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School of Economics and Management

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Anchoring bias in analysts' EPS estimates
– evidence from the Swedish stock market

Authors

Sofia Kratz

Gustav Wenning

Supervisor

Claes Svensson

Abstract

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Authors: Sofia Kratz and Gustav Wenning

Advisor: Claes Svensson

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Purpose: Our purpose with this thesis is to describe existing research results on anchoring bias in financial analysts' forecasts. Additionally, we wish to study the forecasts made by Swedish stock analysts to analyze whether anchoring bias is a factor that affects forecast errors in their EPS estimates. We intend to research both the cross-sectional dimension of anchoring by comparing estimates between different companies, and the time-series dimension using historical information for the same companies.

Theoretical perspectives: The theoretical perspectives used in this study have their basis in the field of behavioral finance.

Method: The research method used in the study is quantitative and deductive since it is based on existing theories and previous research. The relationship between forecast errors and anchored EPS estimates, as well as other independent variables, are estimated through a multiple linear regression model.

Empirical foundation: The study includes 228 Swedish public companies listed on the Swedish Stock Exchange, NASDAQ OMX Stockholm, from year 2008 to 2015. Data are collected from the Institutional Broker's Estimate System (I/B/E/S).

Results: Results do not show that anchoring bias has a positive impact on analysts' forecast errors. Instead, we find that anchoring to the past year annual EPS could have a negative impact on forecast errors, while we find no relationship between forecast errors and anchoring to the industry median.

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1. Introduction

The chapter will introduce the background for our thesis. Former international research lays the ground for our aim and objectives and research purposes. It also presents delimitations, target audience, objectives and the thesis outline.

1.1 Background

The ability to forecast the future is a talent that is truly fascinating to most people. The future is per definition unknown to all of us, and putting together all available information to form a reasonable prediction about what the future might bring is often a difficult task that requires hard work and expert knowledge. That is why a lot of institutional and retail investors put their faith in the predictions of financial analysts to guide them into making the most profitable investment decisions. However, forecasts made by financial analysts are often not as reliable as one might think. In the interest of bringing this to retail investors' attention, the Swedish internet-based bank Nordnet started comparing the median quarterly EPS estimates provided by analysts on SME Direkt[1] for companies included in the OMXS30[2] to the actual EPS reported in the same companies' quarterly reports. They found that in all but one quarter during the fiscal years of 2009 and 2010, at least half of the estimates would end up outside a margin of error of 10%. In the third quarter of 2010, the difference between the median estimate and the actual EPS only fell within this margin for as few as 21% of the companies.

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[1] SME Direkt is the most commonly used analyst consensus service in Sweden.

[2] OMXS30 is the stock market index for NASDAQ OMX Stockholm

Many researchers have provided insights about how outside pressures can potentially affect analysts' judgements and explain some part of the errors in their forecasts. That said, even if we disregard these effects some error should still remain, because even with the most sophisticated models measuring the probability of different outcomes there will still be an element of uncertainty involved in each estimate. Given the high level of uncertainty and the many assumptions that financial analysts have to make in order to make their predictions, they have to rely to some degree on intuition and rules of thumb, which leaves them vulnerable to subconscious cognitive biases. One such bias that could potentially have an effect on analysts' EPS forecasts is the failure to adjust properly from historical or arbitrary numbers that they have used as reference points. This is also known as *anchoring*.

1.2 Financial Analysts' Role in the Stock Market

There are several different types of financial analysts, the most common being buy-side and sell-side analysts. The distinction stems from the fact that sell-side analysts work for banks or brokerage-firms while buy-side analysts work for institutional investors like mutual funds or pension funds, but the occupations also differ in many other respects. Some of the main differences, apart from the intended target audience, are the scope of coverage, sources of information, compensation, and private versus public dissemination of reports. While buy-side analysts' job is to give investment recommendations to money managers at their own firm, sell-side analysts' reports are public and aimed at both retail and institutional investors. They also typically have a larger research department and greater opportunity to get diverse feedback through interactions with sales representatives and traders at their firms and with many of their clients. Compensation for sell-side analysts is usually tied to the new business that they create for the firm by generating trading volume in the stocks that they cover (and thereby increasing commission revenues), while buy-side analysts get payed to provide support to portfolio managers and get rewarded for new ideas that differ from the market consensus (Groysberg, Healy & Chapman, 2008).

Consensus is a term that will be used repeatedly throughout this thesis, and refers to the combined opinions of analysts on the market. In the Institutional Broker's Estimate system (IBES), consensus is provided in the form of mean forecasted EPS, unadjusted as well as adjusted for the analysts' accuracy rankings. For the purpose of this thesis, analyst consensus will be defined as the unadjusted mean forecasted EPS. A forecast error can thus be defined as $\frac{Actual\ EPS - Mean\ forecasted\ EPS}{Actual\ EPS}$. *This is the same definition that is used by SME Direkt, the most used commonly used estimator of the consensus of analysts on the Swedish market. Note, however, that when consensus is discussed in the context of industry average, it refers to the industry median derived from the mean estimates for each and every company in a particular industry.*

In this thesis, we will specifically discuss the role of sell-side analysts and analysts at research firms that make professional forecasts regarding publicly listed companies and releases these to retail investors. We will use the terms "analyst", "financial analyst" and "stock analyst" interchangeably to refer to those who are in these occupations. Where other definitions may apply (such as buy-side analyst, macroeconomic analyst) this will be specified.

Financial analysts play a central role in the securities market, since they act as intermediaries between sources of firm information and investors. In addition, analysts' earnings forecasts[3] are often used in financial research as proxies for market expectations and differences in opinion. Therefore, it is of great importance that the analyses and forecasts that they make are as close as possible to the actual value that they are trying to predict (Cen, Hilary & Wei, 2013). There is also evidence that financial analysts add value in the capital market, for instance, earnings forecasts have turned out to be more accurate than time-series models, perhaps because of analyst's ability to add more fresh information in their forecasts. The analysts' recommendations and estimates can also affect stock prices (Healy & Palepu, 2001). There has also been research

[3] The words "estimate" and "forecast" will be used interchangeably throughout this thesis.

indicating that financial analysts in the capital market improve the market efficiency. For example, one study finds that a firm's stock price more rapidly incorporates information on accruals and cash flows if it has a higher analyst following than the stock price of a less followed firm (Barth & Hutton, 2004).

Among the duties performed by analysts to be able to make their analyses is to collect information from public and private sources and make an evaluation of the current performance of the firm that they are following. They then make a forecast of future prospects and give a recommendation for investors to buy, hold or sell the stock (Healy & Palepu, 2001). A survey conducted by Barker (1998) let 42 financial analysts answer a question of what kind of sources of information they thought were the most important when they made their analyses. The results from the survey can be seen in Table 1, with the source of information ranked highest at the top of the table and the lowest ranked sources at the bottom.

General	Direct from the company
Direct contact with the company	Personal contact—by phone, writing, or individual contact
Analyst meetings individual contact	Results announcements and analyst meetings
Results announcements	Reports and accounts
Annual report and accounts	Organized site visits and other presentations for groups of analysts
Industry contacts	
Interim reports and accounts	
In-house economics	
Industry information services	
Clients	
Sales desk	
AGM	
Market news	
In-house technical analysis	
Companies house	
Newspapers	
Reports of other brokers	

Table 1.1 - Ranking of analysts' prioritized sources of information (Barker, 1998)

Financial analysts´ main sources of information comes from the annually and quarterly result announcement and financial statements, company press releases and other news related to the firm. But a company cannot be seen as an objective part sending out neutral information, they may want to hide information and statements by practice “creative accounting, “window dressing” and even some “cooking of the books”. Therefore analysts must look for inconsistences in the company reports, and act almost as “financial detectives”. Just using the official reports to analyze a firm is not enough to be a good analyst. The financial analyst also needs to be “out on the streets”, maintaining a good contact with investor relations officers, visit headquarters, production sites and going to companies’ analyst conferences (Mars, 1998).

Analysts often work for an investment bank or a brokerage firm (usually owned by a bank) but can also work for research firm or business magazine. The analyst provides analyses for their firm’s customers, which means that analysts working for banks and other brokerage firms also have to deal with the problem of being able to satisfy both the customers and their employer. A bank or brokerage firm wants the analysts to make recommendations that increase the number of transactions their customers make (i.e that make them buy or sell stocks), since the companies’ then profit on the brokerage. One troubling aspect of this is that both existing stockholders and potential stockholders can react to a buy recommendation but almost only current shareholders react on a sell recommendation, since the only option for those that do not already own it would be to go short. That can put the analysts in a tough position, on one hand wanting to always give rational recommendations, on the other hand help the company make a bigger profit. It should be noted that this problem only affects analysts working for firms making profit on brokerage. That means, for example, that analysts working for a research firm are not affected by this. However, both kinds of analysts run the risk of potentially hurting their relationship with the board of the company they are analyzing if they give a sell recommendation, although the impact being biggest on an investment bank, that may have the company as a current or future customer (Cowen, Groysberg & Healy, 2006).

Forecasts about a company’s future profitability is often delivered in the form of key ratios. One of the most important ratios is earnings per share, as it is explicitly or implicitly included in almost all valuation models (Friesen & Weller, 2006). Unless the analyst makes a perfect prediction where the estimated value is the same as the value that later turns out to be true, there will be a forecast error for every estimate. Forecast errors are usually measured as a percentage, and defined as the difference between actual earnings per share (EPS) and the mean forecasted EPS, divided by actual EPS (Garcia-Meca & Sanchez-Ballesta, 2006). The mean forecasted EPS is often referred to as the "analyst consensus" as it indicates the value of a combination of all available forecasts. Another commonly used term which essentially refers to the same value is "earnings surprise". Depending on what the consensus is at the time of an earnings report release, the actual EPS will yield a negative or positive earnings surprise. If the actual EPS turns out to be higher than expected in the forecasts there is a positive earnings surprise and if it is lower than expected, the earnings surprise is negative (IBES).

Analysts' abilities are usually measured by comparing the accuracy of the recommendations with other analysts analyzing the same company. The degree of ability and accuracy is the basis for analyst's salary, bonuses and career opportunities. This could make analysts less willing to take a risk even though their recommendation stands out from the herd. Therefore analysts have two options, either taking the risk of going against the stream by giving a recommendation completely different than the majority, or play safe and follow the herd. However, analysts working for a brokerage firm often get bonuses depending on the number of transactions made, hence they tend to make too optimistic analyses. Another aspect is that to really stand out from the rest of the analysts and have a chance of becoming a star that the herd follows, analysts must take big career risks and deviate from the consensus estimate. If analysts take the risk and it falls well out, they will be highly graded in the analyst rankings that come out every year, which will lead to bigger career opportunities for the analyst, and the employer that will get more customers. However, if analysts take the risk and it doesn't fall well out it could potentially destroy their whole reputation and career. In fact, sometimes analysts that are being too optimistic in their estimates have had bigger career opportunities than analysts being more accurate in their forecasts. Many analysts choose to play safe and follow the herd instead of standing out and try to reach the top, while they also avoid taking the risk of hitting the bottom. This also makes it more likely for the analysts to risk being wrong when everyone else is wrong rather than taking the much larger risk of going out on a limb and being the only one that is wrong. Therefore many analysts try to be as close to the consensus estimate as possible or a bit over it. (Hong & Kubik, 2003)

1.2.1 Financial analysts in a Swedish context

The Swedish stock market consists of three different exchanges. Companies listed on Aktietorget are small and often entrepreneur-led growth companies (Aktietorget). The companies listed on the Nasdaq First North exchange are mostly growth companies that may not yet be able to live up to heavy regulations but rather want to focus on business development. Many of them later go on to be listed on the main exchange. The more established companies that are able to live up to the regulations are listed on the main exchange, Nasdaq OMX Stockholm (Nasdaq OMX Nordic).

Compared to for example the U.S. stock market, it consists of a large number of firms with low market capitalization and only has a small amount of firms with high market capitalization. Firms with the highest market capitalization, like H&M and Nordea, have around 40 analysts following them while the smallest ones have only a few (SME Direkt). Many Swedish companies have the names and contact information of the analysts following them listed on their websites, indicating that they view them as an important part of investor relations.

Financial analyst is a relatively new profession on the Swedish financial market, beginning to gain attention in the 1980's after a series of financial crises in the 1970's. During this time, the same analyst would often value companies in several different industries and they were mostly seen as a support for brokers. This changed after the Swedish market started to expand in the 1990's. Today's financial analysts generally focus on just a few companies and usually within the same industry. Due to globalization, analysts also have to know about companies in the same industry that are registered on other stock markets. Swedish financial analysts are a quite small group of people working close to their colleagues and competitors. This can easily enhance the previously mentioned type of herd behavior, where analysts become afraid of making recommendations that stand out from the rest of the group and therefore adjust them to fit in better (Aktiespararna). To reduce the risk of making a biased analysis, most financial analysts do not own shares in the company that they are analyzing, nor are they getting paid by the company to make the analysis. If they do own shares this is often stated in a disclaimer provided in the forecast. It is very important for the analyst to remain unbiased as a company's share price and value can sometimes depend on a single analytical firm's analysis, at least in the short term (FFFS 2005:10).

1.3 Behavioral finance

Most traditional finance theories assume that markets are more or less efficient, with the differences in efficiency depending on the information available to market actors. Additionally, they often assume that market actors behave rationally and only make the most logical decisions according to the information that is available. Traditional theories often do not take into account the psychological pitfalls that impact investors, managers, and financial analysts, and thereby could potentially reduce the efficiency of market outcomes. Since companies and capital markets are ultimately run by human beings, it seems quite foolish to assume that the psychologically induced mistakes that humans often have been showed to make would have no effect at all on them. This notion laid the foundation for the field of behavioral finance, which focuses on the impact of behavioral and cognitive psychological factors on financial decision-making. It has long been a controversial field in finance research, but has gained some acceptance in recent years as more and more researchers incorporate behavioral aspects into their financial theories (Baker & Nofsinger, 2010). Still, finance researchers can be divided into two groups; traditionalists and behavioralists. While traditionalists assume that inefficiencies are small and will disappear quickly from the market, behavioral finance explores the possibility that some market inefficiencies may in fact be large and occur for longer periods of time (Shefrin, 2007).

One of the first and most important contributions in the field of behavioral finance, "Judgment under uncertainty: Heuristics and biases" was written by Daniel Kahneman and Amos Tversky (1974). The authors did not specifically focus on finance at the time, but introduced the idea that different heuristics, or rules of thumb, that people commonly use can lead to biases when making decisions. One of the heuristics they described was adjusting to an anchor, which is a psychological phenomenon explaining how people tend to form an estimate by beginning with an initial number and adjusting it to reflect new information or circumstances. However, they tend to make insufficient adjustments relative to that number, thereby leading to anchoring bias. Given the amount of uncertainty involved in making a financial forecast, rules of thumb can no doubt be useful to financial analysts. The use of them would however also include the risk of not adjusting properly and thereby ending up at the correct conclusion.

1.4 Objectives

As mentioned previously it is important that financial analysts remain unbiased, not only for the sake of the investors but also so that they can be successful in their analytical careers. But what if analysts have biases that make it impossible for them to make unbiased assessments, without them even knowing? Considering the uncertainty that financial analysts have to deal with in making their analyses, it is reasonable to believe that they could be subject to some decision-making biases. For example, what if they subconsciously attach too much weight to historical information when forming forecasts about the future? Or if they rely too much on previous forecasts made by themselves or other analysts? The forecasts would then be biased to end up closer to the previous number than they should be. This psychological phenomenon is called anchoring bias and has been studied within many different fields of research related to decision-making. It has also been applied in the context of analysts' estimates for U.S. companies, but not yet on the Swedish market. Are financial analysts active on the Swedish stock market driven by their own predictions about the future of the companies they value or do they rely too much on historical data or other arbitrarily chosen numbers?

1.5 Relevance

The theory of anchoring bias has previously been applied in the context of financial forecasting in a few studies on the US market, showing that anchoring bias can in fact affect analyses when analysts rely too much on historical data or previous estimates. No such studies have been performed on forecasts made by Swedish financial analysts who work under very different conditions, with a small amount of analysts analyzing companies in a small stock market, and working relatively close to each other and the different industries.

1.6 Research purpose

Our purpose with this thesis is to describe existing research results on anchoring bias in financial analysts' forecasts. Additionally, we wish to study the forecasts made by Swedish stock analysts to analyze whether anchoring bias is a factor that affects forecast errors in their EPS estimates. We intend to research both the cross-sectional dimension of anchoring by comparing estimates between different companies, and the time-series dimension using historical information for the same companies.

1.7 Delimitations

Our study includes earnings per share estimates and actual EPS values for companies listed more than a year on the Nasdaq OMX Stockholm exchange between 2008 and 2015. Companies that have been listed for less than a year or that for other reasons do not have a value for estimated earnings per share for at least one fiscal year, have been excluded from this study.

1.8 Target audience

The intended target audience for this thesis is students in the fields of business and economics. We further believe that this thesis may be of interest to retail investors and persons with a general interest in financial markets.

1.9 Thesis outline

Introduction

In chapter 1, we provide an introduction is given to the role of financial analysts in the Swedish stock market. We also provide an introduction to the field of behavioral finance.

Theoretical Framework

In chapter 2, we give a theoretical background as well as a description of the previous research results in the fields of anchoring and analysts' forecasts, ending with a description of research where the two areas overlap. We also provide a summary of the existing literature and position our study against previous research.

Methodology

In chapter 3, we lay out our methodology choices and also criticize them. The regression model is then explained and we discuss the reliability, replicability, and validity of our results.

Empirical results

In chapter 4, we present the descriptive statistics for our data as well as test performed to improve the model, and the results of the regression analysis.

Analysis

In chapter 5, we analyze the results from chapter 4 and connect it with our hypotheses and theories from the theoretical framework.

Conclusions

In chapter 6, we draw our conclusions from the empirical results and our analysis while also giving ideas for future research.

2. Theoretical framework

The chapter gives a theoretical background as well as an overview of the current research on anchoring bias as well as analysts' forecasts, ending with our thesis hypotheses. We will come back to this chapter later in the analysis.

2.1 Theories in behavioral finance

2.1.1 Bayes' Theorem

Bayes' theorem stems from the field of statistics where it is an important part of probability theory. It describes the probability of an event, taking into account the evidence that might be relevant to the event (Encyclopædia Britannica). The theorem is often mentioned in the context of behavioral finance, since it shows how a person would logically judge probability in the absence of biases and heuristics. Anchoring bias is inconsistent with Bayes' theorem since it leads people to not make sufficient adjustments when relevant evidence is presented, and therefore end up with the wrong calculated probability.

2.1.2 Heuristics

A heuristic can be defined as a rule of thumb used to make a decision. The problem is that while people rely on heuristic principles to simplify the complex tasks of assessing probabilities and predicting values, they sometimes lead to severe systematic errors (Shefrin, 2007).

Representativeness

The heuristic of representativeness is often used when answering questions such as; "What is the probability of that object A belongs to class B?", "What is the probability that event A originates from process B?", and "What is the probability that process B will generate event A?". When evaluating probabilities in those situations, people tend to base their assumptions on how representative A is of B (i.e. the degree to which A resembles B). For example, when A is highly representative of B, the probability that A originated from B is judged to be high. Conversely, if A was not similar to B, the probability that A originated from B is judged to be low (Kahneman & Tversky, 1974).

Availability

The availability heuristic can be defined as "situations where people assess the frequency of a class or the probability of an event by the ease with which instances or occurrences can be brought to mind". This basically means that people tend to rely more on information that is readily available to them. One of the factors responsible for this heuristic is familiarity. In other words; people tend to have an easier time with processing information that they are already familiar with than information that is previously unknown to them (Kahneman & Tversky, 1974).

Adjustment and anchoring

The adjustment and anchoring heuristic (in this thesis frequently referred to as *"anchoring bias"*) occurs when people make estimates by starting from an initial value and adjust it to arrive at the final answer. This initial value may be suggested in the formulation of a certain problem that the subject has been asked to solve, or be the result of a partial computation. The adjustment does however tend to be insufficient, which leads the final answer to be "anchored" to the initial value. This means different starting points yield different estimates even when all the relevant factors are the same (Kahneman & Tversky, 1974).

2.2 Behavioral Finance literature

Previous research that is considered relevant in behavioral finance can be derived from two different fields within the social sciences, namely cognitive psychology and finance. For this reason, some of the literature we have decided to use for this thesis is not strictly related to finance but rather to the psychological process of making judgements. We do however think that they are applicable to financial decisions and that they therefore are of interest to our thesis.

2.2.1 "Judgement under Uncertainty: Heuristics and Biases"

The three previously mentioned heuristics were first theorized by Daniel Kahneman and Amos Tversky in their 1974 article "Judgment under Uncertainty: Heuristics and Biases".

Daniel Kahneman and Amos Tversky are thought of by many as the founding fathers of behavioral finance. However, their research started in the field of cognitive psychology, and has inspired a lot of research relating to the behavioral aspect of decision making in general.

In the article they mention an experiment on *representativeness*, where subjects were shown brief descriptions of the personalities of several individuals, allegedly chosen at random from a sample of 100 professionals consisting of engineers and lawyers. For each description the subjects had to assess the probability that each of the individual belonged to a specific professional category. In one experimental condition, they were told that the sample consisted of 70 engineers and 30 lawyers. In another, they were told that it consisted of 30 engineers and 70 lawyers. The probability that any particular individual is an engineer should be higher in the first sample, where the majority are engineers, and yet the subjects in the two conditions produced the same probabilities for that to be the case. The authors concluded that the subjects evaluated the probability that a particular individual belonged to a specific category over another based on how representative the personality description was of the two stereotypes, and completely disregarded the previous probabilities that they had been given.

To test their theory of *availability*, the authors let the subjects listen to lists of well-known personalities of both sexes and then asked them to estimate whether the list contained more names of men or women. On some of the lists, the men were relatively more famous than the women, and on others the opposite was true. In each of the experiments, the subjects thought that the class (men or women) that had the more famous personalities constituted the larger group on the list, even though this was not the case. Their familiarity with some of the names led them to overestimate the occurrence of names that belonged to that particular class. Another factor that Kahneman and Tversky describe is the degree to which information is salient to the subjects. For example, information based on events that have occurred more recently tends to influence judgements and decisions more than events that have occurred earlier in time.

To demonstrate the *adjustment and anchoring* effect, Kahneman and Tversky conducted an experiment where subjects were asked to estimate various numbers. For example, one of the tasks in the experiment was to estimate the percentage of African countries in the United Nation. Before they were asked the question, a number between 0 and 100 was determined by spinning a wheel of fortune. For one group, the wheel stopped at the number 10, while the other group received the number 65. The numbers appeared to be chosen at random and should therefore be irrelevant to the estimates. The subjects were then asked if the number of African countries in the United Nation, in percentages, was higher or lower than the number shown on the wheel. The results showed that the subjects had been relying on the initial numbers after all, since the group that received 10 as a starting point had a median estimate of 25% being African countries while the corresponding percentage for the group that received 65 as a starting point was 45%.

As mentioned earlier, anchoring is a result not only of the subject using initial values, but can also occur as a result of incomplete computation. Kahneman and Tversky tested this inclination in an experiment by asking two groups of high school students to estimate, within 5 seconds, the answer to a numerical expression that was written on a blackboard. One group had to estimate the product of the following expression: 87654321, while the other had to estimate the product of: 12345678. To be able to provide an answer to this type of numerical question in a timely manner, people tend to perform only a few steps of the computation and then extrapolate the rest to estimate the product. Since the adjustments tend to be insufficient, the final number will tend to be an underestimation of the actual answer. Additionally, since the first few steps of calculating the first expression will give a higher result, the estimated product of it will be judged as higher than for the latter expression, even though the actual products are identical. These theories were confirmed by the experiment as the median estimates were 2,250 for the descending sequence and 512 for the ascending sequence. The correct product of both expressions is 40,320.

2.2.2 The Anchoring Heuristic

Since the original study on anchoring was published in 1974, there have been many studies that provide further evidence for the existence of this psychological phenomenon. Over the years, researchers have shown that anchoring arises not only when the subject is asked a general-knowledge question, but also for more consequential judgments, such as buying and selling prices, purchase quantity decisions, credit card repayments, appraisals of real estate, personal injury verdicts and criminal sentences by legal experts (Simmons, LeBoeuf, & Nelson 2010).

Several studies also show that anchoring bias is quite difficult to avoid. In Kahneman and Tversky's example with the African countries in the United Nations, the anchor had no relation to the prediction at all, which shows that an anchoring effect can occur even when the number is completely uninformative and therefore not one the subject should want to bring into the calculation. Another study, authored by Strack and Mussweiler (1997), shows that people still have trouble avoiding anchoring when the anchor given is clearly inaccurate. They ask the subjects to answer whether Mahatma Gandhi died before or after age 9, or before or after age 140, and afterwards specifically at what age. The group that was given the number 9 in the initial question had an average answer of 50 while the group that was given the number 140 had an average answer of 67.

Even when the subjects are told beforehand that anchoring will likely affect their responses and are asked to correct for it, the behavior does not change (Wilson, Houston, Etling, & Brekke, 1996). There have also been several studies that show that incentives reduce anchoring very little, if at all (Chapman & Johnson, 2000). This has been seen as bothersome by many researchers, as an important prediction of the original theory is that people who are more motivated to make accurate assessments should be less likely to think their estimates are “good enough”, and hence be more likely to adjust extensively. However, the failure to adjust sufficiently even under those circumstances could be due to the subject's’ uncertainty about in which direction the adjustment should take place. When the subject is certain about in which direction to adjust, incentives do seem to have a positive effect on accuracy after all (Simmons et al., 2010).

2.3 Analysts’ forecast literature

There is a considerable amount of research on analysts’ forecast errors and what causes them. As mentioned in the previous chapter there is reason to believe that apart from any subconscious biases that analysts may exhibit, they can also be influenced by biases that are completely rational. One such example is that analysts might have incentives to be overly optimistic in their forecasts. Agrawal and Chen (2008) find that the level of optimism (i.e. estimates that are higher than the actual value) in analysts’ long term growth forecasts is positively related to how large a share of their firm’s revenue is made from brokerage commissions. Another reason that analysts may have a tendency to make overly optimistic forecasts is provided by Das, Levine, and Sivaramakrishnan (1998). They suggest that analysts that make more optimistic estimates are more likely to get access to non-public information that is otherwise only available to the management of the analyzed company. Their results show that analysts make more optimistic forecasts for low predictability firms than for those with high predictability, suggesting that analysts are more eager to get access to non-public information if there is high uncertainty and therefore issue more positive estimates.

Another bias that has been studied in regard to analysts is the tendency to follow the herd. Trueman (1994) finds that the likelihood that an analyst will release a forecast that is similar to those who have already been released by other analysts is "greater than could be justified by his own information", meaning that even when analysts themselves have information that should cause them to divert from the consensus they often do not. Further evidence is provided by Clement and Tse (2005), who find that herding is common when the analysts are inexperienced but decreases with the analysts' gained experience, prior accuracy, size of their brokerage firm, and the number of industries that they follow. Thus, herding can be attributed to career concerns and not wanting to stand out in a negative way if a bold forecast should prove incorrect.

2.3.1 Comparison between the Swedish and U.S. market

Relative to the U.S. stock markets that most of the research of anchoring bias has been focused on, the Swedish market is small and has fairly low trading activity. It consists of a large number of firms with low market capitalization and only has a small amount of firms with high market capitalization. There are also fewer active analysts on the Swedish market, meaning the competition is lower among those analyzing stocks (Lidén, 2007). This is an important aspect when comparing the conditions of Swedish analysts to those of their U.S. counterparts, as lower competition among analysts has been shown to increase the difficulty of uncovering mispriced stocks (Jegadeesh & Kim, 2010). This is also supported by findings that estimates made for larger firms have higher accuracy (Brown et al., 1987), implying that a larger analyst following leads to more efficient uncovering of information.

In his study comparing stock valuation methods in Sweden, U.S. and U.K., Olbert (1993) found that the average forecast period was significantly longer for the U.S. analysts and that they more often forecast market value of the share. He also found that Swedish analysts did not use technical analysis as frequently as did U.S. and U.K. analysts. A possible explanation for the latter is the fact that, as previously mentioned, the Swedish market is smaller and has less trading activity. Most Swedish analysts have instead focused on fundamental analysis, using factors such as general economic conditions, industry outlook, earnings, etc. for their forecasts.

2.4 Analysts and anchoring

2.4.1 "The Role of Anchoring Bias in the Equity Market"

Cen, Hilary and Wei (2013) study the occurrence of anchoring bias using U.S. data from 1983 to 2005. Their hypothesis is that sell-side analysts may be affected by anchoring bias when they estimate the future profitability of a firm. The reason that they suggest for that is that the complexity and high degree of uncertainty involved in the estimation process is causing them to anchor on salient but irrelevant information. They also suggest that investors' expectations of a firm's profitability are affected by the forecasts and that they act according to those expectations, thereby undermining the efficiency of the market.

The methodology used in the study is quantitative with some qualitative features. The authors first contact financial analysts for discussions on forecasting. From these discussions they get an indication that earnings forecasts for a specific firm are likely to be affected by the levels of forecast earnings per share for other companies in the same industry. According to one of the interviewed analysts, this is because analysts are reluctant to make earnings forecasts that deviate from the current industry "norm". Using the industry median as a proxy for the industry norm, the authors hypothesize that analysts tend to anchor to this number. They use a cross-sectional method to study how the differences between the firm's' actual EPS and the industry median forecasted EPS impacts the forecasts made by analysts. The findings show that when the actual EPS turns out to be lower than the industry median, the forecasts tend to have been optimistic and there are more negative earnings surprises (meaning the earnings are below analyst consensus expectations). The opposite is true if the actual EPS is higher than the industry median (forecasts have been pessimistic and positive earnings surprises are more common). The results suggest that analysts use the median forecasted EPS for the industry as an anchor in their estimates.

Using a portfolio sorts[4] approach they also examine whether or not the found anchoring bias has any significant effect on the market that could potentially be taken advantage of by investors. They find that as the difference between the forecast and the industry median increases, so does the value of the earnings surprises. The results further suggest that a hedge portfolio that goes long on firms that they found to be overvalued according to their model, and short on those that are undervalued, would generate a risk-adjusted return of 0.71 % per month, or 8.52 % per year. The profitability of such a trading strategy remains significant for investment horizons that span at least 12 months. The authors also find evidence that managers, being aware of the analysts' biases, use stock splits to mitigate undervaluation and in some cases even for generating overvaluation by influencing analysts' EPS forecasts.

2.4.2 "Anchoring Bias in Consensus Forecasts and Its Effect on Market Prices"

Campbell and Sharpe (2007) investigate whether macroeconomic expert consensus forecasts, surveyed by Money Market Services (MMS), show any indications of anchoring bias. The MMS-surveys are answered by market agents on a monthly basis and are widely used to signal the current expert view of where the markets are going. The sample consists of forecasts between 1991 and 2006 and covers eight different types of macroeconomic releases: Consumer Confidence, Consumer Price Index (CPI), Durable Goods Orders, Industrial Production, Institute for Supply Management (ISM) Manufacturing Index, New Homes Sales, and Retail Sales. The reason the authors state for their selection is that the aforementioned data releases "have previously been found to have substantial effects on market interest rates".

The authors hypothesize that experts tend to anchor their forecasts to recent past values of the same series, which leads to biased estimates. For example they investigate whether the January sales growth trends forecasts are anchored to the previously released estimate of December sales growth. They find evidence that forecasts tend to be anchored to the recent past releases of the

[4] CAPM-based model where portfolios are constructed by grouping together securities with similar characteristics. The returns of the portfolios are thereafter calculated and evaluated. (Fabozzi, Focardi & Kolm, 2010)

same series. The results show a surprisingly consistent pattern of forecasts that are too close to the previous value and can thereby be viewed as anchored. They also find that the reliance is very high in some cases, i.e that forecasts are very close to the anchor relative to the actual value. In their analysis of the results, the authors conclude that the forecast errors are at least partly predictable due to the anchoring effect. This could mean that there is market inefficiency, but only if the forecasting errors are seen as unpredictable and already included in the prices. However, the results further show that financial markets do not seem to react to the predictable part of the surprises, which means that there is no evidence that anchoring bias influences market prices.

2.4.3 "How Much Does Expertise Reduce Behavioral Biases? The Case of Anchoring Effects in Stock Return Estimates"

Kaustia, Ahlo and Puttonen (2008) study anchoring behavior in an experimental setting, using a sample of students and professionals working in the financial industry. We cannot be sure that financial analysts were among those surveyed as the authors only describe the subjects as "financial advisors and other professionals" but based on the context of the study the subjects have a deep knowledge of financial markets.

The purpose is to study whether people who can be considered experts in the field are able to mitigate their anchoring bias because of their experience and the potential influence of higher incentives. The authors note that previous experimental studies on anchoring have mostly used only student subject that tend to be less sophisticated in their analyses. They do however also note that there have been previous studies on decision making in general where researchers have found mixed results when investigating whether students or professionals tend to be more biased in different contexts. This suggests that expertise may not always be a factor that reduces bias, and could possibly even enhance it in some cases.

The data is collected through surveys over a period of two years between 2004 and 2006 and involves 13 sessions, 12 in Finland and one in Sweden. The authors ask the subjects to estimate historical stock developments for several European countries during 1900-2000, and then to estimate the development for the same countries over the next 20 years. In these controlled experiments they find significant anchoring effects in the future stock estimates, however, the financial professional do not exhibit this behavior to the same extent as the students. In fact, students show an effect that is several times higher than with the professional subjects. Another interesting finding is that the professionals who state in the survey that their knowledge of the 20 year market history had a minor or no effect on their estimate anchor just as strongly to the historical number as those who state that it had a major effect on the estimate.

2.5 Summary of previous literature on anchoring bias among analysts

After examining the available literature, we conclude that while a lot has been written on the two separate topics of analysts' forecast errors and anchoring bias, very few scholars have written about anchoring bias among financial analysts. Only one major study has been made of the effect of anchoring bias on analysts' EPS estimates (Cen et al., 2010). Since it was done on the U.S. market it cannot automatically be assumed to apply to the Swedish market, where there are fewer analysts and the companies that they follow are smaller. The only study mentioning Swedish financial professionals (Kaustia et. al, 2008) is experimental in nature and does not specify what type of professionals are being interviewed. Despite this, it could serve as an indication that Swedish analysts might suffer from anchoring bias if we assume that they would not get substantially different results from other well-versed professionals in the industry. If we do however find that the results from our study differ from those findings, this could be due to a larger sample size, or the fact that following a company for a long time as well as having access to all the historical and current financials would make it easier for biases to be mitigated. Since we do not believe that all the factors put into analysts' estimates can be captured in an experimental study, we find it more useful to study a larger data set that reflects the actual predictions that they make in their professional analytical career.

Cen et al. (2013) find that analysts anchor to the median of all the available mean estimates for companies in an industry. This suggests two things. Firstly, it suggests that analysts largely value the company according to how it performs relative to its peers and secondly, that it matters what previous estimates about the company's EPS from other analysts have predicted. The latter is supported by (Kaustia et. al, 2008) who find that the financial professionals that they survey tend to anchor to a previously given estimate.

Another possible source for anchoring is that analysts rely too much on historical numbers. Campbell and Sharpe (2010) find that analysts tend to anchor to historical actual values for the same series that they are forecasting. This is also supported by Kaustia et al. (2008) who find that financial professionals tend to anchor when they are given historical stock development for a country and are then asked to estimate the future development of that same country.

Author (year)	Contribution	Support for hypothesis
Cen et al.(2013)	Find evidence that financial analysts tend to anchor to the current industry median EPS estimate when forecasting the current year annual EPS for S&P 500 companies. Also find that analysts' anchoring bias is not predicted by investors, leading to market inefficiency.	H1
Campbell and Sharpe (2007)	Find evidence that analysts estimating macroeconomic releases tend to anchor to historical values from the same series of releases that they are estimating. Further finds that this is anticipated by the market and thereby does not have an impact on security prices.	H2
Kaustia et al. (2008)	Find that professionals in the Finnish and Swedish financial industry exhibit anchoring bias in an experimental setting. They show that even though these experts are less prone to anchoring than students, they still rely too much on historical information as well as their own previous estimates.	H1, H2

Table 2.1 - Summary of previous literature on anchoring bias among analysts

2.6 Hypotheses

The studies previously mentioned in this chapter have found that there are several possible anchors that can work as an initial number from which analysts adjust to make their forecast. We have chosen two that we believe will give a good indication of whether or not analysts on the Swedish market are affected by anchoring bias. Both are concerning the companies projected earnings per share.

The earnings per share ratio is one of the most commonly used measurements of a company's profitability. It is also commonly forecasted in financial analyses to serve as an indication of the company's future profitability and thereby the stock's intrinsic value. We therefore find it interesting to research whether analysts' EPS forecasts are affected by anchoring bias and which anchors analysts in that case tend to use. Previous studies indicate that market participants tend to anchor on salient information, and Cen et al. (2013) found evidence that analysts covering S&P500 companies tended to anchor to the industry norm of available forecasts. If this is true of our sample, analysts would underestimate the future earnings of companies with a high forecasted EPS compared to the industry median, and overestimate the future earnings of companies with a low forecasted EPS compared to the industry median. This motivates our first hypothesis:

H1: Analysts covering the Swedish market anchor their annual EPS estimates to the median forecasted annual EPS of the industry.

While the proposed anchor in the first hypothesis can be derived from analysts' perception of the industry as a whole, the company's own history should arguably also be of relevance when forecasting the future of the company. Campbell and Sharpe (2007) found evidence that analysts, when forecasting future releases of macroeconomic data, tend to anchor to the most recent historical data in the same series. This leads us to believe that financial analysts making judgements about a company's future value may look at the recently announced annual EPS from the previous year when forecasting the annual EPS for the current year.

H2: Analysts anchor to the previous year actual annual EPS when forecasting the actual current year annual EPS.

3. Methodology

The chapter presents the thesis methodology and research approach. It also describes the gathering of the thesis data, valuation of the chosen method, sources and other specific choices are presented.

3.1 Research approach

In the thesis we will use a quantitative methodology. There are several reasons why we chose to use a quantitative method, but the main reason is because the data we need for the study are made up of historic numbers and data that can be found in existing databases. Therefore a qualitative method is not applicable since it would be far less effective for our research (Bryman & Bell, 2013). Using a quantitative method is also in line with previous research in the field. Furthermore, we will use a deductive approach, meaning that the hypotheses are deducted from theory which drives the process of data gathering. This is the type of approach that is typically associated with quantitative research. The process can, according to Bryman and Bell (2013), be divided into the following steps:

1. Theory
2. Hypothesis
3. Data collection
4. Findings
5. Hypothesis confirmed or rejected
6. Revision of theory

We will use panel data from historical estimates and EPS actuals for Swedish companies on the Nasdaq Stockholm stock exchange by comparing their earnings per share in several years with the forecast earnings per share provided those same years by analysts. The collected data will then be tested according the hypotheses formed in the previous chapter using a linear regression, leading the hypotheses to be either rejected or accepted (Bryman & Bell, 2013).

We are using data from the existing database IBES which means we are going to use secondary data and thereby make a secondary data analysis. There are several advantages with using secondary data; there is really no need to spend a large amount of time to get data that is already accessible giving us more time focusing on the results, and it is also cost effective.

3.2 Alternative Approaches and Methodology Criticism

The idea for the methodology of this thesis is to some degree dependent on the data available to us and has also drawn inspiration from previous research on the particular subject of anchoring bias in analysts' estimates. Both Campbell and Sharpe (2009) and Cen et al. (2010) try to explain forecast errors with the help of an independent anchoring variable. Campbell and Sharpe use the following equation in their OLS regression:

$$S_t = \gamma(F_t - \bar{A}_h) + \varepsilon_t$$ [5]

[5] While the equation does not include a constant term, the authors note that a constant (γ_0) is included in its empirical implementation.

S represents the forecast error (Surprise), F is the forecasted value, and $\overline{A_h}$ is the used anchor (if h=1, this variable indicates the one month lagged value and if h=3, it indicates the average value over the lagging three months). The estimated parameter is represented by γ and ε stands for the error term.

Cen et al. use a Fama-McBeth[6] regression and their model is estimated through the following equation:

$$FE_{i,t} = \alpha + \beta CAF_{i,t-1} + \gamma^K X_{i,t-1}^K + \varepsilon_{i,t}$$

Again, the forecast error is the dependent variable and the first independent variable (CAF) is calculated by taking the difference between the consensus forecast and the anchor (industry median). However, there are two major differences in how this variable is calculated. One is that the past month value is used for both the forecasted EPS and the industry median EPS, and the other that the variable is scaled by the stock price. The variable FE is also scaled as it is divided by the actual EPS. The variable X^K is a vector of K control variables and includes the logarithm of the firm's market capitalization at the end of the month t-1, the logarithm of the firm's book-to-market ratio, its accounting accruals and the three-day abnormal return around the firm's most recent earnings announcement. All of the control variables are lagged by one month.

Our approach differs from previous studies in several different respects. First, since we use a dummy variable we do not take into account the degree to which an estimate is anchored. This means our results will only show if the forecast error is impacted by whether or not the estimate is between the actual value and the anchor, and not whether strong anchoring (where the estimate is very close to the anchor) has a larger impact on the forecast error than weak anchoring (where the estimate is closer to the actual value). It could also be the case that a forecast is very close to the anchor but does not end up between the anchor and the actual value. If so, the analyst may have been affected by the anchor but adjusted in the wrong direction. However, anchoring can be

[6] Method used to estimate parameters for asset-pricing models in two steps; first regress each asset against the proposed risk factors to determine that asset's beta for that risk factor, then regress all asset returns for a fixed time period against the estimated betas to determine the risk premium for each factor. The standard errors from this method do not correct for time-series autocorrelation. (Fama and McBeth, 1973)

seen as behavior where analysts underweight other information that should be important to the forecast (Campbell & Sharpe, 2009). Under this definition of anchoring, analysts should start with the initial value (anchor) and adjust their estimate to be closer to the actual outcome, thereby ending up with an estimate somewhere between those two values.

Another difference compared to the previous studies is that we only take yearly estimates, which means the time between the estimate and the actual EPS is rather long. Campbell and Sharpe (2010) use the value from previous month and a three-month average in their study which means that the anchor will change from month to month, and since the actual outcomes are also made up of monthly values these will differ as well. Cen et al. (2013) use the industry median for each month as the anchor and collect the monthly mean estimates, so even though the actual EPS values are on a yearly basis, how the difference between the estimates and actual value changes over each month is taken into consideration. In this study, we only take the mean estimates exactly three months into the fiscal year which means that anything that happens between that point and the earnings announcement that could affect the company's EPS is not taken into account. One reason for this is that people tend to anchor to more salient information (Kahneman & Tversky, 1974) and therefore we wanted the previous year EPS announcements to have been made as recently as possible. Another reason is that anchoring bias has been said to largely be caused by the level of uncertainty involved in the estimate (Cen et al., 2013), leading us to believe that some of the effect could disappear as quarterly earnings reports are released and incorporated in analysts' estimates.

Just like Cen et al. (2010) and Campbell and Sharpe (2009) we use analyst consensus estimate in both our forecast error variable and our anchor variable. Campbell and Sharpe calculate the consensus as the mean of the MMS surveys used in their study, while Cen et al. also use the unadjusted mean from the IBES database. However, the companies in our sample generally have a much lower market capitalization than the S&P500 companies that they study and are followed by fewer analysts (IBES). This could potentially be a problem for us since one single forecast could have a much larger impact on the average. On the other hand, the mean forecast is widely accepted as a measurement for analyst consensus on the Swedish market and has the benefit of not excluding forecasts by inexperienced analysts, who we still find interesting to our study.

In this study we only focus on EPS estimates and thus ignore other functions that analysts have in the market, such as issuing buy or sell recommendations or estimating other key indicators of company performance. One reason that we use earnings per share for our study is that it is one of the most common values forecasted by analysts and therefore easy to find forecasts for. Another reason is that EPS forecasts are an important source of information to investors, a fact that is supported by the amount of attention devoted to earnings forecasts in the financial press and the presence of commercial vendors for such forecasts (Stevens & Williams, 2004). It is also generally considered to be the most important variable in determining the appropriate price of a share (Cen et al., 2013). Although share price is also commonly forecasted in financial analyses it is can be affected to a large degree by market expectations and would not be reliable enough, considering the purpose of this study is to examine possible market inefficiency. Another problem is that price targets, unlike EPS forecasts, do not always have a specific date for when they should have been achieved. P/E and PEG ratios also contain the component of market price. Another possibility is EPS growth, which would not be much different than the EPS value that we are planning on using.

3.3 Data

As mentioned previously, the data will be collected from the database IBES (Institutional Brokers' Estimate System) through Datastream. IBES is an over 40 year old database now owned by Thomson Reuters and used as an industry standard for analysts. It covers over 22,000 companies across 100 countries and contains around 20 years of historical numbers for international companies, including the ones listed on the Nasdaq Stockholm stock exchange. It is not possible for us to access detailed individual estimates so instead we will have to rely on the analyst consensus, proxied by the mean forecasted EPS.

3.3.1 Missing Data Analysis

Our sample will consist of historical EPS consensus estimates for all companies registered on Nasdaq OMX Stockholm between 2008 and 2015. Some of the companies are not represented in our study due to insufficient data in Datastream. The most common reason for which companies are excluded is because they have been listed for less than a year or for other (unknown) reasons do not have any values available for annual EPS estimates. A few companies do not have any available actual EPS data, and in rare cases neither of the values was accessible. For companies that have multiple stocks listed on the exchange, we have included the one that rates the highest in terms of accessible information from Datastream (according to the database's own rating system), and excluded the others. For an overview of companies that have been excluded from the sample, as well as reasons for the exclusion, see Apendix 2.

After removing all companies with unavailable data we were left with 228 companies in our cross-section. The companies are categorized into 10 different groups, based on their four digit Industry Classification Benchmarks (ICB).

Additionally, there is a possibility that some estimates for the remaining companies are missing from the database since the information is gathered monthly from analysts and brokerage firms on a voluntary basis.

3.4 Regression analysis

3.4.1 Panel data analysis

A data set consisting of both cross-sectional and time series elements is known as *longitudinal* or *panel data*. This means panel data will embody information across both space (i) and time (t), i.e. it contains the same entities and measures some quantity of them over time. A panel data equation should thus look something like the following:

$$y_{it} = \alpha + \beta x_{it} + u_{it}$$

The simplest way to deal with this type of data is to estimate a pooled regression by estimating a single equation on all the data together (Brooks, 2014). A regular ordinary least squares regression can then be used to estimate the equation which is the method we are going to use for our study.

A distinction can also be made between *balanced* and *unbalanced* panel data. A balanced has the same number of observations for of time series observations for each cross-sectional unit, while unbalanced panel data has more observations of one type or the other (Brooks, 2014). Our data set does not have the same amount of observations for each company as some do not have available values for all the years within the time period, and is thereby considered an unbalanced panel.

3.4.2 The fixed effects model

When the entities in the sample can be thought of as having been randomly selected from a population, the random effects model is said to be the more appropriate one to use. It should also produce a more efficient estimation compared to fixed effects since there are fewer parameters to estimate and therefore saves more degrees of freedom. However, it is much more stringent than the fixed effects model since it requires the composite error term to be uncorrelated with the explanatory variables. The fixed effects model is more plausible when the sample constitutes the entire population, for example when it consists of all the stocks traded on a particular exchange (Brooks, 2014). Thus, we will use a fixed effects model for our study.

3.4.3 Assumptions for the Ordinary Least Squares Model

For the use of the ordinary least squares model to be appropriate there following five assumptions need to be fulfilled.

E(ut) = 0

The first assumption says that the errors in the regression should have a zero mean. This can be achieved by including an intercept in the regression (Brooks, 2014). In our model, α is included as a constant (C in the statistical software).

var(ut) = σ2 < ∞

The second assumption says that the variance of the errors should be constant and finite over all values of x_t. This is also referred to as the assumption of homoscedasticity. If it is not fulfilled, meaning that the errors are heteroscedastic and thereby not constant over all values, the OLS estimations may lead to incorrect inference (faulty conclusions). (Brooks, 2014)

cov(uj,uj) = 0

The third assumption says that the errors should be linearly independent of one another. If this assumption is not fulfilled, the residuals are said to be autocorrelated and can be tested by using a Breusch-Godfrey test. This is usually not necessary for panel data as it only takes into account the time-series dimension (Brooks, 2014). Since our chosen time period is fairly short, it will be difficult to see trends over time, and the autocorrelation test is therefore not going to be used in this study.

cov(uj,xj) = 0

The fourth assumption says that there should be no relationship between the error and the corresponding x variate, meaning that the errors should not be correlated with any of the independent variables. This is also known as endogeneity and can be tested with a Hausman test (Brooks, 2014). We do not expect any issues of endogeneity in our regressions as it is not common for this type of study.

(Ut ~ N(0, σ2))

The fifth and final assumption says that the residuals (u_t) should be normally distributed. For the errors to be normally distributed they should have a skewness of 0 and a kurtosis of 3. This is estimated with a Jarque-Bera test as well as optical examination of the distribution. If the assumption of normality is not fulfilled, this can be corrected by making logarithmic transformations to reduce extreme values or increasing in sample size. Extreme values can also be removed directly to improve the distribution (Brooks, 2014). To deal with non-normality in our sample we have made a logarithmic transformation of one of the variables and removed extreme values from the dependent variable.

3.4.4 Multicollinearity

Apart from the above assumptions, there are other problems that may have to be mitigated for ordinary least squares to be an appropriate method. For panel data regressions, a multicollinearity test should be performed. Multicollinerarity occurs when any of the independent variables have a higher correlation than 0.8, which can be tested through a correlation matrix (Brooks, 2014).

3.5 The regression model

The equation used for our regressions follows the recommendations mentioned above for panel data equations used in OLS regressions. It can be estimated as:

$$FORECAST\ ERROR_{it} = \alpha + \beta_1 ANCHORED_{it} + \beta_2 FIRMSIZE_{it} + \beta_3 POSITIVE_{it} + u_{it}$$

The variables used are defined as follows:

- FORECAST ERROR = the absolute value of the difference between estimated EPS and actual EPS.
- ANCHORED = dummy variable that takes on a value of 1 if the estimate is between the actual EPS and the chosen anchor, and 0 otherwise.
- FIRMSIZE = the natural logarithm of a company's market capitalization
- POSITIVE = dummy variable that takes on a 1 if the estimate is higher than the actual EPS, and 0 otherwise.
- u = the error term

3.5.1 Dependent variable

The dependent variable in our regressions is analysts' combined forecast error. This variable can be defined as the difference between the mean estimated annual EPS for a given year and the actual annual EPS reported at the end of the same year. We suspect that any anchoring effect caused by this will be the most prominent right after the announcement, and before any quarterly reports have been released. We will therefore use the mean forecast three months into the fiscal year. For the majority of our forecasts, observations have therefore been taken from April 1st of each year. For firms with a broken fiscal year, observations have been taken from the first day of the fourth month of the fiscal year. For example, if a company's fiscal year stretches from September to August, the observations are taken from the December 1st every year. This should not lead to any errors in our data as both the estimated and annual actual EPS value are always taken from the same date. The difference between the mean estimate and the actual EPS is then calculated as a percentage and made into an absolute value. This means that we only measure the size of the forecast error without taking into account whether it is positive or negative. The variable will be called "FORECAST_ERROR" in the estimation output from the statistical software.

3.5.2 Independent variables

The independent variables should be relevant to the hypotheses that are being explored and provide an explanation for the variation in the dependent variable. To explain a forecast error we have to consider variables that could explain the difficulty-level of making a forecast as well as conscious and subconscious biases that could lead to bigger errors.

The first independent variable is the one that we wish to test with the help of our hypotheses, namely the anchoring variable. A forecast in our model is considered anchored if either of the following is true:

$$\text{Actual EPS} > \text{EPS Estimate} > \text{Anchor}$$

or

$$\text{Anchor} > \text{EPS Estimate} > \text{Actual EPS}$$

That is, if the estimate falls somewhere in between the anchor value and the actual outcome, it will be considered anchored. The anchor variable is a dummy variable that takes on a value of 1 if it fits the conditions above and 0 if it does not.

In the first regression, the anchoring variable takes on a value of 1 if the estimate is between the actual EPS and the past year actual EPS and zero otherwise. This variable will be called "ANCHORED_TO_PAST_YEAR".

In the second regression, the anchor variable is calculated based on the industry median. First the industry median estimate is taken from combined estimates for all the companies in the sample. The motivations for using the prior month's industry median estimate is that the current value includes the mean estimate for the specific company, and that we want the analysts to have had time to react to the value and possibly be affected by it. The anchor variable takes on a value of 1 if the estimate is in between the actual EPS and the past month industry median EPS. This variable will be called "ANCHORED_TO_INDUSTRY_MEDIAN".

The second independent variable is the size of the company. This variable is included because the larger companies are given more attention from analysts which should improve the quality of the forecasts. There are several different ways to measure company size (total assets, total sales, market value) that all have different benefits and downsides. In our model, this measure is proxied by the natural logarithm of the market capitalization. This is easily motivated by the fact that this measure is commonly used in research relating to analyst coverage. Several researchers have found that market capitalization has a positive relation to the amount of analysts covering a company (Hong, Lim & Stein, 2000; Lang & Lundholm, 1996) and it should therefore be considered relevant to our study. This variable will be called "LOGSIZE".

The last independent variable is a measure of a conscious bias, namely the tendency among analysts to make overly positive forecasts. If that optimism is not warranted, some of the forecast errors could be explained by whether or not a forecast is too positive. This has been made into a dummy variable, where a forecast is defined as positive and is given a 1 when the estimated EPS is higher than the actual EPS for the same year and negative and given a 0 when estimated EPS is lower than the actual EPS. This variable will be called "POSITIVE".

Dependent variable	Definition	Measurement unit
FORECAST ERROR	EPS estimate-Actual EPS, calculated as an absolute value (no negative values).	%

Table 3.1 – Summary: Dependent variable

Independent variables	Definition	Expected coefficient	Measurement unit
ANCHORED TO INDUSTRY MEDIAN	Estimates that are between the current year actual and the past month industry median.	+	1=anchored,0=not anchored
ANCHORED TO PAST YEAR	Estimates that are between the current year actual and the past year actual.	+	1=anchored,0=not anchored
FIRM SIZE	The company's market capitalization.	-	SEK (thousands)
POSITIVE	Estimate that overshoots the actual EPS (Estimate-Actual gives a positive value).	+	1=positive, 0=negative

Table 3.2 - Summary: Independent variables

3.6 Reliability, Replicability and Validity

3.6.1 Reliability

The research criterion of reliability concerns whether there is consistency in the results of the study and is particularly an issue that relates to quantitative research. For the statistical results to be reliable, they should not fluctuate when similar tests are made on several occasions and the probability of them being impacted of temporary coincidental effects should be low. Additionally, the authors' decisions should not have any impact on the results (Bryman & Bell, 2013). Since our sample size is fairly large we believe that any coincidental factors will have a minimal effect once we combine all our observations. The database from which the sample is collected (IBES) is widely used by analysts themselves as well as in research relating to analysts' forecasts and should be considered a reliable source.

3.6.2 Replicability

Another criterion that is very closely associated with reliability is replicability. If the found results are correct, another researcher should be able to replicate them as long as they follow the same procedures as the original study. Replication studies are not common in the field of business but replicability is nonetheless important for the credibility of the study (Bryman & Bell, 2013). If all the steps included in this and the following chapter are followed, another researcher should end up with the same results. Since the data has been handled manually as it has been transferred from the database and recoded to comply with the statistical program used for the study (Eviews) there is a possibility for human errors in the sample, but as the data set has been double checked multiple times the results should fulfill the replicability criterion.

3.6.3 Validity

The criterion of validity concerns whether or not the study actually measures what it is intended to measure, and whether the conclusions drawn from the results are valid. If not, the research findings will be questionable. Validity can be divided into two categories; internal and external. To see if there is internal validity in the investigated causal relationships, it should be considered whether the explanation for the variation in the dependent variable can be found in the used independent variables, or if there is actually something else that is producing the apparent relationship (Bryman & Bell, 2013).

The variables that we use in our study are in line with the previous research on anchoring bias in analysts' forecasts and can be assumed to be related to the causality that we are trying to question. As has previously been mentioned in this thesis, forecast errors are to some degree unexplainable in nature because they involve both human judgement and predicting the future. Even so, the predictable part of the forecast errors, which is what we are trying to explain with our model, could perhaps be impacted by for example analysts' experience or the size of the firm that employs them. Values for these factors are unfortunately unavailable to us as we only have access to the combined mean forecasts, which could have an impact on the internal validity.

The concept of external validity refers to whether the results are representative enough that they can be generalized and applied to other areas (Bryman & Bell, 2013). Since our sample includes all companies listed on the Nasdaq OMX Stockholm exchange, we believe our study is generalizable for the larger companies on the Swedish stock market. A study of the smaller exchanges Nasdaq First North or Aktietorget may yield different results, but a lot of the companies on those markets lack an analyst following since they almost exclusively contain growth stocks with relatively low liquidity (Nasdaq, Aktietorget). The fact that the time period only stretches over 8 years and that the stock market has mostly been moving upwards in those years may also affect the external validity, since a period with different market conditions may affect the difficulty level of forecasting and thereby the forecast error in a different way.

4. Empirical Results

The chapter will present the empirical research and results from the regression analysis and the validity variables.

4.1 Descriptive Statistics

The study includes a total of 228 companies registered on Nasdaq OMX Stockholm between 2008 and 2015. In table 4.1 we have listed descriptive statistics for the variables included in our regressions. To decrease the likelihood of extreme values, the variable "FIRMSIZE" has been transformed using a natural logarithm.

Variable	Observations	Mean	Median	Maximum	Minimum	Std. Dev.
FORECAST ERROR	1203	0.697	0.377	4.680556	0.021465	0.814
ANCHORED TO INDUSTRY MEDIAN	1203	0.521	1.000	1.000	0.000	0.499
ANCHORED TO PAST YEAR	1203	0.309	0.000	1.000	0.000	0.462
POSITIVE	1203	0.488	0.000	1.000	0.000	0.500
FIRMSIZE	1203	8.197	8.057	13.46	2.333	1.948

Table 4.1 - Descriptive statistics

4.2 Correlation matrix for dependent and independent variables

VARIABLE	FORECAST ERROR	ANCHORED TO INDUSTRY MEDIAN	ANCHORED TO PAST YEAR	FIRM SIZE	POSITIVE
FORECAST ERROR	1.000000	0.051730	-0.155870	-0.186281	-0.013624
ANCHORED TO INDUSTRY MEDIAN	0.051730	1.000000	0.029216	-0.196943	-0.271181
ANCHORED TO PAST YEAR	-0.155870	0.029216	1.000000	0.031272	-0.333991
FIRM SIZE	-0.186281	-0.196943	0.031272	1.000000	0.118967
POSITIVE	-0.013624	-0.271181	-0.333991	0.118967	1.000000

Table 4.2 - Correlation matrix

According to the correlation matrix, there are no signs of multicollinearity as this would be indicated by absolute values of 0.8 or higher (Brooks, 2014). The highest correlation is found between positive forecast variable and the past year anchor variable, that have a negative correlation of -0.33.

4.3 Regression results

Four separate regressions have been performed. In the first regression we use ordinary least squares to study how the variables of industry median anchor, firm size and positive forecasts explain the variation in the dependent variable, forecast error. In a second regression we then use a binary logit model to see whether explaining the industry median anchor variable with forecast error as the only independent variable would give us any further indications regarding the relationship between the two variables. The third regression is nearly identical to the first, but using the past year EPS as the anchor variable. In the fourth regression we use the same binary logit model but with the past year anchor as the independent variable. The binary regressions are only to be seen as complementary to the study as the independent and dependent variables have been switched.

4.4 Rejection or non-rejection of hypotheses

4.4.1 Significance level

The significance of statistical results is usually described through different levels. In this study, we will analyze the results using the 1%, 5% and 10% levels as these are the conventional levels used in research. Since we have a fairly large sample size leading to a decrease in the standard errors, we will use the 1% level to consider whether or not to reject the hypotheses. The hypotheses will be referred to as either *rejected* or *not rejected* after examining the results. (Brooks, 2014)

4.4.2 Hypothesis 1

Regression 1 – OLS with Industry Median Anchor

Dependent Variable: FORECAST_ERROR
Method: Panel Least Squares
Date: 05/11/16 Time: 20:43
Sample: 2008 2015
Periods included: 8
Cross-sections included: 228
Total panel (unbalanced) observations: 1203

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.815073	0.441572	1.845843	0.0652
ANCHORED_TO_INDUSTRY_MED	0.052575	0.053946	0.974574	0.3300
FIRMSIZE	-0.028019	0.053771	-0.521073	0.6024
POSITIVE	0.172321	0.057037	3.021219	0.0026

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.349981	Mean dependent var	0.697025
Adjusted R-squared	0.190339	S.D. dependent var	0.814421
S.E. of regression	0.732825	Akaike info criterion	2.391413
Sum squared resid	518.2367	Schwarz criterion	3.398921
Log likelihood	-1200.435	Hannan-Quinn criter.	2.770887
F-statistic	2.192284	Durbin-Watson stat	2.180777
Prob(F-statistic)	0.000000		

Table 4.3 - OLS regression using the industry median EPS estimate as the anchor variable, with excluded extreme values (5th percentile)

The coefficient of determination, R-squared (R^2), measures how well the model explains the variation in the dependent variable. It takes on a value between 1 and 0, where 1 means that the model fully explains the variation in the dependent variable and 0 that it does not explain any of the variation (Brooks, 2014). The R-squared for our model has a value of ~0.35, meaning that the model explains about 35% of the variation in the forecast error variable. This is quite high compared to models used in previous studies.

The regression shows no significant relationship between the anchor variable and the dependent variable and is therefore not consistent with our first hypothesis. We also do not find any significance for the variable of firm size. The positive forecast variable indicates a positive relationship with the forecast error, and is significant on the 1% level.

It should be noted that extreme values (the 5th percentile of forecast errors) have been excluded from this regression after a normality test indicated a far from optimal distribution (see Appendix 1). When extreme values are included, the amount of included values increase to 1339 observations and the R-squared is reduced to approximately 17%. The anchor variable remains insignificant while firm size becomes significant with a -2.34 coefficient. Judging by these results we can reject the first hypothesis since the anchor variable does not have a significant positive relationship to the forecast error.

Regression 2 – Binary Logit with Industry Median Anchor

Dependent Variable: ANCHORED_TO_INDUSTRY_MED
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/16 Time: 20:53
Sample: 2008 2015
Included observations: 1218
Convergence achieved after 3 iterations
QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.005310	0.076292	-0.069607	0.9445
FORECAST_ERROR	0.125830	0.073156	1.720025	0.0854

McFadden R-squared	0.001847	Mean dependent var	0.520525
S.D. dependent var	0.499784	S.E. of regression	0.499343
Akaike info criterion	1.385335	Sum squared resid	303.2013
Schwarz criterion	1.393718	Log likelihood	-841.6690
Hannan-Quinn criter.	1.388490	Deviance	1683.338
Restr. deviance	1686.453	Restr. log likelihood	-843.2267
LR statistic	3.115332	Avg. log likelihood	-0.691025
Prob(LR statistic)	0.077559		
Obs with Dep=0	584	Total obs	1218
Obs with Dep=1	634		

Table 4.4 - Binary logit regression using industry median anchor as the dependent variable

The binary logit regression shows that out of 1218 included observations, 634 were anchored according to our definition, while 584 were not. Anchored estimates thus made up about 52% of the total observations. The model has a McFadden R-squared of ~0.002, indicating that it only explains 0.2% of the variability. The McFadden R-squared is a pseudo R-squared that is used in binary regressions in a way that mirrors the regular R-squared used in OLS (Brooks, 2014). The independent variable has a p-value of ~0.09 indicating that it is only significant on the 10% level, which is the lowest significance level that is normally used in research (Brooks, 2014). The Expectation-Prediction Evaluation (table 4.5) shows how well the model predicts. The proportion of anchored observations relative to observations that are not anchored is 0.52053, and we have therefore used this as our threshold for a correct forecast. According to table 4.5, 36.75% of the anchored observations are predicted correctly by the model, as well as 69.01% of the observations that are not anchored. Overall, 52.22% of the observations are predicted correctly by the model. As we can also see in the table, the model has a total gain of 4.27, meaning it predicts 4.27% more than a random model.

Expectation-Prediction Evaluation for Binary Specification
Equation: BINARY_INDUSTRY_MEDIAN
Date: 05/17/16 Time: 20:20
Success cutoff: C = 0.52053

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	403	401	804	584	634	1218
P(Dep=1)>C	181	233	414	0	0	0
Total	584	634	1218	584	634	1218
Correct	403	233	636	584	0	584
% Correct	69.01	36.75	52.22	100.00	0.00	47.95
% Incorrect	30.99	63.25	47.78	0.00	100.00	52.05
Total Gain*	-30.99	36.75	4.27			
Percent Gain**	NA	36.75	8.20			

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	280.79	303.21	584.00	280.01	303.99	584.00
E(# of Dep=1)	303.21	330.79	634.00	303.99	330.01	634.00
Total	584.00	634.00	1218.00	584.00	634.00	1218.00
Correct	280.79	330.79	611.58	280.01	330.01	610.03
% Correct	48.08	52.18	50.21	47.95	52.05	50.08
% Incorrect	51.92	47.82	49.79	52.05	47.95	49.92
Total Gain*	0.13	0.12	0.13			
Percent Gain**	0.26	0.26	0.26			

*Change in "% Correct" from default (constant probability) specification
**Percent of incorrect (default) prediction corrected by equation

Table 4.5 - Expectation-Prediction Evaluation for binary logit regression with industry median as anchor

4.4.3 Hypothesis 2

Regression 3 – OLS with Past Year Anchor

Dependent Variable: FORECAST_ERROR
Method: Panel Least Squares
Date: 05/11/16 Time: 20:48
Sample: 2008 2015
Periods included: 8
Cross-sections included: 228
Total panel (unbalanced) observations: 1203

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.909114	0.437098	2.079886	0.0378
ANCHORED_TO_PAST_YEAR	-0.215207	0.058253	-3.694334	0.0002
FIRMSIZE	-0.022629	0.053442	-0.423434	0.6721
POSITIVE	0.081748	0.058235	1.403771	0.1607

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.358415	Mean dependent var	0.697025
Adjusted R-squared	0.200844	S.D. dependent var	0.814421
S.E. of regression	0.728055	Akaike info criterion	2.378353
Sum squared resid	511.5124	Schwarz criterion	3.385861
Log likelihood	-1192.579	Hannan-Quinn criter.	2.757826
F-statistic	2.274630	Durbin-Watson stat	2.167182
Prob(F-statistic)	0.000000		

Table 4.6 - OLS regression using the past year estimated EPS as the anchor variable, with excluded extreme values (5th percentile)

The OLS regression seen in table 4.6 has a coefficient of determination of ~0.36, implying that the model explains 36% of the variation in the forecast error. The anchor variable has a significant but negative relationship to the forecast error. The results also show that the variable for firm size is not significant but remains negative just like in the previous regression OLS. The positive forecast variable is also insignificant on all significance levels.

With included extreme values the R-squared for the second regression is reduced to 17%. The anchor variable then becomes insignificant, while the variable for firm size becomes significant with a -2.40 coefficient. The positive forecast variable then becomes highly significant with a positive 5.63 coefficient, indicating a strong positive relationship with the forecast error.

Regression 4 – Binary Logit with Past Year Anchor

Dependent Variable: ANCHORED_TO_PAST_YEAR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/11/16 Time: 21:00
Sample: 2008 2015
Included observations: 1218
Convergence achieved after 4 iterations
QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.482230	0.084619	-5.698843	0.0000
FORECAST_ERROR	-0.508785	0.104387	-4.874027	0.0000

McFadden R-squared	0.021872	Mean dependent var	0.309524
S.D. dependent var	0.462487	S.E. of regression	0.456461
Akaike info criterion	1.213657	Sum squared resid	253.3618
Schwarz criterion	1.222040	Log likelihood	-737.1171
Hannan-Quinn criter.	1.216812	Deviance	1474.234
Restr. deviance	1507.200	Restr. log likelihood	-753.5999
LR statistic	32.96551	Avg. log likelihood	-0.605186
Prob(LR statistic)	0.000000		

Obs with Dep=0	841	Total obs	1218
Obs with Dep=1	377		

Table 4.7 - Binary logit using the past year anchor as the dependent variable

In the last regression (seen in table 4.7) we put the FORECAST ERROR as the independent variable to explain the variability in the dependent variable ANCHORED TO PAST YEAR. Just like in the previous regression, it shows a negative relationship between the variables, which was our reason for rejecting the second hypothesis. The McFadden R-squared is ~0.022 which indicates that approximately 2.2% of the variability in the anchor variable is explained by the model. According to the results, only 377 out of 1218 are anchored to the past year according to our definition. In table 4.8 we can see how well the model predicts. Our threshold is set to 0.30952 since this is the proportion of estimates that are anchored. The model predicts 74.27% of the anchored observations correctly, and the corresponding number for observations that are not anchored is 41.97%. Overall the model predicts 51.97% of the observations correctly, in terms of them being anchored or not anchored. This is a total gain of 21.02% compared to a random model.

Expectation-Prediction Evaluation for Binary Specification
Equation: BINARY_PAST_YEAR
Date: 05/17/16 Time: 19:56
Success cutoff: C = 0.30952

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	353	97	450	0	0	0
P(Dep=1)>C	488	280	768	841	377	1218
Total	841	377	1218	841	377	1218
Correct	353	280	633	0	377	377
% Correct	41.97	74.27	51.97	0.00	100.00	30.95
% Incorrect	58.03	25.73	48.03	100.00	0.00	69.05
Total Gain*	41.97	-25.73	21.02			
Percent Gain**	41.97	NA	30.44			

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	587.35	253.65	841.00	580.69	260.31	841.00
E(# of Dep=1)	253.65	123.35	377.00	260.31	116.69	377.00
Total	841.00	377.00	1218.00	841.00	377.00	1218.00
Correct	587.35	123.35	710.69	580.69	116.69	697.38
% Correct	69.84	32.72	58.35	69.05	30.95	57.26
% Incorrect	30.16	67.28	41.65	30.95	69.05	42.74
Total Gain*	0.79	1.77	1.09			
Percent Gain**	2.56	2.56	2.56			

*Change in "% Correct" from default (constant probability) specification
**Percent of incorrect (default) prediction corrected by equation

Table 4.8 - Expectation-Prediction Evaluation for binary logit regression with past year as anchor

5. Analysis and discussion

The chapter will present the authors' interpretation and analysis of the results of the empirical research using theories from the theoretical framework.

5.1 Hypothesis 1

The statistical results in our first regression in table 4.3 indicate that we should reject the hypothesis that analysts tend to anchor to the industry median, since the anchor variable (ANCHORED TO INDUSTRY MEDIAN) is insignificant. This is contradictory to the findings made by Cen et al. (2010) who find that analysts tend to anchor to the industry norm, and a surprising result. Since there are fewer analysts on the Swedish market and thereby less competition we expected that they may make biased estimates but this does not seem to be the case. However, a big difference between our study and the one made by Cen et al. is that our study focuses on yearly estimates rather than monthly, which could possibly be a cause for the different results.

The statistical results in our first regression in table 4.3 indicate that we should reject the hypothesis that analysts tend to anchor to the industry median, since the anchor variable (ANCHORED TO INDUSTRY MEDIAN) is insignificant. This is contradictory to the findings made by Cen et al. (2010) who find that analysts tend to anchor to the industry norm, and a surprising result for several reasons. Firstly, since there are fewer analysts on the Swedish market and thereby less competition, we expected that there would be more bias and not less.

If we look at the dummy variable that tells us whether or not estimates are overly optimistic (POSITIVE), it has a positive coefficient and is significant on the 1% level. This is exactly what we would expect as previous research has indicated that analysts have rational biases that make them more optimistic, which could impact the forecast error. Two theories for why this is the case have been mentioned previously. The first is that analysts tend to make more optimistic estimates in an effort to generate trading activity for their firm (Agrawal & Chen 2008; Groysberg et al. 2008). This is a possible explanation for our results as the majority of estimates included in the IBES database are provided by analysts that are employed at a bank or brokerage firm. The second theory is that optimistic estimates make it more likely that the analyst can get access to non-public information that is otherwise only available to management (Das et al., 1998). Most of the companies in our sample have a very limited following and many of them even publish the contact info to analysts on their websites. This seems to show that companies pay close attention to the analysts that follow them, and makes it relatively easy to see how a negative or even conservative estimate could be unpopular with the company's management. If managers systematically use the leverage of being able to disclose additional information to get the forecasts that they want (assuming that managers want forecasts to be optimistic), it could cause an optimistic bias among analysts.

The coefficient is only 0.17 which is not very large considering we have forecast errors that range from 0.02 to 4.68 but if we consider that all of the forecast errors, after the 5^{th} percentile has been removed, have a median of only 0.377 and a standard deviation of 0.814 it could still give us some indication that optimism could possibly have an impact (albeit small). The fact that the variable for the company's market capitalization (FIRMSIZE) is insignificant is surprising as previous research has shown that estimates made for larger firms have higher accuracy (Brown et al., 1987). Before the extreme values are excluded however, this variable is significant with a negative coefficient. A possible explanation for why it is significant when extreme values are included but not when they are removed is that the extreme forecast errors may contain smaller companies with a limited analyst following.

In the results from the binary logit regression in table 4.4, we find a positive relationship between the variables ANCHORED TO INDUSTRY MEDIAN and FORECAST ERROR that is significant on the 10% level. Since the variables have been switched, a non-rejection would indicate that high forecast errors increase the probability of a forecast being anchored to the industry median. This is what we would expect since our hypothesis is that anchoring is a factor that enhances forecast errors. The McFadden R-squared is a lot lower than the R-squared in the previous regression. It is only about 0.2% which means that we should be very careful with drawing conclusions based on the regression. Because the dependent and independent variables have been switched we have not included any additional variables which is a possible reason for why the model is able to explain less of the variability.

Our chosen significance level for rejection or non-rejection of our hypotheses is 1%, but using this model we only find significance for the FORECAST ERROR variable at the 10% level. Additionally, the binary logit regression should only be seen as complementary rather than standing by itself when we analyze the results, especially considering the low McFadden R-squared. Therefore, the results cannot be seen as a reason not to reject the first hypothesis.

5.2 Hypothesis 2

According to the results from our third regression (see table 4.6) the hypothesis that analysts anchor to the past year annual EPS should be rejected. Even though we find that the variable ANCHORED TO PAST YEAR is significant on the 1% level, the results show that it has a negative coefficient with FORECAST ERROR as the dependent variable. This is not consistent with the findings of Campbell and Sharpe (2007) and Kaustia et al. (2008) who find that analysts and other financial professionals tend to anchor their estimates to historical values. In fact, our results indicate that the anchor variable has the opposite relationship to the forecast error compared to what we would have needed to find to justify a non-rejection of our second hypothesis. This is an unexpected finding and one we have struggled to come up with an explanation for. If we are going to speculate however, one explanation for this result could be that analysts when analyzing firms that do not have a lot "going on" that should affect earnings from one year to another play it safe and just add a little bit to the previous year earnings. The biased estimate would then not be too far from the Bayesian estimate (i.e. the estimate that analysts would make in the absence of any biases) which could cause the accuracy would be higher. Conversely then, if a company has many new business opportunities or alternatively is struggling in some way, it could lead analysts to make more exaggerated forecasts causing them to considerably miss the mark.

The POSITIVE variable is not significant in the third regression after extreme values have been removed. We find this a bit problematic since it shows that the variable is not very stable because it does not remain significant even when only one of the other independent variables are changed. Before the extreme values are removed the variable is however highly significant and positive with a rather high coefficient, indicating that it has a positive impact on the forecast error. This effect disappears after the removal of extreme values, which could possibly be due to the fact that some of the most extreme estimates have been those where the analysts overestimate the actual EPS. As previously mentioned, this could have to do with optimistic bias. The FIRMSIZE variable is insignificant after the extreme values have been removed but is negative and significant when they are included, again indicating that the market capitalization might have a negative relationship to the forecast error. However, the relationship disappears when only 95% of forecast errors are included.

The results from the binary logit regression (see table 4.7) show that the FORECAST ERROR variable is highly significant when ANCHORED TO PAST YEAR is the dependent variable. This indicates that whether or not an estimate is anchored can to some degree be explained by the size of the forecast error, with an increase in the error decreasing the chance that an estimate will be anchored. This provides further evidence to our previous results showing that the two have a negative relationship, which was our reason for rejecting the second hypothesis. One surprising statistic is that out of 1218 observations included in the regression, only 377 where anchored.

The correlation matrix shows that both the ANCHORED TO INDUSTRY MEDIAN and the ANCHORED TO PAST YEAR variables have a negative correlation with the POSITIVE variable. This suggest that analysts might be less likely to have used an anchor when they are making overly optimistic forecasts than when they have underestimated the actual EPS.

5.3 Discussion

We have not found similar results to any of the previous studies on anchoring in analysts' estimates. There are several possible causes for this. Firstly, only one of the studies were made specifically on EPS estimates and thus there is no further research yet to support the findings. However, it is still an unexpected result since anchoring bias within the field of behavioral finance is considered a very robust phenomenon that is applicable in many different contexts. The fact that the theory of anchoring bias does not seem to be applicable to this particular context can thus be seen as one of the contributions of this thesis. A possible explanation for why our results differ from previous studies is that we used a long term perspective, only taking yearly data where estimates and actual EPS values are far in between. If we had focused on for example monthly or quarterly figures, there is a chance that the results would have been different. Another possibility is that our time frame happened to only include a period where the conditions where somehow different than normal. One reason for that could be that most of the years included in our study had a steady upward trend in the stock market, perhaps making EPS values easier to predict. There is also a possibility that analysts on the Swedish market do anchor to historical values or estimates, but that we failed in predicting which ones they use.

6. Conclusions

The chapter presents the authors' conclusions made from the analysis and also gives ideas for future research.

The goal of our thesis has been to provide a description on the previous research on the heuristic of anchoring bias, as well as to apply this theory on estimates made by analysts on the Swedish stock market. This has been studied by studying the effect of anchoring on the variability in analysts' forecast errors, while including the variables of firm size and whether or not the forecast is overly optimistic. We did not find any support for our hypotheses that analysts tend to anchor to neither the industry median forecasted EPS, nor the past year EPS for the firm that they are analyzing. That said, it is possible that analysts on the Swedish market are indeed subject to anchoring bias. There could be some other anchor that we have not considered in our study that analysts tend to use in their estimates, for example their own previous estimates.

We have only studied companies on the Nasdaq OMX Stockholm exchange which includes a lot of relatively small companies if we put it in an international context. For those who are interested in the possible effect of anchoring bias in the Nordic markets, an alternative could be to study companies in the large cap segment on the Nasdaq Nordic Market. Potential differences between analysts in Sweden, Denmark, Finland and Iceland could then also be analyzed. One other factor that would have been interesting to bring into our study is the analysts' experience, and whether or not it could affect the tendency for different biases. If there is a possibility to look at individual forecasts rather than the combined mean estimate for all the analysts that are following the company, this could be an interesting subject for future research.

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Appendix 1.

1.1 Normality tests

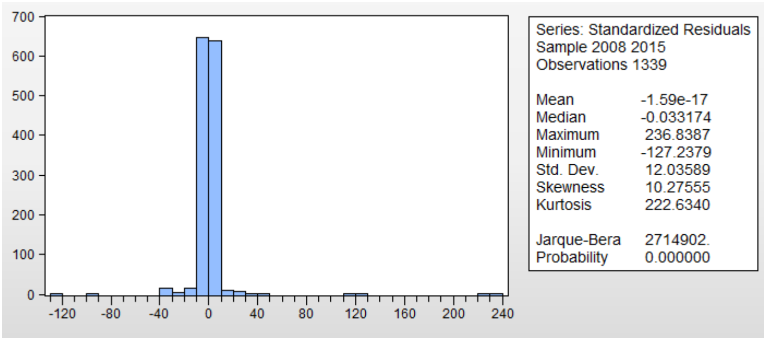

Figure 1.1 - Normality test for OLS regression with industry median as anchor, including extreme values

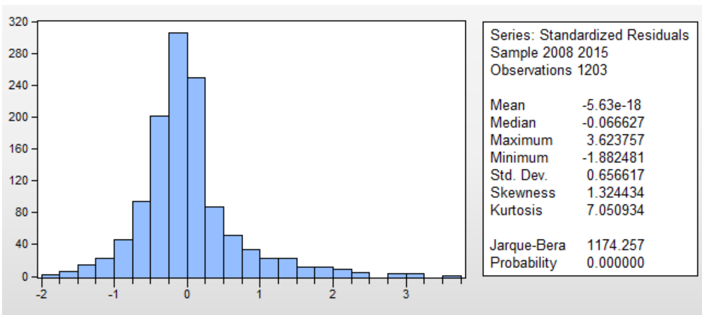

Figure 1.2 - Normality test for OLS regression with industry median as anchor, with excluded extreme values (5th percentile)

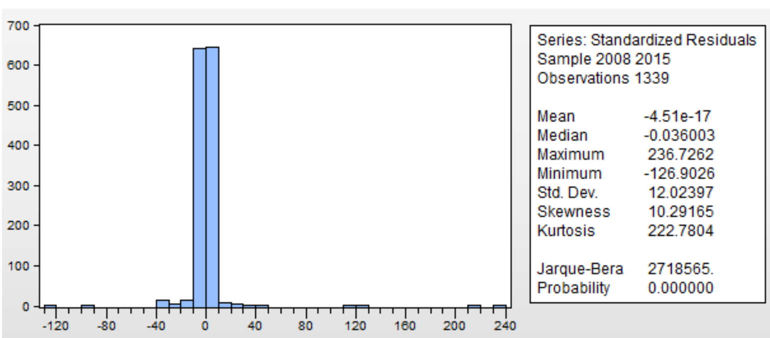

Figure 1.3 - Normality test for OLS regression using past year as the anchor variable, including extreme values

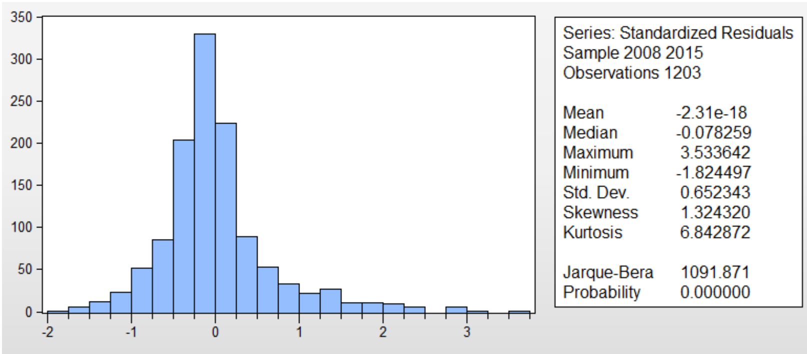

Figure 1.4 - Normality test for OLS regression using past year as the anchor variable, with excluded extreme values (5th percentile)

1.2 OLS regressions, with extreme values included

Dependent Variable: FE
Method: Panel Least Squares
Date: 05/11/16 Time: 20:35
Sample: 2008 2015
Periods included: 8
Cross-sections included: 228
Total panel (unbalanced) observations: 1339

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.32723	7.498978	2.310612	0.0210
ANCHORED_TO_INDUSTRY_MED	-0.021298	0.903456	-0.023574	0.9812
FIRMSIZE	-2.343610	0.908489	-2.579680	0.0100
POSITIVE	5.118114	0.926826	5.522194	0.0000

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.167407	Mean dependent var	0.554699
Adjusted R-squared	-0.011817	S.D. dependent var	13.19052
S.E. of regression	13.26822	Akaike info criterion	8.168406
Sum squared resid	193826.4	Schwarz criterion	9.092621
Log likelihood	-5230.748	Hannan-Quinn criter.	8.514665
F-statistic	0.934068	Durbin-Watson stat	2.014069
Prob(F-statistic)	0.741003		

Table 1.1 - OLS regression using industry median as the anchor, with extreme values

Dependent Variable: FE
Method: Panel Least Squares
Date: 05/11/16 Time: 20:45
Sample: 2008 2015
Periods included: 8
Cross-sections included: 228
Total panel (unbalanced) observations: 1339

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.07898	7.453787	2.291316	0.0221
ANCHORED_TO_PAST_YEAR	1.476512	0.998768	1.478333	0.1396
FIRMSIZE	-2.401175	0.908189	-2.643916	0.0083
POSITIVE	5.627372	0.954504	5.895601	0.0000

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.169056	Mean dependent var	0.554699
Adjusted R-squared	-0.009813	S.D. dependent var	13.19052
S.E. of regression	13.25508	Akaike info criterion	8.166423
Sum squared resid	193442.5	Schwarz criterion	9.090638
Log likelihood	-5229.420	Hannan-Quinn criter.	8.512683
F-statistic	0.945140	Durbin-Watson stat	2.014799
Prob(F-statistic)	0.702529		

Table 1.2 - OLS regression using past year as the anchor, with extreme values

Apendix 2.

2.1 List of excluded companies

The following companies have been excluded from our sample since they either do not have an analyst following, or have been listed on Nasdaq OMX Stockholm for less than a year. Therefore they have no (or a very limited amount of) EPS forecasts to analyze.

Company	Industry	ICB-code
Lifco	Industrials	2700
Bravida	Industrials	2700
Coor Service	Industrials	2700
Nobina	Industrials	2700
Troax	Industrials	2700
Viking Supply	Industrials	2700
Wise Group	Industrials	2700
CLX Communications	Technology	9500
Tobii	Technology	9500
Novotek	Technology	9500
Stockwik	Technology	9500
Blackpearl	Oil & Gas	500
Lundin Mining SDB	Basic Materials	1700
Stora Enso	Basic Materials	1700
Autoliv	Consumer Goods	3500
Dometic Group	Consumer Goods	3500
Gränges	Consumer Goods	3500
Scandic Hotels Group	Consumer services	5300
Melker Schörling	Financials	8600
Latour	Financials	8600
Bure	Financials	8600

Creades	Financials	8600
Collector	Financials	8700
D. Carnegie & Co B	Financials	8600
HEBA	Financials	8600
Hoist Finance	Financials	8600
Öresund	Financials	8600
Havsfrun Investment	Financials	8600
Hexatronic Group	Technology	9500
Midway Holdings	Financials	8600
Nordax Group	Financials	8300
Novestra	Financials	8600
NP3 Fastigheter	Financials	8600
Pandox	Financials	8600
Svolder	Financials	8600
Traction	Financials	8700
Addlife	Health care	4500
Attendo	Health care	4500
Camurus	Health care	4500
Capio	Health care	4500
Feelgood	Health care	4500
Ortivus	Health care	4500

Table 2.1 - Excluded companies

Optimistiska finansanalytiker på den svenska börsmarknaden låter sig inte påverkas av historien.

En ny studie gjord av studenter vid det anrika Lunds Universitet visar att finansanalytiker på den svenska börsmarknaden inte påverkas av så kallad "anchoring bias" i samma utsträckning som deras kollegor på den amerikanska marknaden verkar göra. Dock finner studien tendenser till en annan faktor som påverkar sverigebaserade finansanalytikers träffsäkerhet.

Resultatet är intressant om än inte särskilt häpnadsväckande. Att den svenska aktiemarknaden på många sätt skiljer sig från den amerikanska är något som varit känt sedan tidigare. Anchoring bias ur ett finansiellt perspektiv kan kortfattat beskrivas som ett psykologiskt fenomen där man omedvetet utgår från redan tillgänglig information när man ska ta beslut och göra prognoser. För en finansanalytiker kan det exempelvis betyda att man lägger för stor vikt på förra årets vinst per aktie när man ska estimera nästa års vinst per aktie för ett bolag. Just att titta för mycket på föregående års vinst per aktie är något som verkar vara ett problem för många amerikanska analytiker, enligt flertalet studier som gjorts i ämnet. Konsekvensen kan bli ett stort "forecast error", på grund av att analytikernas estimat ligger för långt ifrån utfallet på vinsten per aktie och för nära förra årets siffror.

Men nu visar alltså en svensk studie att analytiker på den svenska marknaden inte verkar påverkas av anchoring bias i samma utsträckning. I studien jämförde man årliga koncensusprognoser från bolag listade på Stockholmsbörsen mellan 2008-2015 med föregående års vinst per aktie och det verkliga utfallet. Om prognosen hamnade någonstans mellan föregående års vinst per aktie och det faktiska utfallet räknades det som anchoring och betyder att analytikerna fallit i fällan för anchoring bias.

Men inga tester gav någon statistisk signifikans för att sverigebaserade analytiker verkligen påverkades av anchoring bias när man gjorde sina estimat. Man testade även att jämföra med industrisektorns median istället för förra årets vinst per aktie, utan att få fram några signifikanta resultat. Dock fann studien tecken på att analytikernas "forecast error" i högre grad istället beror på att man varit för positiva i sina estimat.

Att analytiker har en förkärlek att vara för optimistiska i sina estimat och rekommendationer är inte något nytt. Det är ett problem som präglat både den amerikanska och svenska marknaden under en längre tid. Efter IT-bubblan i början av 2000-talet har man börjat ta tag i problemet och överdrivet optimistiska estimat har minskat, men är än idag ett fortsatt dilemma.

Den svenska studien skiljer sig från flera andra studier som gjort liknande former av undersökning på andra marknader. Där kan man tydligare se tecken att analytikers "forecast error" påverkas av anchoring bias. Anledningar till att den svenska marknaden skiljer sig jämfört med andra marknader kan man i nuläget bara spekulera i. Storleken på börsen kan ha en betydande roll, då svenska analytiker har färre bolag att bevaka och fler möjligheter att få fram mer information som inte enbart kommer ifrån kvartals- och årsrapporter. Bolagens generellt sett mindre storlek kan också vara en faktor. Vi får helt enkelt se om framtida studier i ämnet kan ge oss fler svar.