothesis. According to their findings, investors value timeliness more than *ex post* accuracy of the forecasts. Although forecast accuracy is also highly important, leading forecasts have more influence and measure analyst performance rating to the investors more efficiently as weaker analysts are able to improve the accuracy of their forecasts by mimicking the forecasts of superior analysts. Although timely forecasts are less accurate, they still improve the accuracy of existing forecasts.

The forecast horizon measures the same characteristic but another way around, i.e. how far ahead the results are forecasted. Although usually forecasts are made for a 2-5 years period, some analysts forecast as far as 10 years ahead in case of companies with long investment cycles and predictable revenue and cost developments, such as in utilities sector. Expectedly, empirical research shows that forecast accuracy decreases with the increase in forecast horizon (Jacob et al. 1999: 78). Forecast horizon is different from the time until results announcement as forecast horizon is a specific characteristic of a forecast set beforehand by the analyst and is measured in years. Time to results announcement is a constantly changing variable and measured in days or weeks in related studies.

Another important analysis-related factor is the frequency of forecasts. Namely, Jacob et al. identified (1999: 78) that analysts who made forecasts more frequently or revised previous ones more often were more accurate in their forecasts. More frequent forecasts are disclosed by analysts either to use the forecasts of other analysts which have been given in the meantime or incorporate new information into the forecasts.
Several studies point out that forecast accuracy declines with increased complexity of the information. As the aim is to rationally consider all available information about the company and the specific industry and to create forecasts upon that information, it is obvious that the task becomes gradually more difficult as the complexity of the information increases. The complexity for the analyst is not measured by the amount of information, instead by new elements and dimensions brought into the forecasting process which affect all other determinants as well as the actual financial results. The complexity increases with observed company’s size (Brown et al. 1987: 65-66), the number of different industries and regions where the company operates, mergers & acquisitions (How et al. 2005: 68, 76-77; Duru and Reeb 2002: 415), capital intensity and financial leverage (Haw et al. 1994: 485-486).

Forecast accuracy improves with more informative company disclosure policies and additional information provided to the markets (Lang and Lundholm 1996: 490). It is important to distinguish the complexity and the quality of information. As explained previously, the complexity decreases analysts’ ability to provide accurate forecasts while the quality of information increases it. According to Healy and Hutton (1999: 489), the quality of the information is higher with increased segment disclosures, in-depth discussion of operations and financial performance, more candid management discussion of the company’s prospects in annual and quarterly reports, improved investor relations through increased analyst access to top management and additional company meetings and presentations for analysts.

This evidence was supported by Bowen et al. (2002: 27-28) who observed that the regular use of conference calls with managements improved analysts’ ability to accurately forecast the results for the next financial period, implying the importance of increased information disclosures. The other observed effect was the reduction in analysts’ forecast dispersion after conference calls were made available.

The second large group of factors influencing forecasting accuracy are brokerage firm, work process and analyst-specific characteristics. Forecast accuracy is positively associated with analysts’ experience (defined by combined ability and skills) and analysts’ firm- and industry-specific experience (defined by time period for which the
analyst has covered a specific stock or industry) (Clement 1999: 302; Mikhail et al. 1997: 131-132). This implies analyst learning curve over time as they learn from their experience and become better forecasters.

In consistent with the theory, Mikhail et al. (1997: 155) also observed that the market reacts more to experienced analysts’ stock recommendations, implying that the market recognizes the increased forecasting accuracy associated with experience. Analysts who are more accurate forecasters are more important in investors’ view, have more influence on the market movement and are more highly regarded by their employers as well.

Brokerage size and the degree of industry specialization of the brokerage firm also affect forecasting accuracy positively (Clement 1999: 302). A larger brokerage firm means there is more interaction between analysts, more brokerage-related experience or knowledge is available and, most importantly, larger brokerage firms are able to identify and attract better forecasters ex ante with higher salary, better reputation and work environment.

Jacob et al. (1999: 79-80) however argue against findings that analysts differ in forecast accuracy per se and that a forecasting learning curve exists. Instead, they offer empirical support to the notion that forecast accuracy is associated with the combination of working for a particular brokerage house, analysts’ aptitude for forecasting tasks and the quality of the alignments between their skills and aptitudes and the idiosyncrasies of the companies they follow. This means that a certain indefinable combination of these three is needed for superior forecasting accuracy and that analysts have a natural aptitude in forecasting results for particular companies or companies in particular industries. This hypothesis has not been fully confirmed by following studies.

Expectedly, the number of firms and industries followed by the analyst affects their accuracy negatively (Clement 1999: 302). This is also coherent with the lower forecasting accuracy of buy-side analysts as one of the main characteristics is the many times higher number of firms and different industries covered compared to sell-side analysts.
Researching brokerage houses which are part of an investment bank alongside with M&A and asset management activities, Irvine et al. (2004: 68-70) found on a sample of 17 larger U.S. investment banks in the time period of 1994-2001 that the sell-side analysts’ forecast accuracy of a company’s results are in positive relationship with the percentage of shares of that company owned by the asset management division of the investment bank. 61 per cent of analysts had higher forecast accuracy if the affiliated investment bank had an investment position in the company’s stock and the accuracy increased with the investment position size, albeit only slightly. It is assumed that the effect is due to positive externalities from the synergy of brokerage and asset management. From one side, the asset management part creates demand for higher quality financial information; from the other side the asset management itself shares its information with the sell-side analysts. (Ibid.: 67-68)

Surprisingly, it was recently noted by Kumar (2009: 41-42) that gender also matters. Namely, differentiating between male and female analysts shows that female analysts tend to issue bolder and more accurate forecasts, while the market also identifies this accuracy, by reacting more strongly to forecast revisions made by female analysts. Although it is widely known that women are better money managers as they exhibit higher risk aversion and lower levels of competitiveness (Ibid.: 2), the reason behind higher accuracy of female analysts’ forecasts is most probably self-selection. According to the self-selection hypothesis, only women with superior forecasting abilities enter the profession due to the perception of gender discrimination in the male-dominated analyst labour market. This hypothesis is yet to be verified.

To conclude, there are several different analyst- and content-related factors which influence forecasting accuracy. As shown, it is quite an easy task to identify how and at what degree these factors influence the forecasting result. The next chapter deals with examples of specific abnormal behavioural biases which have been observed in present financial forecasting practice.
2.2. Intentional Biases which Influence Forecasting Accuracy

The same way, forecasts may prove to be inaccurate due to different factors stated in the previous chapter, forecasts may be biased due to intentional behaviour by the analysts, motivated by different incentives. This chapter identifies and explains the main intentional biases affecting forecasting accuracy based on numerous scientific findings.

These biases include:
- optimism bias,
- selection bias,
- herd behaviour.

As mentioned previously, analysts create value for their firms by providing clients with research reports and brokerage services that generate trading volume in covered stocks or by increasing demand for a new issue that their firms are underwriting or distributing (Groysberg et al. 2008: 26). Consequently, this means that analysts may be prone to conflicts of interest in case where creating additional revenue for the brokerage becomes more important than providing accurate forecasts and profitable investment recommendations to clients. This hazard is also confirmed by the fact that analysts’ compensation is often tied to commissions and revenues from trading the stocks that the analysts’ cover and to their ability to create demand for a new issue that their firm is underwriting or distributing (Ibid.: 27).

Hong and Kubik (2003: 313) looked at analyst career concerns and how their work performance is associated with favourable career outcomes. According to their research, when controlling for relative forecasting accuracy, analysts who are more optimistic are more likely to experience favourable job separations. This is even more evident in the case of analysts who cover stocks which have been underwritten by their houses, as then job advancements were less sensitive to accuracy and more sensitive to forecasting optimism. This evidence suggests that analysts may provide too optimistic forecasts in order to encourage clients to buy stocks simply to increase brokerage commissions or in order to get clients to buy stocks of companies that the brokerage has underwritten regardless of their investment potential.
This was also confirmed by Michaely and Womack (1999: 683) – although underwriter analysts’ forecasts should be more accurate due to having superior information from the data collection done for the underwriting, in reality these forecasts are actually optimistically biased. Furthermore, the investment recommendations made by underwriters are significantly worse compared to the performance of brokerage houses not affiliated with the issuance; the difference between the underwriter and non-underwriter groups is more than 50 per cent for a two-year period beginning from the issuance. Also, the very same investment banks make better investment recommendations on new issuance when they are not underwriters. All of this clearly provides sufficient evidence of optimism bias in case the analyst is affiliated with the underwriting investment house.

In addition to the optimism bias, at least two forms of selection bias have been confirmed by different studies. Firstly, analysts’ are more eager to initiate coverage of firms and perform research duties on firms for which they genuinely have optimistic views (McNichols and O’Brien 1997: 197-198). Although they spend relatively more time researching the companies they favour, this is not shown in forecasting accuracy, as their forecasts for these companies are systematically optimistic.

Secondly, the analysts are selective in using the information they obtain on the company they are more in favour of. This, for example, expresses in tendency to avoid or delay the disclosure of unfavourable news (McNichols and O’Brien 1997: 197-198). Several studies have also confirmed (O’Brien et al. 2005: 623) that analysts are slower to downgrade from buy and hold recommendations and significantly faster to upgrade from hold recommendations in case of relevant information disclosures (public announcements, quarterly results etc.). Similarly to the optimism bias, this is more evident in the case of affiliated analysts where their employer brokerage is also the underwriter for the specific stock. This clearly shows the analysts tendency to avoid losing revenue sources, as hold recommendation brings less revenue from trades on both ways (buying and selling) and sell recommendations pushes investors towards other asset classes besides equity.
Previously discussed studies on optimism bias demonstrated that more optimistic analysts get more often promoted and that optimism is more evident in the case where the employer brokerage also acts as an underwriter for the specific stock. While the studies on the selection bias show that forecast optimism arises endogenously from analyst coverage decisions, some research also suggests that analysts may strategically add optimistic bias to their forecast reports irrespective of the fact if the employing brokerage house also acts as an underwriter. The evidence however is not clear, as it is context confined and very much sample-period specific. The optimism bias in different research papers depends on different overlapping factors: sample period, forecast horizon, whether mean or median forecast is used as evidence, the conduct of statistical tests establishing bias etc. (Ramnath et al. 2008: 69-70)

It has also been noted that the over-optimism, if true, might be changing in time. For example Brown (2001: 221) pointed out that median earnings surprise shifted from small negative to zero and from there to small positive during 16 years from 1984 to 1999. This might lead to a conclusion that over-optimism is not something certain and conclusive that is represented across analysts at any given time, rather it is dependent on the overall business cycle and market expectation, a notion which has been clearly evident throughout the 2009 market crash.

The last intentional bias covered in this chapter derives from the public availability of analysts’ reports. As these reports are received by all clients as well as competition, the analysts have a strong disposition to herding behaviour and risk aversion in order to keep their reputation. Herding is defined as situation where many people take the same action to mimic actions of others (Graham 1999: 237).

A possible loss of reputation exists when an analyst gives a different forecast than the overall market consensus and proves to be wrong. At the same time, the reputation of analysts who make the same incorrect forecasts as other analysts is less likely to be hurt (Groysberg et al. 2008: 32). In other words, the utility (the increase in reputation) for an analyst from issuing a contradicting forecast which proves to be more accurate is less
than the negative utility (the decrease in reputation) for an analyst from issuing a contradicting forecast which proves wrong.

There are two different types of herding evident in analysts’ forecasting behaviours: informational cascades and reputational herding (Graham 1999: 239-240). Informational cascade type of herding occurs when existing information becomes so overwhelming that an individual’s single piece of private information which is inconsistent with the general knowledge is not strong enough to reverse the decision of the crowd in analyst’s view. The analyst then chooses to mimic the action of the crowd, rather than act on his private information. If this scenario holds for one analyst, it is also likely to hold for anyone acting after this person, creating a domino-like effect, referred to as a cascade. Reputational herding, on the other hand takes place when an analyst chooses to ignore his own information and decision-making abilities and mimic the action of other analysts due to positive reputational externalities.

Research has shown that forecast boldness, i.e. the difference from consensus forecast (the opposite of herding) is related to analysts’ self-confidence. Analysts who have more confidence in their forecasting ability are more likely to issue bold forecasts while analysts who have lower confidence are more likely to herd. Also, in case the analyst makes a bold forecast that differs largely from the market consensus, it is usually also more accurate, as the analyst probably uses private information about the firm or is more confident in his forecasting abilities due to more experience (Clement and Tse 2005: 248). Analysts with less experience (thus less confidence in their forecasting ability) are more likely to herd, implying that their career concerns may inhibit certain analyst boldness. (Ramnath et al. 2008: 21)

In an subsequent study by Clarke and Subramanian (2006: 81-82), in addition to confirming the positive relation between forecast boldness and experience, they observe a U-shaped relation between the analyst’s forecast boldness and prior forecasting performance, caused by employment risk. Their explanation is that due to higher employment risk, significant underperformers are more likely to issue bolder forecasts, as they have less to lose while significant overperformers are also more likely to issue bolder forecasts due to lower employment risk as well as higher self-confidence.
Time is also important. Herding becomes more evident as time before results announcement decreases. During that time, more forecasts are being disclosed by different analysts and later forecasters naively assume that with increased number of individual forecasts, the average consensus forecast is becoming more and more accurate. In the end, this could prove wrong as when the first few forecasts where herding started from are inaccurate, then so is the consensus forecast. (Trueman 1994: 115)

Three main intentional biases: optimism bias, selection bias and herding behaviour were discussed in this chapter. However, there also exist factors that might counterbalance the effect of those biases. Analysts have long been benchmarked against each other based on forecast accuracy. This means they have a greater incentive to report more accurate forecasts as the comparison with other analysts affects their reputation as well as compensation (Groysberg et al. 2008: 36). Stickel (1992: 1831-1836) confirms this theory, proving that analysts with above-average forecasting accuracy, i.e. so-called star-analysts give more profitable investing recommendations, have a higher reputation amongst money managers and are significantly better paid compared to average analysts.

For example, one determinant of analysts’ compensation is their ranking in Institutional Investor magazine, where analysts and research firms are ranked based on their forecast accuracy, the profitability of their investment recommendations and other relevant characteristics (Groysberg et al. 2008: 27). This finding, along with the studies discussed previously which showed evidence of connection between forecasting accuracy and work promotion, identifies clear incentives for the analyst to be more accurate instead of giving overly optimistic or in any other way biased forecasts.

The last two chapters identified analyst- and content-related factors which influence forecast accuracy, as well as behavioural determinants which can cause forecasting biases. The next chapter deals with the main theme of this thesis, anchoring and adjustment bias, while giving a short overview how cognitive biases arise in the first place and how they affect forecasting.
2.3. Anchoring and Adjustment Bias

As identified in the previous chapters, forecasting is largely influenced by judgmental decision-making. Classical economics, as well as financial economics uses mostly the *homo oeconomicus* approach, according to which all economic decisions are made based on completely rational logic and unaffected by psychological effects. In reality, this is rarely the case, as individuals are always affected by behavioural and emotional influences, often steering final decision away from what rational logic would have told.

Forecasting is a decision-making process like any other. Analysts have to come to the end decision through choosing among different options, form judgments of the value or likelihood of particular events and outcomes and evaluate the possibilities on available information and their personal judgement (Plous 1993:109). Although one would assume the decision-making process to be utterly logical and driven by rational concerns similarly to the *homo oeconomicus* approach, this is certainly not the case. Judgmental decision-making is closely associated with human behaviour and all the psychological aspects that it is accompanied by.

In their seminal article about judgment in decision-making processes, Tversky and Kahneman (1974: 1124) state that all decisions that involve judgment are made relying on a limited number of heuristic principles. These principles or heuristics reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations. Although these heuristics are generally quite useful, they sometimes lead to severe and systematic errors.

The main reason behind the use of heuristics is the limitation of human judgment. The ability of human mind to process information and make decisions is very similar to memory. The same way memory cannot store every single piece of collected and analyzed data, the human mind has to make compromises to accomplish many different and often extremely complex tasks such as forecasting. This is where the use of heuristics becomes apparent. (Wright, Goodwin 1998: 9-10)
In regards to forecasting, the subjective assessment of probabilities, i.e. probable outcomes resembles the subjective assessment of physical quantities such as size or distance. These judgments are all based on data of limited validity, which are processed according to heuristic rules. For example, the apparent distance of an object is determined in part by its clarity: the more sharply the object is seen, the closer it appears to be. This rule has some validity, because in any given scene the more distant objects are seen less sharply than nearer objects. However, the reliance on this rule leads to systematic errors in the estimation of distance: distances are often overestimated in case visibility is poor because the contours of objects are blurred in vision; on the other hand, distances are often underestimated when visibility is good because objects are seen sharply. Thus the reliance on clarity as an indication of distance leads to common biases. Such biases are also found in the intuitive judgment - the so-called cognitive biases. (Tversky, Kahneman 1974: 1124)

According to Harvey (2001: 59), in addition to being biased forecasts can be suboptimal due to inconsistency. Inconsistency is a random or unsystematic deviation from the optimal forecast, whereas bias is a systematic one. Inconsistency can be characterized as the imperfect reliability of all human behaviour and it is an essential part of the definition of human error. In the long run, inconsistency can only reduce the accuracy of forecasts; in addition, it has nothing to do with potentially beneficial behavioural changes over time, such as changes due to learning, obtaining new information or adapting to new circumstances. Inconsistency is simply an error introduced into every forecast by the natural inconsistency of the human judgment process. (Stewart 2001: 81-82)

An example by Harvey (2001: 59), in case of a time series of 1000 independent data points that have varied randomly around a mean value of five units, forecasts for the next 100 points should theoretically all have the value of five units. If these forecasts have an average value of five units but are scattered around that mean, they exhibit inconsistency. If they all have a value of precisely four units, they show bias but not inconsistency. If they have an average value of four units but are scattered around that mean, they contain both inconsistency and bias.
Inconsistency may arise because of variation in the way the forecasting problem is formulated, because of variation in the choice or application of a forecast method or because the forecasting method (e.g. human judgment) itself introduces a random element into the forecasts. Biases may arise when certain types of judgmental methods (so-called cognitive biases) are automatically applied to forecasting results. (Harvey 2001: 60)

Although a wide number of different cognitive biases exist, this thesis examines more closely anchoring and adjustment bias as it is most closely related to the forecasting paradigm. In addition to anchoring and adjustment bias, representativeness and availability biases are also often associated with forecasting.

People typically rely on the representativeness heuristic in finding answers to questions where some object or observation directly derives from another one. According to representativeness bias, probabilities are evaluated by the degree, to which one object is representative of another, i.e. by the degree to which one resembles the other (Tversky, Kahneman 1974: 1124). People using the representativeness heuristic are employing a form of stereotyping in which similarity dominates other cues as a basis for judgement and decision-making. For example, a particular sequence of events may be seen as more typical or representative of the set of possible sequences than another equally likely sequence. As a consequence, it is wrongly judged to occur more likely. (Wright, Goodwin 1998: 116)

Availability heuristic means that ease of recall is employed as an indicator of importance. Recent data might be over-weighted in a description of a forecasting problem, leading to significant errors if there are important deviations in the trend line which is forecasted. (Wright, Goodwin 1998: 116)

The anchoring and adjustment bias (or anchoring in its shorter form) is more closely related to forecasting than other forms of cognitive biases. According to anchoring, estimates are made in decision-making processes by starting from an initial value that is adjusted to yield the final answer. The initial value may be suggested by the formulation of the problem or it may be the result of a partial computation. In either case,
adjustments are typically insufficient as different starting points yield different estimates and it is hard to estimate how much adjustment is needed to succeed in an accurate result. (Tversky, Kahneman 1974: 1128)

It is important not to confuse anchoring with forecasting techniques. Instead, anchoring is made automatically and often unknowingly and is not a part of the formal forecasting making process. Therefore it is often difficult to find the source of inaccuracy of the forecast as anchoring bias is, like other biases, inserted into the decision-making process subconsciously.

In a classical demonstration of the anchoring effect, subjects were asked to estimate various quantities, stated in percentages. For example, the percentage of African countries in the United Nations was asked. For each quantity, a number between 0 and 100 was determined by spinning a wheel of fortune in the subjects’ presence. The subjects were instructed to indicate first if that percentage was higher or lower than the outcome on the wheel, and then to estimate the value in their opinion. At the same time, the wheel was rigged, giving either 10 or 65 for that group as the outcome. As a result, the median estimates of the percentage of African countries in the United Nations were 25 and 45, respectively. The experiment was repeated with numerous other estimates, yielding a similar result. Payoffs for accuracy did not reduce the anchoring effect. (Tversky, Kahneman 1974: 1128)

Furthermore, there is evidence (Plous 1993: 146) that the effects of anchoring do not disappear with extreme anchors. Absurdly high anchor values work just as well as more plausible anchor values: anchoring is a robust phenomenon in which the size of the effect grows with the discrepancy between the anchor and the pre-anchor estimate (the average estimate offered before being exposed to an anchor) until the effect reaches an asymptotic level.

Tversky and Kahneman state that anchoring leads to systematic errors because adjustment away from anchors is insufficient. Other proposed reason to this phenomenon proposed by different studies is that a memory representation of the
anchor remains active and primes response in its vicinity (Harvey 2003: 12). This effect is identified as semantic priming.

Priming is a process when a stimulus is used to sensitize the nervous system to a later presentation of the same or a similar stimulus (Kolb, Whishaw 2009: 494-495). This means that the sensitivity to the same or resembling stimulus, i.e. the reaction to it is subconsciously similar also in the next time. Semantic priming occurs when the prime and the target are from the same semantic category and share certain features. Semantic priming in case of anchoring means that information which is activated to solve a comparative decision-making task will be subsequently more accessible when participants make absolute judgments. As the strength of the anchor effect depends on the applicability of activated information, semantic priming might cause the anchoring effect in the first place. (Strack and Mussweiler 1997: 437)

There are two most evident examples of the anchoring effect in forecasting according to Harvey (2003: 12-13): trend-damping and non-independent forecasts. Anchoring leads to trend-damping when the last observation is on the trend line and the analyst uses this as an anchor rather the overall pattern and makes an insufficient adjustment for trend. Thus, under-adjustment is observed (see Fig 2.2).

![Figure 2.2. An example of trend damping caused by anchoring in sales’ forecast (Harvey 2003: 12)](image-url)
The second example of anchoring effect is non-independent forecasts, which are observed when an insufficient adjustment towards the mean is made but the average result, as well as past data pattern proposes otherwise (see Fig. 2.3). In this case data pattern as well as the average result again suggests placing the forecast on the trend-line, however the analyst gives too much weight on the last observation and again under-adjustment is observed.

Figure 2.3. An example of non-independent forecasts caused by anchoring in sales’ forecast (Harvey 2003: 13)

Both of these effects show that anchoring causes too much weight being put on the last observation and too little weight on the previous observations as well as on new information. The previous graphs were observed in experimental situations. Although it is rarely possible to observe so clear patterns in real life, the logic behind the anchoring bias is the same. According to Harvey (2003: 17), trend damping is more appropriate for cyclical series, e.g. for financial forecasting as financial results are, in addition to other aspects, influenced by business cycles.

Observing anchoring effect in forecasting paradigm through past observation values as anchors is somewhat untraditional. Anchoring is mostly measured as a judgment bias influenced by irrelevant or uninformative starting points. Thus, many previous experiments show that judgmental values are positively related to the provided anchor,
which is often irrelevant to the measured object. In addition to the before mentioned experiment of estimating African countries in the UN after the spin of a fortune wheel, anchoring has been documented in estimates as diverse as the number of female chemistry professors, real estate prices or even non-numerical problems, while using anchors such as last 4 digits of subjects’ credit card numbers or a random number from 1 to 5 that the subject could first think of (Plous 145-146). Still, in everyday judgments the construction of values may also involve an informative anchor, or even a self-generated anchor. In contrast, demonstrations of anchoring usually involve experimental anchors which are explicitly specified as uninformative so that any influence of an anchor can be identified as a bias (Chapman, Johnson 1999: 116-117). Similarly, the effect of anchoring in forecasting has been studied mainly in different experimental situations. Bailey and Gupta (1999: 39, 50-51) confirmed the anchoring effect in different forecasting situations while controlling the amount of aid given to the forecaster and the presence of anchors. Also, Bolger and Harvey (1993: 779) identified anchoring effect in time series forecasting, finding evidence of strong serial dependencies in made forecasts.

As this thesis’ goal is to measure anchoring effect of financial analysts in a real-life situation, the data is collected from actual forecasts not from an experimental situation where it would be possible to control the presence and strength of the anchor. This way, only a limited possibility of observing the anchoring effect is available, while the anchors itself are presumably past outcomes.

This part of the thesis outlined the main factors which influence forecasting performance, including different analyst- and content-related factors, behavioural determinants and cognitive biases, most important of which being the anchoring and adjustment bias. The next part of the thesis examines main characteristics of equity analysts’ forecasts of listed Baltic companies and measures the effect of anchoring and adjustment based on the theoretical findings given previously.
3. MEASURING ANCHORING AND ADJUSTMENT IN ESTONIAN SELL-SIDE EQUITY ANALYSTS’ FORECASTS

3.1. Methodology for Measuring Anchoring and Adjustment

Most research on anchoring and adjustment effect in forecasting uses laboratory experiments in order to better control different variables and unambiguously identify the effect in wide range of different forecasting situations (Bolger, Harvey 1993: 779; Bailey, Gupta 1999: 40 etc.). These studies control for the presence of a strong anchor in different forecasting assignments, and compare different forecasting results with and without the presence of the anchor. Although this is indisputably the most clear and confident way of identifying anchoring effects in forecasting situations, these studies are also prone to several downfalls.

Firstly, experimental studies will always remain experimental. The experiments try to imitate real-life situations as closely as possible, presenting the subjects with close to real life forecasting tasks and including background information in addition to the information about the company which financial results are forecasted (Lee et al. 2007: 382). These experiments are still imitations and can never be as sophisticated and take into account all these factors which the forecaster considers when giving judgmental forecasts.

Secondly, the precise and measured signalling of the anchor effect is certainly something that does not occur in real life situations. Although this enables the research results to be more accurate and conclusive, it again draws the experimental situation away from what occurs in real life.
Thirdly, several problems emerge when looking at the results these experiments produce. Often the base data which is presented to the experimental subjects is created *ad-hoc* for the specific experiment purposes (Bolger, Harvey 1993: 782). This might not take into account the environment and conditions that equity analysts cope with in their everyday work routine. It is probably impossible to define, for example how natural a time-series on a company’s revenue development looks, but the data created specifically for a particular experiment is certainly artificial.

A similar problem occurs in case of the data collected from subjects’ forecasts. In real-life situations, the analysts assumedly try to result in a precisely accurate forecast. As it was explained in earlier parts of this thesis, their work reputation, as well as reward, depends on their forecasting performance. They have an ample amount of time in their day-to-day duties to produce consistent and accurate forecasts. Unfortunately, this cannot be said about experimental subjects. The subjects often have a limited amount of time; also their incentive to perform well in the forecasting tasks may often be smaller compared to real-life situations. This again paves way to changing the research results too experimental; this type of studies is very good in measuring anchoring effects in particular, but considerably weaker in measuring anchoring effects in real-life situations.

As this thesis’ goal is to measure anchoring effects in the forecasts that Estonian sell-side equity analysts disclose, it is impossible to use same research structure as the experiments which were discussed previously. There are very few studies carried out until this time which discuss forecasts of equity analysts in particular while using real-life data. Amir and Ganzach (1998: 333) studied US analysts’ earnings forecasts in 1976-1990. Anchoring is observed in the case of forecast revisions, as certain events or new pieces of information that are made available are correlated with forecast revisions. Marsden *et al.* (2008: 83) carried out a similar study on anchoring in Australian equity analysts’ forecasts, also identifying the effect in the case of forecast revisions in the presence of a new anchor. They also created a regression model, while incorporating several judgmental heuristics and concluding with similar results with the presence of the anchoring effect.
Friesen and Weller (2006: 333), however, present a Bayesian model as the rational expectations forecasting model and compare actual analyst forecasts with that model, identifying several cognitive biases. Their model first defines the forecasting result without any biases and then compares the actual forecasting results with their model. Again, although they use real-life data, their definition of anchoring in forecasting situations resembles more the anchoring effect which is identified in experimental situations, not in real life.

This thesis identifies possible anchoring effect using the ideas presented by Harvey (2003: 23) while using correlation analysis. As an analyst uses information on past financial results, as well as current information on the present market conditions and the outlook of the company, then anchoring is observed in case too much weight is put on the information about past financial results. In that case, the forecast is more correlated, i.e. anchored to the past financial result, rather than to the actual financial outcome. Thus, anchoring is observed when:

\[
(1) \quad corr(F_t, X_{t-1}) > corr(F_t, X_t),
\]

where \( F_t \) – forecast for the observed period,

\( X_t \) – actual financial result in the observed period,

\( X_{t-1} \) – financial result in the past period.

As it was identified in the previous parts of this thesis, time of the forecast is important, as forecast accuracy increases with time. Therefore this study examines the quarterly forecasts instead of annual forecasts, while using only the latest forecast disclosed by the research firm before the announcement of quarterly results by the company. This way, although the observed forecasts are not always made exactly at the same time, they are the latest and assumedly the most precise forecasts given by respective analysts.
3.2. Data Characteristics of Estonian Sell-Side Equity Analysts’ Forecasts

The sample data used for empirical analysis this thesis comprises of 757 quarterly forecasts made by 15 analysts from 4 research firms in 5 years from 2005 to 2009. The sample includes all Estonian research firms which publicly disclose their research reports during that time period, including 2 investment banks and 2 commercial banks: EVLI, LHV and SEB, Swedbank, respectively. Due to the conditions under which these research reports were given for use, analysts and research firms are coded and not identifiable in this study.

Forecasts are given for 12 largest listed companies from different Baltic stock exchanges, while most of the companies are listed on Tallinn Stock Exchange. The sample included only companies for which more than four quarterly forecasts were available. For example, if a company was covered by a research firm for just one year, it was not included in the sample; if a company was covered for more than a year, but only annual forecasts were given, it was also not included in the sample. This exclusion is done to prevent possible problems with insufficient data that would arise in case very few forecasts have been made on a specific company.

Although the research reports include a wide number of different financial forecasts, four main financial results were analyzed here: sales, EBITDA, EBIT and net profit. Deriving from the structure of the analyst reports, the main financial results’ dynamics which the analysts’ are focused on are yearly sales growth and EBITDA, EBIT and net profit margins.

The sample data does not include forecasts for all consecutive quarters and for all 12 companies. The main problems behind it are the choice of companies under coverage and the changing structure of the reports. None of the research firms give forecasts to all 12 companies during the observed time period and only 2 firms, the telecom companies TEO and Eesti Telekom are covered by all 4 research firms. In addition, not all reports include quarterly forecasts. Sometimes, quarterly forecasts are not given at all, for
example instead of a third quarter forecast, the research firm forecasts the whole half-year financial result.

In order to exactly identify at what degree the forecasts may include anchoring, the forecasting errors are measured here. Depending on the result, medians of different error measurements are given (Bolger, Harvey 1993: 786). The measurements which are used include:

(3) Forecast error: \( FE = F_t - X_t \),

(4) Absolute forecast error: \( AFE = |F_t - X_t| \),

(5) Forecast % error: \( FPE = \frac{F_t - X_t}{X_t} \),

(6) Absolute % forecast error: \( APFE = \frac{|F_t - X_t|}{X_t} \),

where \( F_t \) – forecast for the observed period,
\( X_t \) – actual financial result in the observed period.

Absolute forecast error measurements show the absolute deviation from the accurate result. Without the absolute, the forecast error shows the amount of over- or underestimation in the forecasts, while not considering the extent of error, as over- and underestimations counter-effect each other. For example, forecast error without the absolute which is equal to zero does not mean that the forecasts themselves are accurate.

In terms of sales, EBITDA, EBIT and net profit results, mean and median FPE and APFE are observed. In terms of sales growth and profitability margins, mean and median FE and AFE are observed, in percentage points (pps). In case APFE is larger than 300 per cent, the observation is dropped from the sample due to the extreme value caused probably by analyst’s mistake or data input error. There are 32 such observations, i.e. 4.2 per cent of total observations.

Table 3.1 shows means and medians of different forecast error measures. The mean AFE is 23.7 per cent with a standard deviation of 38.4 per cent, i.e. there is considerable
amount of variance and extremes in different observations’ forecasting errors, and therefore it is more reasonable to consider looking at median measures. Median AFE is 10.1 per cent whereas there is a clear pattern of the error increasing when considering different financial results from top to bottom in the income statement. Sales forecasts’ median AFE is 3.2 per cent vs a 19.1 per cent median AFE in net profit forecasts. This is logical, as forecasting becomes more sophisticated after each income statement line: EBITDA forecast requires forecasting operating expenses in addition to sales, while EBIT forecast incorporates also depreciation and amortization and net profit requires further estimations for taxes and any financial revenues or expenses.

Table 3.1. APFE and FPE in financial results (by the author).

<table>
<thead>
<tr>
<th></th>
<th>APFE</th>
<th>FPE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>Sales</td>
<td>0.0625</td>
<td>0.0317</td>
</tr>
<tr>
<td>EBITDA</td>
<td>0.2202</td>
<td>0.0851</td>
</tr>
<tr>
<td>EBIT</td>
<td>0.3127</td>
<td>0.1531</td>
</tr>
<tr>
<td>Net profit</td>
<td>0.3544</td>
<td>0.1912</td>
</tr>
<tr>
<td>Overall</td>
<td>0.2366</td>
<td>0.1007</td>
</tr>
</tbody>
</table>

Source: Author’s calculations.

Surprisingly, there is a sharp drop in forecasting accuracy from EBITDA to EBIT, implying that either analysts have significant problems in forecasting the company’s investments and asset write-offs or the companies are often changing their depreciation policies. The drop in forecasting accuracy between EBIT and net profit forecasts is about the same magnitude as the difference between sales and EBITDA forecasts.

Considering the median FE, in general the forecasts are neither over- or underestimated. Still, sales and EBITDA results seem to be slightly overoptimistic, especially the latter, while net profit result is strongly underestimated. The reason behind possible overoptimistic EBITDA forecasts may lie behind the fact that EV/EBITDA valuation ratio is the most universal and often used ratio in peer group valuation. If an analyst positively adjusts the EBITDA forecast while keeping the enterprise value at a stable level, the valuation result makes the company look cheaper and therefore a more
profitable investment. This in turn could result in a more favourable investment recommendation, creating more revenue for the brokerage firm.

Table 3.2 shows means and medians of different forecasting error measures in sales growth and profitability margins. The yearly sales growth forecasts’ median AFE is 3.4 pps, with a high standard deviation of 8.5 pps. The median FE shows a slight over-optimism in sales growth forecasts, which is still less than the standard deviation of FE.

**Table 3.2. AFE and FE in sales growth and profitability margins (by the author).**

<table>
<thead>
<tr>
<th></th>
<th>AFE (1/100 pps)</th>
<th>FE (1/100 pps)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>Sales growth</td>
<td>0.0663</td>
<td>0.0340</td>
</tr>
<tr>
<td>EBITDA margin</td>
<td>0.0326</td>
<td>0.0220</td>
</tr>
<tr>
<td>EBIT margin</td>
<td>0.0344</td>
<td>0.0190</td>
</tr>
<tr>
<td>Net profit margin</td>
<td>0.0421</td>
<td>0.0240</td>
</tr>
<tr>
<td>Overall margins</td>
<td>0.0369</td>
<td>0.0220</td>
</tr>
</tbody>
</table>

Source: Author’s calculations.

Profitability margin forecasts’ overall median AFE is 2.2 pps with a standard deviation of 6.3 pps. There are no significant deviations in different profitability margins forecasts’ AFEs which all are in the range of 1.9 pps – 2.4 pps. The standard deviation is higher in net profit margin AFE, suggesting that in some cases it is more difficult to forecast net profit margin than other margins. This is expected as in the case of net profit forecasts, the analyst also has to consider the effect of financing and currency movements in addition to other factors. Looking at the FE estimation results, profitability margins forecasts’ seem to be very slightly over-optimistic, if at all.

Table 3.3 shows means and medians of different forecast error measures in different years. APFE and FPE estimation results are based on sales, EBITDA, EBIT and net profit growth while AFE and FE estimation results are based on sales growth and EBITDA, EBIT and net profit margins. The least accurate years based on APFE were 2005 and 2009; the former had only 30 observations and the latter was the year when all Baltic economies went through a historically extreme slump in terms of GDP.
development (The Economist 2010). These two years also comprised the most optimistic forecasts if looking at FPE and FE estimation results. 2006 forecasts clearly underestimated the actual financial results, which is in accordance with the fact that GDP growth rates were one of the highest on that year. Estonia plays largest role in forecasts’ under- and overestimates as most companies in the sample are based in Estonia, but other Baltic states went through similar macroeconomic developments during that time period.

Table 3.3. AFE and FE in different years (by the author).

<table>
<thead>
<tr>
<th>No. of obs.</th>
<th>APFE</th>
<th>FPE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>2005</td>
<td>30</td>
<td>0.1855</td>
</tr>
<tr>
<td>2006</td>
<td>63</td>
<td>0.1627</td>
</tr>
<tr>
<td>2007</td>
<td>210</td>
<td>0.1591</td>
</tr>
<tr>
<td>2008</td>
<td>267</td>
<td>0.2572</td>
</tr>
<tr>
<td>2009</td>
<td>150</td>
<td>0.3500</td>
</tr>
</tbody>
</table>

AFE (1/100 pps) FE (1/100 pps)

<table>
<thead>
<tr>
<th>No. of obs.</th>
<th>APFE</th>
<th>FPE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>2005</td>
<td>30</td>
<td>0.0371</td>
</tr>
<tr>
<td>2006</td>
<td>63</td>
<td>0.0452</td>
</tr>
<tr>
<td>2007</td>
<td>210</td>
<td>0.1936</td>
</tr>
<tr>
<td>2008</td>
<td>267</td>
<td>0.0556</td>
</tr>
<tr>
<td>2009</td>
<td>150</td>
<td>0.0523</td>
</tr>
</tbody>
</table>

Source: Author’s calculations.

Looking at sales growth and margin forecasts’ accuracy, similar regularities are revealed. 2009 is the least accurate year while the second one being 2006. Again, forecasts underestimated the actual results in 2006 and overestimated the results in 2009. Based on this evidence, it can be said that forecasts are at least on some degree dependant on the economic cycle. Analysts tend to underestimate financial results during years of exceptionally high economic growth and overestimate result during years of recession. Although one would assume that analysts adjust according to overall economic developments, the data suggests otherwise.

Table 3.4 shows means and medians of different forecast error measures for different analysts; the measures are sorted based on the median APFE. The difference between
the most and the least accurate analysts based on the median APFE is 14.8 pps which is quite high.

Table 3.4. AFE and FE in different analysts’ forecasts (by the author).

<table>
<thead>
<tr>
<th>Analyst</th>
<th>No. of obs.</th>
<th>APFE</th>
<th>FPE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Sd</td>
</tr>
<tr>
<td>MinnieMouse</td>
<td>51</td>
<td>0.1094</td>
<td>0.0638</td>
</tr>
<tr>
<td>DonaldDuck</td>
<td>14</td>
<td>0.1186</td>
<td>0.0721</td>
</tr>
<tr>
<td>Bashful</td>
<td>105</td>
<td>0.2535</td>
<td>0.0765</td>
</tr>
<tr>
<td>Dopey</td>
<td>48</td>
<td>0.2426</td>
<td>0.0801</td>
</tr>
<tr>
<td>Huey</td>
<td>40</td>
<td>0.1218</td>
<td>0.0905</td>
</tr>
<tr>
<td>Sleepy</td>
<td>65</td>
<td>0.1549</td>
<td>0.0909</td>
</tr>
<tr>
<td>MickeyMouse</td>
<td>135</td>
<td>0.2889</td>
<td>0.1000</td>
</tr>
<tr>
<td>Doc</td>
<td>15</td>
<td>0.1840</td>
<td>0.1111</td>
</tr>
<tr>
<td>Sneezy</td>
<td>24</td>
<td>0.1983</td>
<td>0.1188</td>
</tr>
<tr>
<td>Grumpy</td>
<td>8</td>
<td>0.1148</td>
<td>0.1274</td>
</tr>
<tr>
<td>Dewey</td>
<td>89</td>
<td>0.2081</td>
<td>0.1395</td>
</tr>
<tr>
<td>Louie</td>
<td>17</td>
<td>0.3138</td>
<td>0.1491</td>
</tr>
<tr>
<td>Happy</td>
<td>4</td>
<td>0.2655</td>
<td>0.1648</td>
</tr>
<tr>
<td>Goofy</td>
<td>105</td>
<td>0.3581</td>
<td>0.2114</td>
</tr>
<tr>
<td>Overall</td>
<td>720</td>
<td>0.2366</td>
<td>0.1007</td>
</tr>
</tbody>
</table>

Source: Author’s calculations.

Coincidentally, the only female sell-side equity analyst (code “MinnieMouse”) is also the most accurate analyst in this sample, a notion which was also discussed in the previous part of this thesis. The median FPE suggests that there are analysts who are clearly overoptimistic, as well as analysts who are rather pessimistic in their forecasts. The most optimistic analyst’s forecasts result in a median FPE of 15.92 per cent (code “Happy”), albeit with only 4 observations. The most pessimistic analyst’s (code “Grumpy”) forecasts result in a median FPE of -12.7 per cent, albeit with only 8 observations.

Table 3.5 shows means and medians of APFE for different companies; the measures are sorted based on the median APFE. The difference between the companies for which highest and lowest accuracy forecasts are made based on the median APFE is 28.4 per cent. Expectedly, highest forecast accuracy is in the case of non-cyclical companies, i.e.
two telecom companies and a utility provider in the sample. These companies’ financial results are relatively easiest to forecast as their operations are stable and less dependent on the economic cycle. In addition, their cost developments and margins are more stable over time compared to cyclical companies, meaning that there are less extreme deviation and unforeseeable surprises in the financial results. On the other extreme there are highly cyclical companies such as the construction company Merko Ehitus, which financials went through extreme growth in the economic expansion years of the Baltic states and were also hit the most during the recession.

Table 3.5. APFE in forecasts for different companies (by the author).

<table>
<thead>
<tr>
<th>No. of obs.</th>
<th>APFE Mean</th>
<th>APFE Median</th>
<th>APFE Sd</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tallinna Vesi</td>
<td>90</td>
<td>0.1000</td>
<td>0.0352</td>
</tr>
<tr>
<td>Eesti Telekom</td>
<td>107</td>
<td>0.0823</td>
<td>0.0488</td>
</tr>
<tr>
<td>TEO LT</td>
<td>113</td>
<td>0.1005</td>
<td>0.0690</td>
</tr>
<tr>
<td>Baltika</td>
<td>61</td>
<td>0.2903</td>
<td>0.1111</td>
</tr>
<tr>
<td>Eesti Ekspress</td>
<td>47</td>
<td>0.2946</td>
<td>0.1407</td>
</tr>
<tr>
<td>Tallinna Kaubamaja</td>
<td>42</td>
<td>0.4287</td>
<td>0.1584</td>
</tr>
<tr>
<td>Apranga</td>
<td>36</td>
<td>0.1986</td>
<td>0.1684</td>
</tr>
<tr>
<td>Eesti Ehitus</td>
<td>58</td>
<td>0.4145</td>
<td>0.1808</td>
</tr>
<tr>
<td>Olympic EG</td>
<td>63</td>
<td>0.3567</td>
<td>0.2215</td>
</tr>
<tr>
<td>Norma</td>
<td>18</td>
<td>0.2265</td>
<td>0.2305</td>
</tr>
<tr>
<td>Tallink</td>
<td>55</td>
<td>0.3886</td>
<td>0.2417</td>
</tr>
<tr>
<td>Merko Ehitus</td>
<td>31</td>
<td>0.4167</td>
<td>0.3193</td>
</tr>
<tr>
<td>Overall</td>
<td>721</td>
<td>0.2366</td>
<td>0.1007</td>
</tr>
</tbody>
</table>

Source: Author’s calculations.

To conclude, the forecasting error in the sample period is of the same magnitude as in the research that was discussed in the previous parts of this thesis. Although net profit and EBIT forecasting accuracy is significantly lower in Estonian analysts’ forecasts compared to their foreign counterparts, this effect can be explained by the highly volatile economic environment during the sample period. This is also confirmed by the fact that the forecasts of non-cyclical companies’ financial results are significantly more accurate compared to those of cyclical companies.
### 3.3. Estimation Results of Anchoring and Adjustment

Based on the structure of analyst reports and what the analysts focus on in their forecasts, it can be said that anchoring and adjustment effect, if at all, is possible to observe in yearly sales growth or margins development. It would be unjustified to try to identify anchoring in absolute growth levels or absolute financial results; the analysts, as well as the investors are not so much interested in the specific level of achieved sales or profits, rather than sales growth and profitability margins’ development.

Therefore it is tested if the analyst uses the previous quarter’s actual yearly sales growth as an anchor. In case an insufficient adjustment is made in the forecast towards the actual level of the current period, there is evidence of anchoring as the analyst puts too much weight on the recent observation, i.e. the anchor, and too little weight on the private information he has obtained in making the forecast.

Similar approach is used in profitability margins. The annual change in pps of the previous quarter’s profitability margins is used as a possible anchor for the annual change in pps of the current period’s profitability margins.

When measuring anchoring and adjustment effect of Estonian sell-side equity analysts, based on the model given in chapter 3.1 of this thesis, we get the following results (* marks if the correlation is statistically significant at 0.05 confidence level):

**Table 3.6. Correlations in different financial results’ forecasts (by the author).**

<table>
<thead>
<tr>
<th></th>
<th>corr(F&lt;sub&gt;t&lt;/sub&gt;X&lt;sub&gt;i&lt;/sub&gt;,1)</th>
<th>corr(F&lt;sub&gt;t&lt;/sub&gt;X&lt;sub&gt;i&lt;/sub&gt;)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales growth</td>
<td>0.7808*</td>
<td>0.9087*</td>
</tr>
<tr>
<td>EBITDA margin</td>
<td>-0.0992</td>
<td>0.0614</td>
</tr>
<tr>
<td>EBIT margin</td>
<td>0.0931</td>
<td>0.3242*</td>
</tr>
<tr>
<td>Net margin</td>
<td>0.3625*</td>
<td>0.4911*</td>
</tr>
</tbody>
</table>

Source: Author’s calculations.

These results show that when grouped by different financial results, no evidence of anchoring effect can be seen. The results are similar if correlation tests are repeated with Spearman or Kendall correlation, confirming the results.
Table 3.7 shows same correlations grouped by different years for which quarters the financial results were forecasted. Based on these correlations, the forecasts were anchored to previous financial results only in 2008. This particular year was a turning point for Estonian and Latvian economies, as previously high GDP growth turned into recession (The Economist 2010). In accordance with the theory, the evidence of anchoring effect becomes clearer when there are major changes in the specific industry or the overall economy.

**Table 3.7. Correlations in different years (by the author).**

<table>
<thead>
<tr>
<th>Year</th>
<th>corr(F_{X_{t-1}})</th>
<th>corr(F_{X_t})</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>0.7913*</td>
<td>0.8823*</td>
</tr>
<tr>
<td>2006</td>
<td>0.2697*</td>
<td>0.7970*</td>
</tr>
<tr>
<td>2007</td>
<td>0.9277*</td>
<td>0.8371*</td>
</tr>
<tr>
<td>2008</td>
<td>0.7498*</td>
<td>0.7018*</td>
</tr>
<tr>
<td>2009</td>
<td>0.2937*</td>
<td>0.0699</td>
</tr>
</tbody>
</table>

Source: Author’s calculations.

The correlations above show that analysts were putting too much weight on past financial results while the overall economic situation contradicted those results. In case analysts had adjusted accordingly to the available macroeconomic data as well as to leading indicators, the forecasts would have not been affected by anchoring effect and would have been more accurate. Instead, analysts anchored to previous financial results in their forecasts. Therefore they are more prone to anchoring effect and subsequent forecasting errors in case the industry or the overall economy moves between different stages of a macroeconomic cycle.

Table 3.8 shows same correlations grouped by different companies on which the financial results were forecasted. In the case of at least two companies: Merko Ehitus and TEO LT, there is evidence of anchoring effect in analysts’ forecasts. In case of Merko Ehitus, it is possible that as the economy as a whole and the construction sector specifically grew (and later contracted) at an abnormal rate in the sample period, the analysts were more comfortable in mentally anchoring their forecasts to past financial results.
In case of TEO LT, it is possible that as the company is a financially stable non-cyclical telecom provider, the analysts were more confident in anchoring their forecasts compared to taking into account the actual current market developments. This is not confirmed in the case of the other telecom company in the sample, Eesti Telekom. The difference between these two companies is that Eesti Telekom also offers mobile services while TEO LT’s product portfolio is only limited to fixed line services.

**Table 3.8. Correlations in different companies’ forecasts (by the author).**

<table>
<thead>
<tr>
<th>Company</th>
<th>corr(F_{t-1})</th>
<th>corr(F_{t-1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apranga</td>
<td>0.9250*</td>
<td>0.9932*</td>
</tr>
<tr>
<td>Baltika</td>
<td>0.8880*</td>
<td>0.9502*</td>
</tr>
<tr>
<td>Eesti Ehitus</td>
<td>0.7639*</td>
<td>0.7732*</td>
</tr>
<tr>
<td>Eesti Ekspress</td>
<td>0.9153*</td>
<td>0.9144*</td>
</tr>
<tr>
<td>Tallinna Kaubamaja</td>
<td>0.9021*</td>
<td>0.9198*</td>
</tr>
<tr>
<td>Merko Ehitus</td>
<td>0.7464*</td>
<td>0.6833*</td>
</tr>
<tr>
<td>Norma</td>
<td>0.2613</td>
<td>0.9671*</td>
</tr>
<tr>
<td>Olympic EG</td>
<td>0.7822*</td>
<td>0.8125*</td>
</tr>
<tr>
<td>Tallink</td>
<td>0.6156*</td>
<td>0.6322*</td>
</tr>
<tr>
<td>Eesti Telekom</td>
<td>0.8726*</td>
<td>0.9750*</td>
</tr>
<tr>
<td>TEO LT</td>
<td>0.7599*</td>
<td>0.6290*</td>
</tr>
<tr>
<td>Tallina Vesi</td>
<td>-0.0956</td>
<td>0.1684</td>
</tr>
</tbody>
</table>

Source: Author’s calculations.

Table 3.9 shows the same correlations grouped by different analysts who gave the forecasts. There are a few analysts who clearly stand out as being subjected to the anchoring effect. In the case of “DonaldDuck”, “Grumpy” and “MinnieMouse”, there is significant evidence of anchoring and adjustment.

As identified in the previous chapter, analyst “Grumpy” is also the most pessimistic analyst in the group with a median FPE of -12.7 per cent. Surprisingly, the analyst “MinnieMouse” is the most accurate forecaster in the sample with an overall APFE of 6.4 per cent. This suggests that anchoring might actually be positive for forecasting accuracy in certain situations. This however needs further investigation to test if the relation is actually correct.
Table 3.9. Correlations in different analysts’ forecasts (by the author).

<table>
<thead>
<tr>
<th>Character</th>
<th>$\text{corr}(F_{t} X_{t-1})$</th>
<th>$\text{corr}(F_{t} X_{t})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bashful</td>
<td>0.9089*</td>
<td>0.8942*</td>
</tr>
<tr>
<td>Dewey</td>
<td>0.8441*</td>
<td>0.9484*</td>
</tr>
<tr>
<td>Doc</td>
<td>0.9194*</td>
<td>0.9354*</td>
</tr>
<tr>
<td>DonaldDuck</td>
<td>0.9096*</td>
<td>0.6658*</td>
</tr>
<tr>
<td>Dopey</td>
<td>0.4329*</td>
<td>0.9597*</td>
</tr>
<tr>
<td>Goofy</td>
<td>0.8464*</td>
<td>0.8660*</td>
</tr>
<tr>
<td>Grumpy</td>
<td>0.8487*</td>
<td>0.4198</td>
</tr>
<tr>
<td>Happy</td>
<td>0.1529</td>
<td>0.6270</td>
</tr>
<tr>
<td>Huey</td>
<td>-0.0924</td>
<td>0.1113</td>
</tr>
<tr>
<td>Louie</td>
<td>0.8381*</td>
<td>0.9640*</td>
</tr>
<tr>
<td>MickeyMouse</td>
<td>0.5895*</td>
<td>0.6442*</td>
</tr>
<tr>
<td>MinnieMouse</td>
<td>0.7900*</td>
<td>0.6912*</td>
</tr>
<tr>
<td>Sleepy</td>
<td>0.0163</td>
<td>0.7180*</td>
</tr>
<tr>
<td>Sneezy</td>
<td>0.1675</td>
<td>0.7271*</td>
</tr>
</tbody>
</table>

Source: Author’s calculations.

To conclude, it can be said that no evidence of anchoring and adjustment is found in general in the sample data. There are however, 2 out of total 12 companies and 3 out of total 15 analysts where the correlations show proof of anchoring and adjustment effect. Also, year by year, the correlations revealed the possible presence of anchoring in 2008. This suggests that analysts are more prone to anchoring during extremely volatile economic situation, as it becomes more difficult to estimate financial results in these conditions. 2008 was the turning point for Baltic economies, as both Latvia and Estonia entered recession after several years of above average GDP growth while Lithuania followed the next year. Although there were clear signs of recessionary developments, analysts were more anchored to the financial results achieved in previous periods, while the adjustment was insufficient. In case more weight would have been put on present day situation, the forecasts would have been more accurate in the absence of the anchoring effect.
SUMMARY

This thesis focuses on anchoring and adjustment bias in Estonian sell-side equity analysts’ forecasts. The study does not cover all aspects of the anchoring and adjustment bias in relation to the current forecasting paradigm, nor does it outline all characteristics of Estonian sell-side equity analysts’ forecasting performance, but instead concentrates on the main aspects which are important in the forecasting accuracy, as well as the influence of anchoring and adjustment bias on forecasting tasks.

The following topics were studies in this thesis:
1) The importance of investment analysts and investment valuation, as well as the added value of forecasting tasks in giving out investment recommendations.
2) Which factors and intentional biases influence forecasting accuracy and how large impact do they have on the forecasting results.
3) How anchoring and adjustment bias is present in the forecasting process and what is the influence of this bias.
4) Evidence of anchoring and adjustment bias in Estonian sell-side equity analysts’ forecasts.

As identified, there is no question that forecasting adds value to the investment valuation process. Also, the more accurate the forecasts are, the more profitable investment recommendations can be given. Therefore it is also crucial to understand how and which factors influence forecasting accuracy.

The theoretical literature review revealed that forecasting accuracy has received a lot of attention in the academic research during the past few decades. All possible factors that influence forecasting accuracy have been successfully identified and repeatedly tested
on different samples in different situations. Unfortunately, same cannot be said for the research in cognitive biases, especially anchoring and adjustment bias in case of sell-side equity analysts’ forecasts. Although there has been research in that field on real life empirical data, there is no uniform method of measuring the effect of anchoring and adjustment in this situation.

Numerous research papers exist which study the effect of anchoring and adjustment in experimental forecasting situation. Unfortunately this type of research is prone to several downfalls, as presented in the last part of this thesis. Therefore, a different correlation model of measuring anchoring and adjustment in equity analysts’ forecasts is presented.

Firstly, the forecasting accuracy of Estonian sell-side equity analysts is examined, to identify if anchoring and adjustment is possible in the case of sample data. The accuracy analysis reveals that Estonian analysts’ forecast accuracy is of the same magnitude than their foreign counterparts’. However, some discrepancies exist in the case of large error margins in net profit forecasts, while this can be explained with the very high volatility of the financial results in Baltic companies during the sample period.

Secondly, the presence of anchoring and adjustment bias is tested through correlation analysis. In general, there is no evidence of anchoring and adjustment the forecasts of any particular type of financial results, as the forecasts are more correlated to the actual result rather than the anchor in any specific financial result. However, there is evidence of anchoring in the case of forecasts for the financial results of 2 particular companies and in the case of forecasts of 3 particular analysts. Comparing the estimations in different years, anchoring was present in 2008.

Therefore, this thesis presents evidence of anchoring at some extent in the sample data, while in general there is no anchoring and adjustment bias in the analysts’ forecasts. The tests were repeated with different correlation measures which yielded in the same results.

A possible suggestion for future research is to repeat the empirical study with same methods on different samples. Although the sample data used in this thesis comprised of
almost all quarterly forecasts made by Estonian sell-side analysts in the given time period, the main problem lies within the sample period itself. During 2007-2009, the economic cycle movement was very rapid, changing in greater magnitude than normally expected. Baltic economies went through a fast growth cycle in 2005-2007 while contracting significantly in 2008 and 2009. This however leaves an undisputed mark on the observed companies’ financial results, while making forecasting of these results a significantly more difficult task for the analysts. Therefore it is important to see if the forecasting accuracy is also same in different time points of economic cycle and if anchoring effect is absent in the case of a more normalized economic environment.

The second proposed research question for further study is to examine how different individual characteristics of the analysts’ themselves influence forecasting accuracy, as well as anchoring and adjustment. Although it is shown in this thesis that the forecasting accuracy of Estonian analysts is similar to their foreign counterparts, it is important to identify if this is also the case in how different factors influence forecasting accuracy. There may be different country- or region-specific features present that have not been identified in other research and it would be important to understand the reasons behind these unique characteristics. In addition, there may be individual characteristics which determine if anchoring is affecting the forecasts. Revealing these characteristics may give a better understanding of the reasons behind anchoring in financial forecasting and how it could be avoided.
REFERENCES


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KOKKUVÕTE

ANKURDAMISEFEKT EESTI AKTSIAANALÜÜTIKUTE PROGNOOSIDES

Sander Pullerits

Kasumlike investeerimisvõimaluste leidmine on igapäevaseks võtmeküsimsuseks finantsturgudel töötavatele spetsialistidele. Antud ülesande saavutamisel on oluline roll finantsprognooside tegemisel: hinnates täpsemalt ettevõtete tuleviku finantsnäitajaid, on võimalik paremini määrrata investeeringu tasuvust ning sõeluda kasumlikud investeerimisvalikud kahjumlikest. Seetõttu on oluline teadvustada, millised on olulisemad mõjurid ja kuidas need mõjutavad finantsprognooside tegemise täpsust.

Viimastel aastakümnetel on kiirelt esile tõusnud käitumusliku majandusteaduse (ing. k. behavioural economics) uurimissuund, mis seob omavahel teadmisi psühholoogia ja majandusteaduse valdkondadest. Rahanduses ning eriti finantsturgudel on palju uuritud kognitiivsete kõrvalekallete (ing. k. cognitive biases) temaatikat, mis käsitleb individuaalsete hinnangute andmise süstemaatilist ekslikkust. Ankurdamiseefekt on kognitiivne kõrvalekalle, mis on eelkõige seotud arvuliste hinnangute andmise ja nõude korral, seetõttu võib tulemuseks olla nihke prognoos. Finantsnäitajate prognoosimise korral esineb ankurdumiseefekt juhul kui analüütitik paneb rõhku näiteks mineviku finantsnäitajatele, eirates olemasolevat informatsiooni tuleviku kohta.

Investeerimisvõimaluste hindamisel toetuvad nii institutsionaalsed kui erainvestorid avalikult käitesaadavatele prognoosidele, mis on tehtud erinevate maaklerfirmade analüüttikute poolt. Siit tuleneb küsimus, kas antud prognoosid on täpsed või
ankurdamisefekti tõttu süstemaatiliselt ebatäpsed. Antud magistritöö eesmärgiks on määrata ankurdamisefekti olemasolu Eesti aktsiaanalüüütikute prognoosides.

Eesmärgist tulenevalt on püstitatud neli uurimisülesannet:
1) Kirjeldada aktsiaanalüüütikute investeeringute hindamise protsessi ning näidata prognoosimise olulisust aktsiainvesteeringutele hinnangute andmisel.
2) Anda ülevaade erinevatest prognoosimise täpsust mõjutatud testeguritest olemasoleva teaduskirjanduse põhjal.
3) Anda ülevaade ankurdamisefekti teoreetilisel tagapõhjast ning suuremate testläbiviidud teaduslikuest uuringustest antud teemal.
4) Määrata ankurdamisefekti mõju olemasolu Eesti aktsiaanalüüütikute prognoosides.

Magistritöö annab ülevaate köigist siiani leitud teguritest, mis mõjutavad prognooside tegemise täpsust, näidates samas ka erinevate kognitiivsete kõrvalekaldete, sh. ankurdamisefekti mõju olemasoleva teoreetilise teaduslikest teaduslikest uuringutest. Lisaks koostatakse mudel ankurdamisefekti olemasolu määramiseks Eesti aktsiaanalüüütikute prognoosides.


Kuigi nii prognooside tegemise näitab, kas ankurdamisefekti mõju prognoosidele on olemasolevas teaduskirjanduses põhjalikult uuritud, puudub ühtne mudel ankurdamisefekti olemasolu määramiseks aktsiaanalüüütikute prognoosides. Seetõttu pakub antud magistritöö olemasoleva psühholoogiaalase teaduskirjanduse põhjal välja omapoolse, korrelatsioonikordajatel põhineva mudeli ankurdamisefekti olemasolu määramiseks.
Läbiviidud empiirilise analüüsi tulemusena on leitud, et kuigi üldiselt kogu valmis ankurdamisefekti mõju puudub, esineb antud efekt kahe ettevõtte finantstulemuste prognoosides ning kolme analüütitiku puhul. Lisaks, erinevate aastate puhul esineb ankurdamisefekt 2008. a. finantsprognoosides.

Antud tulemus on kooskõlas teadaoleva teoreetilise taustaga ankurdamisefekti kohta. 2008. a. toimus Balti riikide majanduses oluline murdepunkt, kuna nii Eesti kui Läti majanduskasv muutus mitmeaastase kiire toosu järel negatiivseks, Leedu majanduslangus algas järgmisel aastal. Analüütitud ankurdusid prognooside andmisel eelmiste perioodide finantsnäitajate külge, pannes ebapiisavalt rõhku hetke majanduses toimuvale ning andes seetõttu ebatäpsemaid finantsprognoose:


Teiseks võimalikuks edasiseks uurimistemaatikaks on analüütituke erinevate individuaalsete eripärades mõju prognooside täpsusele ning ankurdamisefekti olemasolule. Kuigi antud magistritöös on leitud, et Eesti analüütituki prognooside täpsus on sarnane teiste riikide analüütituke täpsusele, on oluline märata, kas erinevad täpsust mõjutavad tegurid suurendavad tegurid Eesti analüütitiku puhul sarnase mõjuga nega muut. Lisaks võivad esineda spetsiilised individuaalised eripärad, mis määrad an originalisefekti mõju analüütitiku prognoosides. Neid teades on võimalik paremini mõista ankurdamisefekti finantsprognoosimisel esiinemise põhjuseid ning võimaluse korral efekti mõju vältida.