An analysis of analysts' anchoring behavior

Master thesis financial economics

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Abstract

This thesis carries out a research into the behavior of security analysts. The main aim is to find if these analysts use anchors for their earnings per share predictions, and if so, which anchor they use. Two proposed anchors are tested; the prior year earnings per share and the consensus of the first three forecasts made after the announcement of the prior year earnings per share. I find evidence that the prior year earnings per share as anchor, especially when the change between the actual earnings per share and the prior year earnings per share is positive. The consensus of the first three forecasts is used more when the change in earnings per share is negative. This thesis does not find a conclusive answer to which anchor is used most.

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1 Introduction

The field of behavioral finance has always interested me, because I think the only true way to perceive the behavior of mankind can be achieved through seeing mankind as human. Although this might sound odd, most courses I have completed during my studies have assumed mankind in financial markets as completely rational beings. It is only human to make mistakes, and what might seem irrational might be true but on the other hand what might seem true can be irrational. Still a lot of the theories that assume human rationality are used today. When the opportunity came along to conduct research that questioned the complete rationality of the best forecasts in the market, I gladly accepted. The only way the field of finance can move forward is to stop assuming rationality, and this is an opportunity to help. The subject of anchoring is attractive because I think it is a bias almost everybody uses to make an estimation.

Behavioral finance

One of the first articles where psychology meets economics was written by: Daniel Kahneman and Amos Tversky in 1974. In their paper about judgment under uncertainty, they address multiple heuristics in human behavior that lead to biases that should not be able to exist under theories that assume rationality. One of the heuristics they present is anchoring and adjustment. Their definition comes down to this: a person is likely to use an anchor, when he needs to make an estimate of the occurrence of a phenomenon. He then adjusts his estimate from this anchor, but does not adjust sufficiently. This will result in an estimate that will fall between the anchor and the real value. In other words, people tend to overuse their anchor, which results in an underuse of other information.

Analyst literature

Quite some literature has been written about analyst forecasts and why these are inaccurate. Explanations were found for some systematic errors, which can be caused by intentional biases as well as non-intentional biases. It seems that as these analysts have a job that forces them to perceive the markets and make forecasts, they are excellent subjects to test for biases in their behavior. They can be called experts, as they devote a lot of time to produce these forecasts. Also there is evidence that the magnitude of earnings per share forecast errors could lead to job termination (Hong, Kubik, & Solomon, 2000), so they have a clear incentive to be accurate.

Hypotheses

The earnings per share (EPS from this point forth) forecast of an analyst is a good proxy for an expert opinion. If I are able to find that a heuristic is used in the forecasts of these analysts, I can conclude that even these agents do not live up to the assumption of rationality. The main focus of this thesis will be to see if the EPS forecasts of analyst are subject to the heuristic called anchoring and adjustment and what situations. It becomes easier to forecast the EPS for a given year when the first three quarters for that given year are known. To establish an environment where analysts are prone to using anchors, the forecasts have to be made in a time that there is not much certainty about the EPS. Thus only the forecasts made in the first three months are going to be tested. This is defined in the following hypothesis:

H1: Analysts use anchors for their EPS forecasts in the first three months after the earnings announcement under specific circumstances and fail to adjust sufficiently

The question that arises is what anchors these analysts would use. The anchor used should be a valid anchor and a relevant one at the time when the forecast is made. In the first three months after the announcement of the EPS, the prior year EPS is an anchor that is likely to be used. Therefore I expect that the analysts will use the prior year EPS as an anchor. In this thesis the emphasis will be on the properties of anchoring. The main goal of this thesis is to establish which analysts will express the heuristic of anchoring and adjustment, why and for which companies. Hong Kubik and Solomon (2000), as well as Mikhail, Walther and Willis (1997) show that experienced and inexperienced forecasters forecast differently. Because I expect experienced analysts to be better at forecasting I expect them to display the heuristic of anchoring less often. Therefore the following hypotheses will be tested:

H2a: Analysts use the prior year EPS as an anchor if they are inexperienced

As the volatility of company earnings becomes bigger, there will be more uncertainty about what the next EPS will be. Therefore I expect that there will be a positive relationship between the volatility of earnings for a company and the use of anchors. This is defined in the following hypothesis:

H2b: Analysts use the prior year EPS as an anchor if the volatility of the company is bigger

When companies are smaller, less is known about the company, because there normally is less analyst attention. For smaller companies it will be harder to forecast the EPS. My expectation is therefore that the size of the company has a negative influence on the behavior of anchoring. This is defined in the following hypothesis:

H2c: Company size has a negative influence on the behavior of anchoring

Das et al. (1998) and Easterwood and Nutt (1999) show that systematically analysts' forecasts are too optimistic. Analysts might only anchor then when the change in EPS from the prior year to the actual EPS is negative. Considering the optimism found in earlier papers, the expectation is that analysts use the prior year EPS more often as an anchor when the company produces a smaller EPS than the prior year. This is defined in the following hypothesis.

H2d: Analysts use the prior year EPS as an anchor if the company produces a smaller EPS than the year before

In literature concerning analysts, much attention has been dedicated to the evidence found that suggests that analysts herd. Herding means that analysts make forecasts close to a consensus. The consensus forecast could be seen as an average of the forecasts that are made by other analysts. In research, by Hong Kubik and Solomon (2000), proof has been found that herding is a consequence of career concerns. The authors find a theoretical basis for herding, because especially inexperienced analysts are more likely to be terminated when they make bold forecasts. As herding is a well-established phenomenon, the second anchor that analysts use might therefore be the first consensus of three forecasts. Evidence has been found that inexperienced analysts herd more often, so I expect to find that the inexperienced analysts also anchor more on the first three forecasts. This leads to the following hypothesis:

H3a: Analysts anchor on the consensus of the first three forecasts if they are inexperienced

The expectation is that when the volatility of earnings becomes bigger for a company, the job of forecasting the EPS will become harder. Therefore a test will be executed if the analysts anchor more when the earnings volatility becomes bigger. To test this property of anchoring, the following hypothesis is defined:

H3b: Analysts anchor on the consensus of the first three forecasts if the volatility of the earnings of a company is bigger

Company size is expected to have a negative influence on the heuristics of anchoring, because smaller companies will be harder to forecast the EPS for. Less is known about smaller companies because there is less analyst attention for these companies. The following hypothesis is therefore defined:

H3c: There is a negative relation between the company size and the amount of anchored forecasts on the consensus of the first three forecasts

As discussed above, analysts have the tendency to be too optimistic in their forecasts (Das et al (1998), Easterwood and Nutt (1999)). Therefore I expect that analysts will anchor more on the first three forecasts when the direction of the earnings change is negative. This is defined in the following hypothesis:

H3d: Analysts anchor on the consensus of the first three forecasts if the company produces a smaller EPS than the prior year.

The two different anchors are going to be tested with two regressions. The forecasts that are made using an anchor are going to be coded with a one; the forecasts that have not used an anchor are going to be coded with a zero. The anchor variables are going to be the dependent variable. With a binary regression the effect of the dependent variables experience, company size, earnings volatility and negative earnings change will be determined. To control for the year 1999, there will also be a dummy for this year. The testing period runs from 1993 to 2003. The data over these years will be pooled, so an overall measure of the effects of the independent variables will be measured.

Relevance

At this point not much has been written about anchoring in the analyst literature. Furthermore, only testing for the first three months after the announcement of prior year EPS is an approach, which has not yet been used in the literature concerning analyst behavior. The anchor proposed in this thesis, using the first three forecasts after the announcement of the EPS combines the herding literature with the anchoring literature. This subject has barely been tackled in economic literature.

In the next chapter the literature discussed in short above will be treated more extensively. Chapter three will contain the methodology. The fourth chapter will cover the data transformation, and descriptive statistics. In the fifth chapter the regression results, and tables of the econometric analysis will be presented. This will be accompanied by a discussion and an economic interpretation of the results. In the sixth and last chapter this thesis will be summarized.

2 Literature review

The field of behavioral finance consists of two different sciences, psychology and finance. Therefore the literature of this thesis will discuss papers from both sciences. First the papers about anchoring will be covered, to discuss which properties have been found in psychology literature and economic literature. Next literature about analysts will be treated. The analyst literature is split up in different sections because there are a lot of different perceptions on why analysts make errors. First there will be an intro into the strategic bias of forecasts. Subsequently I will discuss two different strategic biases in depth. First there will be a paragraph on optimistic bias, next there will be a paragraph on herding bias. The paragraph after this will discuss different papers that have tested analyst characteristics and their influence on accuracy of analysts. The following subchapter will discuss the papers that covered analysts and anchoring. The last subchapter will give a small summary of the whole chapter.

2.1 Anchoring

Over 37 years ago, Kahneman en Tversky (1974) published a paper that described several behavioral heuristics and biases. The three heuristics they discuss are ‘representativeness’, ‘availability’ and ‘anchoring and adjustment’. They define anchoring and adjustment as a way of underestimating new information and overestimating the chosen anchor. If someone has to make a forecast, say the number of people living in the second city of France, they choose a point with some relevance (for instance the amount of people living in Paris) and then adjust from that point and make an estimate. The shortcoming that people show is that the estimate is typically not adjusted enough, thus leading to a number that will typically be between the anchor and the real value. For the example concerning the number of people living in the second city of France, Kahneman and Tversky predict that, when given the number of people living in Paris, people will overstate the number of people living in the second city of France.

The properties of this heuristic have been tested more than once in different psychological and economic papers. Northcraft and Neale (1987) found some very convincing evidence by conducting a laboratory experiment (or field experiment). They tested if two different subgroups, real estate agents and a group of students, display the bias of anchoring and adjustment. The setup is that they see if a listing price of a house will influence their opinion on the price of this house. The individuals get a document containing ten pages of information on the house. The information is the same for everyone, except for the listing price. Apart from the information that they receive, they are also driven around the house to see the neighborhood and the surroundings of the house. The results show that the anchor has a significant influence on the price tag they put on the house. The results are the same for different subgroups, and even if the anchor is not realistic at all, it still has a big influence. We can thus conclude that the experts, who did not admit using the anchor, as well as the students with not so much experience in valuing houses both display this behavioral distinction.

Adding to the evidence that experts might display anchoring and adjustment, Wright and Anderson (1989) constructed another field experiment. They view anchoring and adjustment as a two-staged phenomenon. First people tend to remember a previous number (the anchor) and then adjust but fail to do so appropriately. They expect that if they increase the situation-familiarity, that the part of unintended anchoring disappears. In that way subjects might skip stage one of the estimation process and make an estimation based on new information. Again, the subjects display the bias. The subjects are asked if they think the chance on a phenomenon is bigger (smaller) than 0.25 (0.75) and how much bigger (smaller). In both the familiar situations to the subject (i.e. an phenomenon in a field they know) and the unfamiliar situations, the chances given, i.e. 0.25 and 0.75, have a big influence on their estimate. Again this can also be seen as evidence that experts also use anchors.

Adding to the fact of anchor relevance, Whyte and Sebenius (1997) test if multiple anchors have a decreasing effect on the anchoring bias. According to the authors, there is reason to believe that multiple anchors, somewhat creating confusion, might decrease the effect of anchoring and lead to better estimates. Their results show that the first number the subjects see has a significant influence. Even after they have been presented with more relevant numbers later on, the first number they see still has an effect. Interestingly they documented the same conclusion as Northcraft and Neale (1987) that even when the number does not have any relevance at all, the anchor still has an influence. They even go as far as including a number in a document and tell the subjects that this number is a typing error. The conclusion that can be induced from this research is that any number could be of influence on the anchoring of human beings. This research suggests that there are numerous possible anchors for analysts from which they can depart to make their forecast.

One would assume that groups would not be subject to anchoring, but this does not hold either. Ritov (1996) tested if, in negotiations, anchoring will also influence the price the negotiators agree to. In a field experiment, she tests whether the format of the profit schemes in a negotiation between a buyer and seller will have an influence on the outcome of the price they buy and sell at. In this setup, Ritov gives the subjects the same profit schedule, but gives some buyers an ascending profit schedule and some buyers a profit schedule that is descending. The different formats lead to different outcomes again, thus showing the effects of anchoring. Similar to the other papers discussed above, she also finds that anchoring is a phenomenon that is very likely to be detected at experts as well. She repeats the set-up and finds that the effects of anchoring do not decrease, implying that anchoring is not conditional on experience. Papers that will be discussed later in this thesis suggest that experienced analysts behave differently then inexperienced analysts. In this thesis the expectation is to find contradicting evidence.

Given the literature on anchoring, the conclusions seem to be overwhelming. First of all, it seems that it does not matter if the subjects are experts on the phenomenon to be estimated. The experiments show that there will still be anchoring. Strangely, it even persists in negotiations, where one might expect that different opinions and discussions on the matter might decrease the influence of the anchor.

Most interesting and maybe alarming are the conclusions from Northcraft and Neale (1987) and (Whyte & Sebenius, 1997), that the anchor might not be relevant at all but still persists in the estimates, even for experts. With regard to this thesis that would imply that financial analysts could base their EPS forecasts on the time of the alarm clock when they wake up, or the number of the floor they need to go to when they go to their jobs.

2.2 Analysts' forecast literature

A lot has been documented on analysts for a few simple reasons. When Kahneman and Tversky(1974) put the rationality of humans but especially economic agents to discussion, they suggested that there might be a lot of different, non-rational biases in expectations and forecasts. To test these implications, we need to define economic agents first, and second, we have to find their documented expectations. It goes without saying that security analysts belong to a group that satisfies both these constraints. As they have made a living out of interpreting economic information, processing it and making an estimate about future earnings, they seem to be the perfect subjects to test the rationality of economic agents. We can safely assume that the analysts invest an optimal amount of time in making forecasts. Hence, we can call analysts experts in the field of stock markets.

The next subchapter will be about the optimistic bias because this was documented already two decades ago. Later in this chapter some extensive literature on the herding bias will be dealt with. Finally the papers that cover the characteristics of the analysts will also be discussed in order to give a complete overview of the factors influencing analysts' behavior.

2.2.1 Strategic bias

If we can detect biases that are unintended in the behavior of analysts, we can thus assume that the markets are not rational, because they are a proxy for the best opinion in the market (Bondt & Thaler, 1990). Another important reason for testing securities analysts is that they are found to have influence on the stock market (Brown, Foster, & Noreen, 1985)). Also they have proven to outperform different time-series models in forecasting, so we can assume they are good at what they do (Conroy & Harris, (1987)).

The problem with actually finding human errors with these economic experts is that there are strategic reasons for them to bias their forecasts, including herding. Due to career concerns, they might be better off mimicking the forecasts of others. In this way, the analysts might underestimate their own information or simply discard it, because they think the likelihood of their information being right seems small if a lot of other analysts come to a different conclusion, according to Scharfstein and Stein (1990). Also, the reputations of analysts are jeopardized if they make bold forecasts that are wrong. There are also strategic reasons to divert away from the existing consensus at the moment of forecasting. Standing out of the crowd by making a bold forecast that proves to be right, can also enhance a reputation. Apparently analysts get better bonuses when they are elected for top analyst rankings (Stickel (1992)).

Another widely discussed form of strategic bias is the optimism bias. As analysts work for big brokerage houses and investment banks, companies could be favored if their EPS forecasts are positive. Optimistic forecasting by analysts could lead to underwriting business for the investment banks they work for (Hong and Kubik (2003)). Another reason to forecast optimistically could be to generate trading flow if the analyst works for a brokerage or investment bank. It is even documented that some analysts get bonuses for the trading flow they cause. Another possible reason is documented by Das et al.(1998), who state that analysts who forecast too negatively can be excluded from information by companies. Taking this into account, being optimistic might be a direct exchange of favors

2.2.2 Optimistic bias

In 1990, De Bondt and Thaler published an article concerning biases in analysts' forecasts. Because they were puzzled about the reversal anomaly of stock return, they investigated overreaction in the stock market. In this paper, they assume that the forecasts of security analysts are the best proxies of market expectations, and investigate if overreaction occurs. They regress the forecasted change on the actual change and come to three conclusions. They find that forecasts are too optimistic, too extreme and more extreme if the forecasts are two years ahead. Therefore they conclude that the market is not rational.

Abarbanell and Bernard (1992) retest the work of De Bondt and Thaler, because they think they have misinterpreted their findings. In their search for an explanation for anomalies in the stock market, they find that the analysts' forecasting error can be contributed to the lack of fully processing the last EPS change. They also find the same overreaction results as De Bondt and Thaler, but only for the first quarter. For the other three quarters they find underreaction. Their main conclusion is that security analysts underreact to news rather than overreact.

The papers above are conflicting, but Easterwood and Nutt (1999) seek to reconcile both underreaction and overreaction. They view the question as follows. If analysts systematically underreact to news, this is evidence of non-rationality or continuous misinterpretation. If analysts systematically overreact, this would also be an example of consistent errors in interpretation. If they are systematically optimistic, this would mean that they consistently underreact to negative earnings news, and overreact to positive earnings information. They state that systematic optimism would show that analysts misinterpret the information on purpose. Their research uses the mean and median of the forecasts made after the prior year earnings are announced. They first test the same equation as De Bondt and Thaler (1990) and find similar outcomes of overreaction. They also test the equation of Abarbanell and Bernard(1992) and they also find significant underreaction. It seems that none of them is wrong according to these authors.

The authors then divide the earnings in quartiles and use dummies for the highest and the lowest quartile. The results are that the changes in the analysts' forecasts are too small when the earnings fall in the lowest quartile, and too extreme when earnings are in the highest quartile. Analysts may not be irrational, but upwardly bias their forecasts too much for strategic reasons

Another interesting study is conducted by Das et al (1998). They argue that when companies have low predictable earnings, analysts can stand out of the crowd by predicting right. They state that analysts will try to get more private information on those companies in order to make a better estimate. According to the authors, the analysts who forecast pessimistically are removed from mailing lists and excluded from conference calls. It will give an incentive to forecast too optimistically for these companies, if this will lead to getting private information. That is why they test cross sectional on analyst optimism for different companies. They rank predictability in three different ways to make sure that their method is not biased. First, they match predictability with the variability in the time-series of earnings. Secondly, they examine the same time-series of earnings with the variability of the market return. Thirdly, they specify the predictability of companies through the ranking of value line on predictability of companies. They find a negative relation between predictability and optimistic bias, for all three measures of predictability. Their explanation of analyst' optimism seems a plausible one.

As we have seen, the optimistic bias in forecasts has been analyzed empirically and explained by economic incentives. The mere fact that analysts make errors in their forecasts is not yet a reason to close the door on rationality, because, as has been determined, they might have good reasons for it. Some more literature on analyst' optimism will be covered in the section on forecast accuracy.

2.2.2 Herding bias

Scharfstein and Stein (1990) were one of the first who tried to rationalize the behavior of forecast herding. They construct a model in which agents receive different information. The agents do not know whether their information is relevant or not. The labor market for the agents will determine if the information that analysts have used is good by looking at the accuracy of the forecasts. The paper describes the situation in which an agent has information that differs from the other agents. The agent might be rational to discard his information and make a forecast that mimics other forecasts. If an agent uses his different information, and it turns out not to be good information, the market will perceive his skills as low. On the other hand, if he is the only one with good information, but uses the forecasts of others to make his own forecast, he will not perform worse than other forecasters. It seems that, when the information of one forecaster is different from the information of other forecasters, it is rational to herd; their reputation will not be hurt too much.

In Stickel (1990), the author tries to predict the forecasts made by analysts. He shows that using the consensus change, one can predict the revision of individual analysts. The R^2 of his regression is 0.38 implying that he can explain 38 % of the variance in these revisions. This indicates that either the analysts show signs of herding, or all use the same information and process it the same way. Later on in this chapter the second explanation will be discussed.

Cote and Sanders (1997) investigate the model of Scharfstein and Stein (1990) and try to find some properties of herding. They conduct a field experiment and choose their subjects carefully to mimic the surroundings of analysts. For this reason they picked an investment club and let the subjects forecast the earnings of different companies. While they are members of this investment club, they can lose their good reputation if their forecasts are completely wrong. In other words, they have a reputation to protect.

They suggest conditions needed for herding and test these. One condition they suggest is that analysts with low self-esteem or low self-assessed ability are prone to herding. Otherwise said, this is a reason for analysts to think that their information is bad. Another condition for herding is superiority of other subjects. If an all-star analyst makes a forecast, people are prone to believe that his forecast will be better than the one they come up with. In this way, the subjects weaken their own beliefs and herd towards the forecast of the one they believe will make a better forecast. They think herding is source-dependent.

Another interesting property they suggest is, that people might tend to herd more when the consensus itself has low dispersion. This means that if the consensus seems to be a forecast many people agree with, it gives way to herding. This theory might work the other way around as well. If there is a big variation in the forecasts of the consensus, this might point to the fact that the EPS are hard to forecast, thus giving way to the low self-assessed forecasters to herd their forecast to someone they think highly of. The results are as follows. They find herding at people with low self-assessed ability. Next to this a consensus with low variation is a consensus that will be used to herd on. They also find that given an opportunity to build or keep a reputation, people will herd more. A dispersed consensus does not induce herding behavior.

In Hong, Kubik and Solomon (2000) the authors try to determine if these features of herding show up in the analysts' business as well. They look at analysts' incentives in two ways. On the one hand, they need to be accurate for the buyers of their forecasts, on the other hand they need to be optimistic for the brokerage firms they work for in order to generate investment banking services and trading volume for the brokerage. Ultimately, they try to determine what could be career outcomes for analysts if they are experienced or if they herd or not.

They look up the analyst' codes to see if they move to bigger brokerages, in their definition these are brokers who supply jobs for more analysts. They can also see when the analysts' codes are removed from the sample, thus suggesting they are terminated from their job. Of course there are far more reasons for being terminated, such as job switches, promotions to other jobs at the same bank, etc. But naturally, all analysts who lose their jobs will also be deleted. They investigate some conditions that could lead to being fired, they investigate if the chance of being fired has a negative relationship with accuracy and they investigate if the chance of being fired increases by being bold, controlled for accuracy. They test both chances for inexperienced analysts and for experienced analysts. They conclude that the worst forecasters are fired fastest, measured by past accuracy. Also, being bold and inexperienced leads to faster job termination. Ultimately, they conclude that being bold and wrong increases the chance of being terminated, but also being bold and right does not significantly lead to a job at a better broker. This could very well be seen as empirical evidence that herding might be rational. Next to this they come to other conclusions that are interesting. They find that inexperienced analysts herd more than experienced analysts. This could very well be because they will be terminated earlier than experienced analysts for being bold. They also find that experienced analysts enter their forecasts significantly earlier than inexperienced analysts.

Clement and Tse (2005) extend the paper of Hong Kubik and Solomon by investigating which analyst' characteristics influence bold and herding behavior of analysts. They find similar results as Hong, Kubik and Solomon concerning being fired for making a bold forecast whether you are inexperienced or experienced. In addition, they also find empirical support for inexperienced analysts to have an incentive to herd. Most importantly, herding does not improve the accuracy of the forecasts. This means that, although analysts have strategic incentives to herd, it causes them to be less accurate. They also find characteristics that could explain bold forecasts. For instance bold forecasts are more often made by experienced analysts, albeit other factors explain bold forecast at least as well. These comprise accuracy, the size of brokerage firms the analysts work for, and the frequency of the forecasts.

As we have been able to see there are reasons for herding to exist, and in this line of thinking there are reasons to bias forecasts on purpose. This means that a lot of analysts working in the business do not display their true skills through their forecast, but rather mimic the forecasts of others. On the other hand, it might not be their fault, as has been proven, that they do have clear economic incentives to herd. Luckily there is also evidence that experienced analysts do not herd, and their forecast do show their real believes.

2.2.3 Analysts' accuracy and characteristics

After my discussion of the biases that some analysts seem to exhibit in their forecasts on purpose, I will now discuss literature that examines the accuracy and the characteristics of accurate forecasters. Although some articles touch upon the subject of herding, the main focus of these articles is on accuracy.

Analyst rankings and performance-based compensation

Stickel (1992) is an article about the analysts ranked in the Institutional Investors All-American Research Team. This ranking is based on analysts who are elected by institutional election through voting. Being on the team increases salary a great deal according to Stickel. As he thinks that analysts who often revise are more accurate, he uses this as a proxy for analyst performance. Apart from this, he also uses accuracy and the impact on the stock market of the individual forecasts as measure for performance. He finds a positive relationship between reputation and performance. He also finds that if analysts are on the list they are more accurate and revise more often. Interestingly, getting on the list increases the accuracy in the next period, which might be a sign that self-assessed ability is an explaining factor for accuracy. However being removed from the list does not decrease the accuracy of analysts.

Mikhail, Walther and Willis (1999) state that the bonus on top of the salary of analysts is not determined by accuracy, but rather by the trading volume they stimulate and the investment business for the brokerage they generate. This bonus can be one to three times as large as the base salary, thus implying that incentives to be accurate are outweighed by incentives to attract business for the brokerage. They conclude that in the end, being less accurate than peers who forecast in the same industry, will lead to job termination. This means that, although the bonuses are not given for accuracy, the analysts still need to be reasonably accurate if they want to keep their jobs.

Kutsoati and Bernhardt (1999) see this matter quite differently. They think the bonus structure is a driver for accuracy. They argue that accurate analysts attract more clients to the brokers. Brokers will receive more commissions because of their growing client base, and hence generate more profits. For this reason relatively better forecasters are wanted by the brokers and will be rewarded with more salary. This can be interpreted as a bonus for attracting business. As relatively better forecasters are wanted, they have incentives to overuse their private information, so their skill can be determined quickly. They want to test if their reasoning is right and investigate if the last forecast is biased away from the consensus and will overshoot or undershoot the actual EPS. This is because they put too much weight on their private information. The idea is that analysts are not irrational, but issue bold forecasts on purpose because they are judged on being relatively good, and not on absolute forecast errors. This is a reason not to herd.

They find that 62% of the last forecasts are biased away from the consensus, and overshoot the actual EPS. In other words, if the existing consensus before the last forecast will be below the actual EPS, the last forecast will be above the actual EPS. The same holds when the consensus was above the actual EPS. They find that just by taking the average of the two (the consensus and the last forecast) will yield a better forecast than both apart. They do find that when there are more analysts following a company, the bias becomes smaller. This shows that the last forecaster might not be influenced if 10 forecasts were made before his, but will be influenced to not overweight his information if 40 analysts have made a forecast close to the consensus. On top of this, they find that investors in the stock market do value this last forecast. Stocks react positively if the last analyst makes a forecast that overshoots the actual value positively and vice versa.

Hong and Kubik (2003) test if analysts move to bigger brokerages if they are more accurate. This is another way to examine if there are incentives to be accurate. They do find some significant evidence that being accurate might lead to a better job, but also that being optimistically helps a great deal. The latter occurred especially during the inflation of the dot-com bubble. In these years, being optimistic was more important than being accurate.

Analyst experience and forecast accuracy

Brown, Richardson and Schwager (1987) constructed a model to investigate if company-characteristics lead to superior forecasts. As will be seen later, they control for timing advantage, as later forecasters have had more chance to pick up new information that earlier forecasters could not have incorporated yet. Their main conclusion is that the size of the company and the prior dispersion in forecasts has a significant relation with superior forecasts.

An interesting research has been conducted by Clement. Clement (1999) tests the cross section of analyst forecast errors to determine why analysts perform better, measured by accuracy. He controls for firm-year effects because he thinks that some companies are more difficult to predict in some years than other companies. Accuracy is the dependent variable in the regression and the independent variables are experience, the size of the brokerage firm the analyst works for and the number of companies that an analyst follows. These variables proxy for respectively skill, the access to information for the analyst and the difficulty of the job for the different analysts. He finds a positive correlation for the size of the brokerage firm and experience and a negative correlation between accuracy and job difficulty.

Mikhail, Walther and Willis (1997) theorize that the explaining factor for forecast accuracy should be experience in making forecasts for the same company. They are puzzled about the way this experience is obtained. They use a mechanism behind experience that they call 'learning by doing' (LBD), that proved to be a good explanation for accuracy. Their measure for experience is the amount of quarters that an analyst has forecast. They find that forecast errors of analysts decrease with frequency, thus supporting their LBD-model. Also, they find that forecast errors decrease when there is more information available on companies. The authors also explore how the market reacts to these forecasts. It seems that, measured by the three-day cumulative average stock return, forecasts of experienced analysts have a significant influence on the stock market, which outweigh that of inexperienced analysts. This seems intuitive; especially experienced analysts seem less prone to herding.

Although the explanations based on experience seem plausible, Jacob Lys and Neale (1999) find some other explanations. They also conduct research towards the difference in forecast errors amongst analysts. They are also fascinated by how experience is gained, and propose, in addition to the LBD explanation of Mikhail et al. (1997), two more explanations superiority in forecasting. Their first proposed explanation is aptitude. They think that the ability to become good at something is more important than just experience. This explanation of skill thus suggests that there are different levels of aptitude amongst analysts, which essentially means that some analysts just have more talent to forecast a certain company than others, and hence pick up this skill fairly quickly. Other analysts might not be good at forecasting a particular company and switch to another company. The third explanation for development of forecast skill concerns environmental factors. They use brokerage firm size as a proxy for this factor.

First they test for experience as a measure for forecast accuracy. As most of the other papers written, they find that experience has a significant positive influence on forecast accuracy. Conversely, the amount of different companies forecasted, which Mikhail et al. (1997) use as a proxy for job difficulty, has a negative correlation with forecast accuracy. Apart from the two factors, number of companies and experience, industry specialization, for example, is a factor that captures analysts who only forecast in a particular industry. Industry specialization has a positive relationship with accuracy. Another example is the phenomenon that frequent forecasters are more accurate than forecasters that do not revise much. With regard to environmental factors, they also find some important results. Brokerage firm size has a significant influence on accuracy, as well as the amount of analysts within the brokerage that forecast in the same industry. This shows that the environment of the brokerage firm itself can be an important factor. Also, the percentage of analysts that leave a certain brokerage firm seems to have a negative effect on the accuracy of the analysts of that particular brokerage firm.

The authors come with an important note, that it is not experience that might be an explaining factor but something else. They mention that maybe good forecasters stay longer in the profession of forecasting, while most importantly; less accurate forecasters lose their job, and leave the sample. In this way experience can be interpreted as survivorship bias. The group of experienced analysts is just the forecasters that survive for a long time because of this fact.

They retest the regression with analyst firm pairs to control for aptitude and find that the significance of the factor experience disappears. The interpretation of this result is that it is not learning by doing that is the explaining factor for experience, but the ability to become good at forecasting. If it would be learning by doing, all analysts would be able to get good at forecasting. This is not the case because aptitude differs between analysts, and the ones that have this ability will stay in the sample longer and form the group of experienced analysts. The ones that do not have the ability disappear from the sample. They conclude that differences in accuracy are dependent of the environment of the analysts and their aptitude.

Analyst accuracy and timing of forecasts

Cooper, Day and Lewis (2000) show some interesting insights on how herding analysts and non-herding analysts time their forecasts. On the one side, analysts have incentives to generate trading volume while on the other side not being accurate can lead to job termination. Hence, good and bad forecasters have incentives to time their forecasts differently. Superior analysts have incentives to bring their forecasts early, because this will create more trading volume, and they are confident that they are good forecasters. Conversely, forecasters who know they are not that good have an incentive to wait to bring their forecasts until they have a chance to pick up some information from the better forecasters.

The authors construct a time line to examine the timing of forecasts. Typically, an early forecaster, called a lead-analyst, will submit his forecasts randomly and not specifically right after others. Followers will be quick to revise or submit after the forecast of a lead-analyst. Lead-analysts are defined by the cumulative days of forecasts issued, divided by the cumulative days of forecasts made after his forecast.

They conclude that when using stock price response, forecast accuracy or abnormal trading volume as measure of identifying informative forecasts, the lead-analysts make the most informative forecasts. They explain that accurate forecasts can also be measured for herding analysts who mimic the forecasts of good forecasters. This is an important conclusion as it puts the best forecasters in a completely different frame than most other articles do.

Combining and concluding literature

Brown (2001) investigates which analyst characteristics best explains forecast accuracy. Brown conducts a quite small research to determine if either Clement (1999) or Stickel (1992) best captures analysts' characteristics. I.e. which model is the better in predicting forecast accuracy. Stickel (1999) uses past accuracy measured by mean average forecast error, while Clement (1999) defines five analysts' characteristics that should explain forecast accuracy. These comprise general experience, company experience, the amount of companies covered, the amount of different industries and the brokerage firm size for which the analysts work. He also controls for the days until fiscal year end, to adjust for the better accuracy from being later with forecasts.

The model of Clement, which is more complicated and uses more explaining variables, does not perform better. Surprisingly, both models work equally well with some small advantages for the past accuracy model. For example, the best decile of past forecast accuracy performs 31.9 % better than the average. The best decile of the analyst characteristics performs 31.6% better than the average. The conclusion is that, although analyst' characteristics capture properties that are useful when determining whether an analyst is good or not, the best way to determine which analysts are best is by checking the previous accuracy of the analysts.

2.3 Anchoring in analysts' forecasts

Research in analysts' forecasts is scarce. The first research that I have found combining analysts' forecasts and anchoring, is Stevens and Williams (2003). They conduct a field experiment with analysts and try to find out whether the subjects show biases in their forecasts (Stevens & Williams, 2003). They find evidence that the subjects anchor on their own forecasts when they need to revise.

Campbell and Sharpe (2009) do not test security analysts' EPS forecasts, but find interesting evidence of anchoring. They use the Money Market Services surveys (MMS-surveys) to test forecasts. The MMS-surveys are surveys that ask market agents to forecast certain macro-economic variables on a monthly basis. They use both the average and median forecast, because forecasts can experience a skewed distribution. They find significance evidence that the agents who filled in the MMS-survey, anchor on the previous month's value of the variables they need to forecast. Paradoxical as it seems, they find evidence that the market itself is not irrational or biased. Although their research suggests a bias in predictions of the forecasters, they find that their bias does not influence market prices of assets that use these macroeconomic variables. They interpret this as evidence that the markets know that the forecasts are biased, and correctly adjust for anchoring by analysts.

Cen, Hilary and John Wei (2010) conduct research on the same topic as this thesis, although there are substantial differences with my approach. The authors first interview six security analysts and ask them which values they might use to forecast the EPS. From these interviews they infer that analysts use the industry median forecast as an anchor. The interpretation is quite odd, because this means that the number of shares of a company within an industry is a determining factor for the forecasts made for that company. However, earlier we discussed that even the most irrelevant anchors may be used. Their results show that the anchor variable is significant, also when including additional control-variables. They also find that if the average forecast of analysts is above the industry median, this will lead to positive stock returns, especially around announcement dates. They also test if the median price of industry could be an anchor, but find no significance.

2.4 Conclusions on literature

As can be inferred from this chapter, both experts and non-experts are prone to anchoring when it comes down to predicting numbers. The heuristic does not disappear when more anchors are added, as people seem to focus on the first revealed number. Next to this, even in negotiation with individuals with different opinions, anchors still influence the outcome of estimations. Although thinly covered equity analysts may also exhibit anchoring behavior. The only difficulty might be to find the right anchor. Northcraft and Neale (1987) show that even if the subjects are told a number has no relationship with the phenomenon to be forecasted, it can still be used as an anchor.

Next I discussed the topic of optimistic biases. It seems that being optimistic in your forecasts can really help your career. This means that there might be an asymmetry in the forecasts, because when the EPS change is positive, the forecasts might overshoot the EPS, and when the EPS change is negative analysts will not disperse as much from the prior year EPS. This leads to the expectations that anchoring might be conditional on the direction of change.

Herding bias could be a special case of people anchoring on the forecast of lead-analysts. The results of this thesis might put a different perspective on the phenomenon of herding. This is why the consensus of the first three forecasts is also a proposed anchor.

Subsequently, we covered the characteristics of analysts' accuracy. As Jacob, Lys and Neale (1999) show, the groups of inexperienced analysts and not experienced analysts probably have different compounds. If we follow their theory, the group of inexperienced analysts consists of skilled and less skilled analysts. The group of experienced analysts consists predominantly of skilled analysts. Adding to that, it has been documented that inexperienced analysts might herd more, or maybe anchor more often on other forecasts.

Sharpe and Campbell (2009) find strong evidence that forecasters herd on the last piece of relevant information the analysts have got. This means that I might find significant anchoring after the prior year earnings are announced, as this definitely seems a logical anchor to use.

3 Methodology

In this chapter the methodology will be described. First I will discuss where the idea came from, subsequently the dependent variables will be treated. After that I will state the independent variables. The last subchapter will deal with the regression model and the interpretations that will be used.

3.1 Methodology idea

The idea for the methodology of this research is based on the definition of Kahneman and Tversky (1974). They define the use of anchoring and adjustment as follows: "When people use an initial value to estimate a quantity, they adjust to obtain the final answer, but do not adjust sufficiently". This means that in this thesis, anchoring will be defined as a forecast that lies between the anchor and the actual value of the EPS. In the papers discussed in the previous chapter there are two that have investigated anchoring in analysts' behavior through their forecasts. They both use the same definition to determine anchoring. Kahneman and Tversky(1974) cover that individuals seem to make errors because of anchoring, and their theory should thus be tested on individual forecasts. Although the two papers (Campbell & Sharpe, 2009) and (Cen, Hilary, & Wei, 2010) use the consensus approach, the way they determine anchoring and adjustment for a forecast is the same. Something they also have in common is that they try to explain forecast error through anchoring. This is where this thesis will differ from their approaches.

In the paper of Campbell and Sharpe, they test the following equation:

$$S_t = \gamma(F_t - A_h) + e_t \tag{1}$$

In this equation:

- S_t stands for surprise and is defined as: S_t = (Actual EPS) - (mean forecast)
- γ stands for the parameter that will be estimated
- F_t stands for the forecast value
- A_h stands for the anchor that they test

- e_t stands for the error term

In their research Campbell and Sharpe find a significant and positive γ meaning that they find evidence that at least the consensus is biased, using anchoring. This is evidence that an anchor can be defined as an estimate between the anchor and the actual value, for that is the only situation γ is positive for.

3.2 The dependent variables

In this research, I test individual forecasts. This gives us the opportunity not only to investigate if anchoring and adjustment impact forecasts of experts in financial markets, but also to see in what situations this occurs. I think it is not important to explain forecast error by anchoring, but instead explain anchoring by the characteristics of the analysts and the companies. This might give some properties to the phenomenon of anchoring, and will give it meaning instead of just determining that the phenomenon exists. If I can see that anchoring occurs mostly with inexperienced forecasters or companies that experience high volatility in their earnings, it might be seen as intentional to hide lower forecast ability. If all analysts use anchoring, we have reasons to extrapolate their forecasts to obtain better forecasts, and we can conclude that other reasons may prevail.

As there is no scale in anchoring, the best way to make the dependent variable is to make it a binomial variable, which is a unique approach. Anchored forecasts will be coded with one, and zero will code non-anchored forecasts. By the ratio of anchored forecast versus non-anchored forecasts, a reasonable conclusion about the phenomenon of anchoring can be made. As I investigate two possible anchors in this thesis, this enables me to detect which anchor is used most. The result of this thesis can also very well be that both anchors are not the anchors that are used in practice, or even more strongly, that anchoring that does not appear in EPS forecasts.

The first of the two different anchors that are going to be tested in this thesis is the prior year EPS. The prior year EPS is a logical anchor to use in the first three months after the earnings announcement. Also Campbell and Sharpe (2009) finds evidence that forecasters in the financial markets anchor on the previous value of the number to be forecasted. We want the forecasts that are made when there is much uncertainty about the next EPS, so only the forecasts made in the first three months after the announcement of the EPS are tested. In this way the prior year EPS will also still be a relevant anchor to use.

The second anchor that will be tested is the first consensus of three forecasts. As there are three forecasts, the average can be used, as well as the median of those three. This idea comes from the herding literature and from the paper of Cooper, Day and Lewis (2000). It seems that analysts often make forecasts that are dependent of other forecasts, or even similar. Cooper, Day and Lewis (2000) find that follower-analysts often revise their forecasts when lead-analysts make a forecast, and mimic this last forecast. When the first three forecasts are determined, the forecasts made in the first three months after the announcement of the prior year EPS are taken. In this period there is much uncertainty about what the EPS will be.

For both the different anchors the way of coding will be the same. A forecast will be coded one if they are between the anchor and the actual EPS, and zero if they are not:

Anchor-variable = 1 if Actual > Forecast > Anchor or Anchor > Forecast > Actual.

Otherwise the anchor-variable will be equal to zero. If for instance the actual value is \$1.00, and the prior year EPS is \$0.40 all forecasts that are between \$0.40 and \$1.00 are anchored forecasts.

3.3 The independent variables

One of the independent variables that are going to be used is the earnings volatility, because this is a measure of difficulty-level of forecasting the earnings for a company. The earnings volatility is going to be taken over the five previous years. This implies that if a company has not been in the S&P 500 for at least six years between 1993 and 2003 we cannot use the forecasts for that company. I take total earnings and calculate the volatility five years. This variable is named "LNEARNVOL"

Another measure of difficulty-level is company size. As the size of a company becomes smaller there will be less analyst attention, and thus less known about the company. For the variable company size, I will use the natural logarithm of the total assets. The variable will be called "LNSIZE"

Experience is another widely documented important analyst-specific variable. As has become clear from other papers, groups of experienced and inexperienced analysts behave differently. I obtain data from January 1988 until and including December 2003, but test from January 1993 until and including December 2002, this enables us to make a clear distinction between experienced and inexperienced analysts. The cut-off line will be at three years, which requires no further modification, because I can look five years back in my sample. Experience becomes a binary variable, with a value of one for inexperienced analysts, and zero for experienced analysts. This variable is named "INEXPERIENCE"

The forecasts in the running up of the dotcom crisis have to be handled carefully, as the article of Hong and Kubik (2003) finds that being positive was more important than being accurate in that period. This implies that in this period, we might find a higher frequency of forecasts overshooting the actual EPS. Therefore I will control for the year 1999, by introducing a dummy-variable, which equals one if the forecast is made in the year 1999 and a zero otherwise. This variable will be called "YEAR1999"

The forecasts where the actual EPS is smaller than the prior year will also be coded. This is because of the possibility that I might find optimism that analysts seem to show on purpose. Moreover it enables us to see if analysts anchor more when the EPS change is negative or positive. It would then be of value to see if analyst use one of the two anchors if they expect the EPS to be higher or lower then the previous year. Following Hong Kubik and Solomon (2003), we would expect a lot more anchoring in years that the EPS drops relatively to the prior year. When the actual EPS is less than the prior year EPS, the dummy will take a value of one when that is the case, and a zero otherwise. This variable will be called "NEGATIVE"

3.4 The regression

The sample used for this thesis exists of homogeneous datapoints. All the different years and different companies are put in the same sample thus I have a pooled sample. This implies that all the observations will be tested as being equal. As the dependent variable in this thesis is binomial, the chance that the independent variables are linearly related to the dependent variable is minimal. The linear probability model also gives results that are more than one and less than zero, which would imply that the chance that a particular forecast is anchored is more than 100 % (Brooks, 2008). Therefore it is best to use a transformation that scales the outcomes of the function between zero and one. In this thesis I will use a generalized linear model (GLM). A GLM will transform the results of a linear regression with a link-function between zero and one. The GLM estimates the regression using Maximum Likelihood estimation. The parameters for the model are thus chosen to jointly maximize the Log Likelihood Function.

If we fill in the variables discussed in the previous subchapter, the regression will look like:

$$Z_i = \beta_0 + \beta_1 * LNEARVOL + \beta_2 * LNSIZE + \beta_3 * NEGATIVE + \beta_4 * INEXPERIENCE + \beta_5 * YEAR1999 + \epsilon_i \quad (2)$$

The variables used stand for:

- LNEARNVOL stands for the natural logarithm of the earnings volatility
- LNSIZE stands for the natural logarithm of the total assets
- NEGATIVE is a dummy variable which equals one when the actual EPS is less than the prior year EPS, otherwise it equals zero
- INEXPERIENCE is a dummy variable which equals one when the analyst is inexperienced when the forecast is made, otherwise the dummy equals 0
- YEAR1999 is a dummy variable that equals one when the forecast is made in the year 1999 and otherwise equals zero
- ϵ_i stands for the error term

For a binary dependent variable it is best to use either the logit link-function or the probit link-function according to (Brooks, 2008). The logit link-function will transform the outcomes of the model above in the following way:

$$P_i = \frac{1}{1+e^{-(z_i)}} \quad (3)$$

- P_i is the probability for observation i to be equal to one.
- Z_i is the outcome of formula 2.

The probit function uses the cumulative distribution function. The formula transforms the outcomes of Z_i to a probability using this formula:

$$P_i = \frac{1}{\sigma\sqrt{2\pi}} e^{-0,5(Z_i^2/\sigma)} \tag{4}$$

- P_i is the probability for observation i to be equal to one.
- Z_i is the outcome of formula 2.

Normally, the probit and logit models give similar outcomes. This is not the case when the proportion of the dependent variable is close to one or close to zero. In that case, we might as well use them both, so we can at least interpret the chances for some independent variable between two percentages (the logit outcome and the probit outcome). The logit outcome will be discussed in the empirical results chapter, the probit output can be found in the appendix.

To interpret the coefficients, we cannot use the magnitude of the betas given by the Eviews output. The Eviews output for the coefficients can be used to investigate the significance of the coefficients. To interpret the magnitude of the coefficients, the marginal effects will be displayed. The marginal results will be obtained by using the model and the logit link-function and fill in the coefficients. Then the model will the generate probabilities of finding an anchored forecasts. The formula that will be used to obtain the probabilities will be in full:

$$P_i = {}^{1}/_{1 + e^{-(\beta_0 + \beta_1 * LNEARVOL + \beta_2 * LNSIZE + \beta_3 * NEGATIVE + \beta_4 * INEXPERIENCE + \beta_5 * YEAR1999 + \epsilon_i)}}$$

(5)

Where:

- P_i stands for the probability of finding a forecast that is anchored.
- LNEARNVOL stands for the natural logarithm of the earnings volatility
- LNSIZE stands for the natural logarithm of the total assets
- NEGATIVE is a dummy variable which equals one when the actual EPS is less than the prior year EPS, otherwise it equals zero
- INEXPERIENCE is a dummy variable which equals one when the analyst is inexperienced when the forecast is made, otherwise the dummy equals 0
- YEAR1999 is a dummy variable that equals one when the forecast is made in the year 1999 and otherwise equals zero
- ϵ_i stands for the error term

To find the marginal effects of i.e. the LNEARNVOL-variable, the average value of the sample for LNSIZE will be entered in the equation, and the most common values for the dummies will be filled in. If we, for example have the 60% negative EPS changes in my sample, 80% inexperienced forecasts and only 10% of all forecasts are made in the year 1999, I will fill in a one for the NEGATIVE-variable, a one for the INEXPERIENCED-variable, and a zero for the YEAR1999 variable. Then different values of the LNEARNVOL-variable will be filled in, and the model will generate different probabilities, so we can see the marginal effects of the LN-EARNVOL variable.

For the LNSIZE variable the same will be done, except that the average of the sample for LNEARNVOL will be filled in, and different values of LNSIZE will then be filled in. To obtain the marginal effects of the dummy variables, the averages of sample for LNSIZE and LNEARNVOL will be filled in the equation, and then the eight different possible combinations of the dummies will be filled in.

4 Data

The data for this research were partly obtained from the IBES-file in the Wharton Research Data Service database. The IBES-file contains the EPS forecasts of all analysts made for the stocks from the S&P 500. From this file, all forecasts on the S&P 500, for companies that have been in the S&P 500 for longer than six years, are extracted from 1988 until 2003. The other part of the data is also from the Wharton Research Data Service but originate from the Compustat-file. From the Compustat-file I retrieve total assets and the income before extraordinary items and discontinued operations less preferred dividend requirements, but before adding savings due to common/ordinary stock equivalents (IBCOM), in USD millions. These data were also obtained for the same period, 1988 to 2003.

The testing period runs from January first 1993 to December thirty-first 2002, which sums up to 10 years of forecasts. The five years that were obtained extra (1988-1993) was for the purpose of coding experience and the past earnings volatility. The file obtained from IBES contained over 286 thousand forecasts. To ensure that all analysts that are in the file three years or longer are coded right, these forecasts were used to code the experience of the forecasters. In other words, if an analyst has made a forecast between 1988 and 1990 he will start in the file as an experienced forecaster.

When experience was coded, the years 1988 till 1992 were deleted from the sample. With the remaining sample, all of the prior year EPS actuals and announcement dates were matched with the actual EPS, so a window of anchoring on the previous EPS could be formed. After this, all forecasts before 1993 are deleted. As both tested anchors need to be relevant, the forecasts made later than three months after the announcement date and the ones made before the announcement date of the prior year EPS were deleted. Next, the factors negative change and the year 1999 were coded. The forecasts that are anchored on the prior year EPS were also coded at this moment.

From all companies left in the file I obtain total assets and the IBCOM from the Compustat-file from 1988 till 2003. The IBCOM variability was calculated using the previous five years that were then matched with the right company-years for the Y1 file. At this point, total assets were also linked with the right company-years. As the companies are only included if they are in the S&P 500 for six years, all other company-years were deleted from the sample. In the end to test the prior year EPS as anchor, there are 54,347 forecasts left. These forecasts consist of 390 companies, and 2781 company-years. The average error of the forecasts is $0.142 when the forecast is measured (forecast – actual). The standard deviation of the errors is $0.693. The average of the absolute value of the error is $0.339. In this sample there are 3,624 different analysts. Of the 54,347 forecasts, inexperienced analysts made 16,285 forecasts, and experienced analysts made 38,062 forecasts. Of all forecasts 27,058 were anchored forecasts, and 27,289 were not anchored forecasts. For an overview, see Table 1. The second anchor-variable is defined as the consensus of the first three forecasts made after the announcement of the prior year EPS. If the forecasts made hereafter are between this consensus and the actual value, these are considered as anchored. This approach does not only exclude the first three forecasts made for every company in the sample, but also logically all companies that have less than four forecasts made in the three months after the announcement of the prior year EPS. For this anchor variable there are 46,129 forecasts to regress. In this sample there are 378 companies and 2,627 company-years. The average error is $0.142 and the standard deviation of the error is $0.690. The average absolute error is $0.341. Of the 46,129 forecasts 14,079 were made by inexperienced analysts, and 32,032 forecasts were made by experienced analysts. Of these forecasts 23,314 were anchored forecasts, and 22,815 were not anchored forecasts. For an overview see Table 2.

Prior year EPS anchor	**Number of forecasts**	**Average error**	**Standard deviation**	**Average absolute error**	**Inexperienced forecasts**	**Percentage inexperienced**	**Anchored forecasts**	**Percentage anchored**	**Negative**	**Percentage negative changes**
total sample	54,347	0.142	0.693	0.339	16,285	30.0%	27,058	49.8%	18,431	33.9%
1993	5,261	0.156	0.865	0.375	948	18.0%	2,277	43.3%	1,574	29.9%
1994	5,370	-0.010	0.638	0.227	994	18.5%	2,970	55.3%	1,106	20.6%
1995	5,189	0.036	0.606	0.323	1,346	25.9%	2,806	54.1%	1,345	25.9%
1996	5,494	0.220	0.997	0.434	1,769	32.2%	3,041	55.4%	1,924	35.0%
1997	5,093	0.153	0.485	0.256	1,674	32.9%	2,400	47.1%	1,593	31.3%
1998	5,367	0.239	0.504	0.312	1,690	31.5%	2,469	46.0%	2,254	42.0%
1999	5,511	0.009	0.693	0.333	1,750	31.8%	3,173	57.6%	1,444	26.2%
2000	5,587	0.172	0.740	0.410	1,812	32.4%	2,576	46.1%	1,766	31.6%
2001	5,789	0.334	0.794	0.430	2,004	34.6%	2,568	44.4%	3,433	59.3%
2002	5,686	0.099	0.473	0.280	2,298	40.4%	2,778	48.9%	1,992	35.0%

Table 1: descriptive statistics of binary variables used in the sample to test anchoring on the prior year EPS

Consensus anchor	**Number of forecasts**	**Average error**	**Standard deviation error**	**Average absolute error**	**Inexperienced forecasts**	**Percentage inexperienced forecasts**	**Anchored forecasts**	**Percentage anchored forecasts**	**Negative EPS changes**	**Percentage negative changes**
total sample	46,129	0.142	0.690	0.341	14,079	30.5%	23,314	50.5%	16,085	34.9%
1993	4,374	0.163	0.881	0.379	794	18.2%	2,242	51.3%	1,343	30.7%
1994	4,516	-0.012	0.423	0.227	842	18.6%	2,091	46.3%	965	21.4%
1995	4,360	0.036	0.612	0.329	1,165	26.7%	2,132	48.9%	1,157	26.5%
1996	4,650	0.228	0.767	0.449	1,504	32.3%	2,246	48.3%	1,720	37.0%
1997	4,252	0.154	0.484	0.256	1,439	33.8%	2,044	48.1%	1,361	32.0%
1998	4,555	0.242	0.497	0.312	1,471	32.3%	2,242	49.2%	1,961	43.0%
1999	4,717	0.005	0.695	0.335	1,508	32.0%	2,498	53.0%	1,278	27.1%
2000	4,793	0.162	0.721	0.407	1,587	33.1%	2,449	51.1%	1,500	31.3%
2001	5,015	0.325	0.739	0.422	1,773	35.4%	2,961	59.0%	3,011	60.0%
2002	4,897	0.098	0.470	0.281	2,014	41.1%	2,409	49.2%	1,789	36.5%

Table 2: descriptive statistics of the binary variables used in the sample to test anchoring on the consensus of the first three forecasts

If we take a look at tables one and two we can see some interesting facts. For both the samples in the years 1997 and 2002 the analysts were most accurate, measured by absolute error. Another interesting fact is that as time passes, the proportion of inexperienced analysts grows. Apparently hired more new security analysts are hired and at the same time experienced analysts leave the business, because the number of forecasts does not grow with the same proportion. Concerning which anchor is used most differs much per year. In the years 1993, 1997, 1998 and 2000 until and including 2002, a bigger proportion of the forecasts is anchored on the first consensus, otherwise a bigger proportion is anchored on the prior year EPS. Interestingly, the proportion of forecast that are anchored on the prior year EPS in 1993 is the lowest proportion of all years, while the proportion of forecasts made in the year 1993 that are anchored on the first consensus is the third highest compared to other years. For the year 1994 we see it the other way around, as the year with the lowest proportion of anchoring on the first consensus, is the year with the second highest proportion of forecasts anchored on the prior year EPS. Similar effects of the year 1993 are seen for the year 2001, where the highest proportion of forecasts anchored on the first consensus is accompanied by the second lowest proportion of forecasts anchored on the prior year EPS. It seems that when analysts use the prior year EPS as an anchor relatively more than other years, they will use the consensus relatively less, and vice versa.

The percentage of negative changes gives an interesting insight into which years were good and bad for the stock markets. For instance we can see that for all the forecasts made in 2001, when the effects of the dot-com-bubble burst swept across the world, respectively 59.3% and 60.0% of all the EPS' in the two samples were smaller then the EPS of the year before. The year 1998 also has a lot more negative EPS changes compared to the average for all the years (42.0% versus 33.9% for the first sample and 43.0% versus 34.9% for the second sample). For the forecasts made in the years 1994 and 1995 we can see that the EPS changes were exceedingly positive compared to the averages of the samples (20.6% for 1994 and 25.9% for 1995 compared to 33.9% for the first sample and 21.4% for 1994 and 26.5% for 1995 versus 34.9% for the second sample)

I will investigate if size and the volatility of the earnings have an influence on EPS forecasts. Naturally for the two different anchors, the averages of this variable differ slightly. A similar approach for the standard deviation of the Earnings volatility is followed. The descriptive statistics of these variables are shown in table 3 and table 4 for the sample that will be used to test if the analysts anchor on the prior year EPS and for the sample that will be used to investigate if the analysts anchor on the consensus respectively.

Prior-year-EPS-sample	**ln size**	**ln earnings volatility**
Lowest	4.865	0.678
Highest	13.696	9.187
Average	9.036	4.986
Median	9.026	4.960
Standard deviation	1.341	1.260

Table 3: descriptive statistic for the size-variable and the earnings volatility-variable for the sample used to test anchoring on the prior year EPS

First-consensus-sample	ln size	ln earnings volatility
Lowest	5.064	0.678
Highest	13.696	9.187
Average	9.079	5.052
Median	9.101	5.053
Standard deviation	1.322	1.249

Table 4: descriptive statistics for the size-variable and the earnings volatility-variable for the sample used to test anchoring on the consensus of the first three forecasts

5 Emperical results

This chapter consists of three parts. The first part will evaluate the regression that tests if analysts anchor on the prior year EPS, interpret the coefficients and marginal effects of the coefficients. While interpreting these coefficients the hypotheses H2a, H2b H2c and H2d, defined in the introduction, will be rejected or accepted. The second part will do the same for the second regression, which examines when the analysts anchor on the consensus of the first three forecasts. Also the hypotheses H3a, H3b H3c and H3d will be rejected or accepted in this part. After that the differences between the two regressions, and the two forms of anchoring will be discussed. Concluding, the main hypotheses, H1: “Analysts use anchors for their EPS forecasts in the first three months after the earnings announcement under specific circumstances and fail to adjust sufficiently”, will be evaluated.

5.1 Results prior year EPS anchor

In this subchapter the following hypotheses defined in the introduction are going to be evaluated:

H2a: Analysts use the prior year EPS as an anchor if they are inexperienced

H2b: Analysts use the prior year EPS as an anchor if the volatility of the company is bigger

H2c: Company size has a negative influence on the behavior of anchoring

H2d: Analysts use the prior year EPS as an anchor if the company produces a smaller EPS than the year before

To accomplish this, we will look at the regression results, where I will evaluate the significance of the model as a whole, and the significance and the sign of the coefficients. Subsequently we will look at the predictions the model makes, to see how well it predicts. Finally I will discuss the marginal effects of all the variables, so an interpretation of magnitude of the effects can be made.

Dependent Variable: ANCHOR
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 11/01/11 Time: 20:59
Sample: 1 54347
Included observations: 54347
Convergence achieved after 4 iterations
QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0,13371	0,060241	2,219598	0,0264
LNEARNVOL	0,086426	0,009643	8,962554	0
LNSIZE	-0,032084	0,008815	-3,639807	0,0003
NEGATIVE	-0,896654	0,018809	-47,67205	0
INEXPERIENCE	-0,039792	0,0192	-2,072481	0,0382
YEAR1999	0,280047	0,028955	9,671726	0
McFadden R-squared	0,033696	Mean dependent var		0,497875
S.D. dependent var	0,5	S.E. of regression		0,488402
Akaike info criterion	1,339785	Sum squared resid		12962,32
Schwarz criterion	1,340768	Log likelihood		-36400,65
Hannan-Quinn criter.	1,340092	Deviance		72801,31
Restr. deviance	75339,96	Restr. log likelihood		-37669,98
LR statistic	2538,651	Avg. log likelihood		-0,669782
Prob(LR statistic)	0			
Obs with Dep=0	27289	Total obs		54347
Obs with Dep=1	27058			

Table 5: Eviews output of the logistic regression for the sample that tests if analysts anchor on the prior year EPS. The dependent variable is a binary variable which is 1 if a forecast is anchored, otherwise zero. LNEARNVOL is the natural logarithm of the volatility of the earnings of the company, LNSIZE is the natural logatithm of the total assets of the company. NEGATIVE is a dummy variable, which equals one if the EPS is smaller than the prior year EPS, otherwise the value of the dummy will be zero. INEXPERIENCE is a dummy variable, which equals one if the analyst who made the forecast has been active for less than three years, otherwise it equals zero. YEAR1999 is a dummy, which equals one if the forecast is made in the year 1999, if the forecast is made in any other year the value will be zero.

The results of the regression are shown above in Table 5. This is the logit-regression, while the probit-regression results can be found in the appendix in table 14. As can be seen from the table the McFadden R-squared, also known as the pseudo R^2, is quite low, this means that the model does not fit well, but this is normal when there are a lot of observations (Brooks, 2008). The LR-statistic shows that the model works better then a model with no variables, and is strongly significant.

If we look at the coefficients in table 5 we can see that the constant is positive and significant at the five percent level, but not at the one percent level. LNEARNVOL, which is the natural logarithm of the volatility of the earnings for the previous five years, is positive and significant at the one percent level. This implies that when the earnings have been more volatile the last five years, the chances of a forecast to be anchored on the prior year EPS will be bigger. The LNSIZE-coefficient is negative and significant at the one percent level. This implies that when a company becomes smaller the chances that the EPS forecasts are anchored on the prior year EPS of that company becomes bigger. The NEGATIVE-variable is significant at the one percent level and negative. Apparently the opposite of what was expected is true, as analysts anchor more when the actual EPS is bigger then the prior year EPS. The INEXPERIENCE-variable is negative and only significant at the five percent level. This is also different from what I expected, because this implies experienced forecasters use the prior year EPS more often as an anchor as inexperienced forecasters. The YEAR1999 is significant and positive. In the year 1999 the chance to find an anchored forecast is bigger.

In table 6 we can see how well our model predicts. As the proportion of anchored forecasts is 0.4979, our threshold for a correct forecast is set at this point. This means that if our model predicts a chance of more than 0.4979, and the forecast is anchored, this is a correct prediction. The model predicts 75.89% of all observations that are anchored correct. For the observations that are not anchored, the model predicts 43.68% correctly. Overall the model correctly predicts 59.71% of all forecasts. This is 9.5% more than a random model.

The coefficients of a logit-model have to be interpreted somewhat differently than a normal regression. Because the model is not linear, the coefficients do not represent the change in percentage on the chance of a forecast being anchored. Therefore for the different combinations of the dummy variables combined with the average natural logarithm of size and earnings volatility the chances of a forecast being an anchored forecast are calculated. The results are shown in table 7.

Expectation-Prediction Evaluation for Binary Specification

Equation: Y1

Date: 11/01/11 Time: 21:00

Success cutoff: C = 0.4979

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	11919	6525	18444	27289	27058	54347
P(Dep=1)>C	15370	20533	35903	0	0	0
Total	27289	27058	54347	27289	27058	54347
Correct	11919	20533	32452	27289	0	27289
% Correct	43,68	75,89	59,71	100	0	50,21
% Incorrect	56,32	24,11	40,29	0	100	49,79
Total Gain*	-56,32	75,89	9,5			
Percent Gain**	NA	75,89	19,08			

Table 6: Expectation-prediction evaluation for the regression-model that has anchoring on the prior year EPS as dependent variable

		Inexperienced	Experienced
Negative	1999	40.6%	41.5%
	Other years	34.0%	34.9%
Positive	1999	62.6%	63.5%
	Other years	55.9%	56.8%

Table 7: Probabilities generated by the regression-model that has anchoring on the prior year EPS as dependent variable. The probabilities for the different combinations of the binary-variables, NEGATIVE, INEXPERIENCED and YEAR1999 are calculated. For the size-variable and for the earnings-volatility-variable the averages of the whole sample are entered in the formula and are the same for all the eight possible combination of the binary variables.

From table 7 we can see that for the average firm size in the sample there is a big difference if the actual EPS is bigger or smaller than the prior year EPS. This means that analyst tend to anchor on the prior year EPS when they expect a higher EPS. The optimism of analysts, that I expected to find, seems to be quite the opposite in this sample. Because of anchoring on the prior year EPS, when the analysts expect the EPS to be higher, they forecast too pessimistically. This means we can reject hypothesis H2d: Analysts use the prior year EPS as an anchor if the company produces a smaller EPS than the year before.

If an analyst has more experience, anchors do not influence forecasts less. On the contrary, the chance that an analyst with experience uses the prior year EPS for his forecast is bigger than for an inexperienced analyst. On the other hand the difference in chance is only 0.9% and can be neglected. For hypothesis H2a: Analysts use the prior year EPS as an anchor if they are inexperienced we can see that it is not true, and therefore we can reject this hypothesis. The table shows that making a dummy for the year 1999 was necessary. It seems to differ for 6.5 % compared to other years. In the year 1999 apparently analysts anchored more often than in other years

The natural logarithm of size and earnings volatility cannot be interpreted in this way because these are not binary. Therefore in Tables 8 and 9 these variables are interpreted in a different manner. In table 8 the marginal effects for different values of the size variable are shown. For the LNEARNVOL the average value is entered, and the for values of the dummies NEGATIVE, INEXPERIENCE and YEAR1999 zero's are filled in because that are the most common values in the sample as we can see from table 1. Next, for the size variable the highest value, and then every five percent value is calculated and filled in the formula. In example, of the 53437 observations, the first five percent value will be: 0.05*53437= 2717.35, so the 2717th value. From table 8 can be concluded that although the size-variable is significant and negative, the influence is not that big. If all other variables stay the same, from the lowest value of ln-size to the highest value, the difference in chance is only 6,95 % percent chance.

Percentage	# of forecast	Value ln_size	Chance anchored
Highest	1	13.696	53.1%
5%	2,717	11.304	55.0%
10%	5,435	10.685	55.5%
15%	8,152	10.412	55.7%
20%	10,869	10.162	55.9%
25%	13,587	9.909	56.1%
30%	16,304	9.703	56.3%
35%	19,021	9.528	56.4%
40%	21,739	9.360	56.6%
45%	24,456	9.215	56.7%
50%	27,174	9.026	56.8%
55%	29,891	8.807	57.0%
60%	32,608	8.587	57.2%
65%	35,326	8.424	57.3%
70%	38,043	8.245	57.5%
75%	40,760	8.044	57.6%
80%	43,478	7.856	57.8%
85%	46,195	7.625	57.9%
90%	48,912	7.353	58.1%
95%	51,630	7.003	58.4%
Lowest	54,347	4.865	60.1%

Table 8: The probabilities generated by the regression model that has anchoring on the prior year EPS as dependent variable, for different values of the size-variable. For the earnings-volatility variable the average is filled in, the variables NEGATIVE INEXPERIENCE and YEAR1999 equal 0.

If you take into account that between the 5% and the 95% values, the difference is 3.39%. We can say that there is an effect, but it is not that big. It seems that the size of the company will have an effect on the uncertainty of analysts. There is a negative significant relation, meaning that the bigger the company, the smaller the chance that a forecast will be anchored. Apparently for smaller companies insecurity might be bigger, which will lead to more anchoring with smaller companies. If we look at hypothesis H2b: Analysts use the prior year EPS as an anchor if the volatility of the company is bigger we can accept it.

In table 9 the same is done for the ln-earnvol-variable. Here, we can perceive, that it really matters if the earnings have been volatile. The difference between the highest and the lowest is almost 18%. This should be interpreted with care, because the difference between the highest and the 5% value is more than 4% and the difference between the lowest and the 95% value is almost 5%.

Even then, the influence of the earnings-volatility is bigger than the influence of the size variable. The relation between forecasts anchored on the prior year earnings and the LNEARNVOL-variable is positive and significant, so, as was to be expected, when earnings have been more volatile over the previous 5 years, analysts tend to use the prior EPS more often for their forecasts. So this measure of uncertainty seems to affect the analysts to anchor their forecasts. When there is more uncertainty about future earnings analysts view the prior year EPS as a valuable measure. This means hypothesis H2c: Company size has a negative influence on the behavior of anchoring, is true.

Percentage	# of forecast	Value ln_earnvol	Probability anchored
Highest	1	9.187	65.4%
5%	2,717	7.175	61.4%
10%	5,435	6.609	60.2%
15%	8,152	6.291	59.6%
20%	10,869	5.998	59.0%
25%	13,587	5.766	58.5%
30%	16,304	5.609	58.1%
35%	19,021	5.457	57.8%
40%	21,739	5.298	57.5%
45%	24,456	5.141	57.2%
50%	27,174	4.960	56.8%
55%	29,891	4.788	56.4%
60%	32,608	4.639	56.1%
65%	35,326	4.464	55.7%
70%	38,043	4.296	55.4%
75%	40,760	4.137	55.0%
80%	43,478	3.955	54.6%
85%	46,195	3.701	54.1%
90%	48,912	3.371	53.4%
95%	51,630	2.969	52.5%
Lowest	54,347	0.678	47.6%

Table 9: The probabilities generated by the regression model that has anchoring on the prior year EPS as dependent variable, for different values of the LNEARNVOL-variable. For the LNSIZE-variable the average is filled in, the variables NEGATIVE INEXPERIENCE and YEAR1999 equal 0.

5.2 Regression results consensus EPS anchor

In this section the following hypotheses defined in the introduction are going to be evaluated:

H3a: Analysts anchor on the consensus of the first three forecasts if they are inexperienced

H3b: Analysts anchor on the consensus of the first three forecasts if the volatility of the earnings of a company is bigger

H3c: There is a negative relation between the company size and the amount of anchored forecasts on the consensus of the first three forecasts

H3d: Analysts anchor on the consensus of the first three forecasts if the company produces a smaller EPS than the prior year.

This subsection will evaluate the second regression that is run by me. In the pooled sample of the second regression variables are coded into the sample the same way as is done for the regression, which is discussed in the previous subchapter. The difference between the two regressions is the dependent variable. For this regression, the dependent variable is forecasts that are anchored on the consensus of the first three forecasts. The results of the logit-regression can be found in table 10. The regression results of the probit-regression can be found in the appendix in table 15.

If we look at table 10, we can observe again that the Mc-Fadden R^2 is quite low, even smaller then the Mc-Fadden R^2 displayed in table 5. This means that this model fits worse than model that uses anchoring on the prior year EPS as dependent variable. As I have discussed above, this is still no reason to discard this model. When we look at the LR-statistic we can see that the model is significantly better than a model with no variables.

When we look at the coefficients of the model, we can see that again there is a positive significant constant. LNEARNVOL is not significant, and this is not as expected. Analysts do not anchor more on the consensus of the first three forecasts, when the earnings volatility becomes higher, as was the case with the regression from subchapter 5.1. We can thus reject the hypothesis H3b: Analysts anchor on the consensus of the first three forecasts if the volatility of the earnings of a company is bigger. The variable LNSIZE is negative and significant. Company size has a negative influence on the frequency of anchored forecasts on the consensus, which was also the case for forecasts anchored on the prior year EPS.

Dependent Variable: ANCHOR

Method: ML - Binary Logit (Quadratic hill climbing)

Date: 11/01/11 Time: 21:04

Sample: 1 46129

Included observations: 46129

Convergence achieved after 4 iterations

QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0,237527	0,067017	3,544309	0,0004
LNEARNVOL	-0,001821	0,010303	-0,176769	0,8597
LNSIZE	-0,0487	0,009757	-4,991506	0
NEGATIVE	0,670015	0,020023	33,46269	0
INEXPERIENCE	-0,046305	0,020528	-2,255744	0,0241
YEAR1999	0,178078	0,031476	5,657569	0
McFadden R-squared	0,018967	Mean dependent var		0,505409
S.D. dependent var	0,499976	S.E. of regression		0,49343
Akaike info criterion	1,360146	Sum squared resid		11229,7
Schwarz criterion	1,361283	Log likelihood		-31365,1
Hannan-Quinn criter.	1,360504	Deviance		62730,19
Restr. deviance	63942,97	Restr. log likelihood		-31971,49
LR statistic	1212,783	Avg. log likelihood		-0,679943
Prob(LR statistic)	0			
Obs with Dep=0	22815	Total obs		46129
Obs with Dep=1	23314			

Table 10: Eviews output of the logistic regression for the sample that tests if analysts anchor on the first consensus of three forecasts. The dependent variable is a binary variable which is

1 if a forecast is anchored, otherwise zero. LNEARNVOL is the natural logarithm of the volatility of the earnings of the company, LNSIZE is the natural logatithm of the total assets of the company. NEGATIVE is a dummy variable, which equals one if the EPS is smaller than the prior year EPS, otherwise the value of the dummy will be zero. INEXPERIENCE is a dummy variable, which equals one if the analyst who made the forecast has been active for less than three years, otherwise it equals zero. YEAR1999 is a dummy, which equals one if the forecast is made in the year 1999, if the forecast is made in any other year the value will be zero.

The coefficient for the NEGATIVE-variable is significant and positive. This is as expected. It is however different from the first model. Apparently analysts anchor more on the prior year EPS when the actual EPS is bigger than the actual EPS, and anchor more on the consensus of the first three forecasts when the EPS is bigger than the prior year EPS. The INEXPERIENCE-variable is in this model as well as the model with anchoring on the prior year EPS as dependent variable, negative and significant, but only on the five percent level. Inexperienced analysts less often use the first consensus as an anchor. Finally, we can see that the YEAR1999-variable is positive and significant. Forecast made in the year 1999 were more often anchored on the first consensus of three forecasts than in other years.

In table 11 we can observe how well this model predicts. To reflect the increased probability for a forecast to be anchored on the consensus the cut off point is 0.5054, as 50.54% of all forecasts are anchored forecasts. We can see that this model predicts 57.89% right overall. The model predicts 71.88% of the observations, which are not anchored correct, and 43.21% of the observations that were anchored correct. The model predicts 6.85% better than a random model does. Interestingly this model is better in predicting when forecasts are not anchored on the consensus, and the model from subchapter 5.1 predicts best the forecasts that are anchored on the prior year EPS.

Expectation-Prediction Evaluation for Binary Specification
Equation: Y2
Date: 11/01/11 Time: 21:04
Success cutoff: C = 0.5054

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	16399	13240	29639	0	0	0
P(Dep=1)>C	6416	10074	16490	22815	23314	46129
Total	22815	23314	46129	22815	23314	46129
Correct	16399	10074	26473	0	23314	23314
% Correct	71,88	43,21	57,39	0	100	50,54
% Incorrect	28,12	56,79	42,61	100	0	49,46
Total Gain*	71,88	-56,79	6,85			
Percent Gain**	71,88	NA	13,85			

Table 11: Expectation-prediction evaluation for the regression-model that has anchoring on consensus of the first three forecasts as dependent variable

In table 12 the same analysis is performed for the regression-model, which has anchoring on the first consensus as the dependent, as in table 7 for the previous regression-model. When we look at the marginal effect of the NEGATIVE-variable, we can conclude that it is quite big, especially compared with the marginal effect of the other dummies. As mentioned before, the effects are the opposite of the effect that is shown in table 7. When the actual EPS is smaller then the prior year EPS the chances of a forecast being anchored on a consensus are between 16% and 17% bigger. Thus we can accept hypothesis H3d: Analysts anchor on the consensus of the first three forecasts if the company produces a smaller EPS than the prior year. Experienced forecasters have an increased chance of using the prior consensus as anchor for their forecasts, but the increase in probability is only 1.1%. This is not as expected, and therefore hypothesis H3a: Analysts anchor on the consensus of the first three forecasts if they are inexperienced, is rejected. Again we can see justification for controlling for the year 1999, which was also the case in table 7.

		Inexperienced	Experienced
Negative	1999	64.3%	65.4%
	Other years	60.1%	61.2%
Positive	1999	48.0%	49.1%
	Other years	43.5%	44.7%

Table 12: Probabilities generated by the regression-model that has anchoring on the first consensus of three forecasts as dependent variable. The probabilities for the different combinations of the binary-variables, NEGATIVE, INEXPERIENCED and YEAR1999 are calculated. For the size-variable and for the earnings-volatility-variable the averages of the whole sample are entered in the formula and are the same for all the eight possible combination of the binary variables.

In table 13 the effect of firm size, measured by the natural logarithm of total assets, is calculated in the same manner as in table 8. The most common outcomes for the dummy variables, as table two shows, are forecasts that were made for a firm with a positive earnings change, by an experienced analyst in a year other than the year 1999. So again all the dummy variables equal zero, and for the EARNVOL the average is filled in, and different value for LNSIZE are filled in the equation. Again size has a negative significant influence, but it does not seem to differ much for the outcome of the probability. We can still conclude that when the company gets smaller analysts tend to anchor more this means that hypotheses H3b: Analysts anchor on the consensus of the first three forecasts if the volatility of the earnings of a company is bigger, is true. The earnings volatility variable is not significant, and for that reason not interpreted here. In the appendix in table 16 the effects are shown of the different volatilities of earnings.

Percentage	# of forecast	Value of ln_size	Probability anchored
Highest	1	13.696	39.2%
5%	2,306	11.304	42.0%
10%	4,613	10.689	42.8%
15%	6,919	10.424	43.1%
20%	9,226	10.190	43.3%
25%	11,532	9.939	43.6%
30%	13,839	9.735	43.9%
35%	16,145	9.556	44.1%
40%	18,452	9.397	44.3%
45%	20,758	9.253	44.5%
50%	23,065	9.101	44.7%
55%	25,371	8.877	44.9%
60%	27,677	8.642	45.2%
65%	29,984	8.471	45.4%
70%	32,290	8.306	45.6%
75%	34,597	8.119	45.8%
80%	36,903	7.902	46.1%
85%	39,210	7.686	46.4%
90%	41,516	7.418	46.7%
95%	43,823	7.078	47.1%
Lowest	46,129	5.064	49.5%

Table 13: The probabilities generated by the regression model that has anchoring on the first consensus of three forecasts as dependent variable, for different values of the size-variable. For the earnings-volatility variable the average is filled in, the variables NEGATIVE INEXPERIENCE and YEAR1999 equal 0

5.3 Comparison between forecasts anchored on the prior year EPS, and forecasts anchored on the first consensus of three forecasts

To evaluate the main hypothesis I will discuss the results in short. The main hypothesis is:

H1: Analysts use anchors for their EPS forecasts in the first three months after the earnings announcement under specific circumstances and fail to adjust sufficiently

As I have tested two different anchors, we can approach this hypothesis in two different ways, and compare the two anchors as well. We have seen some similarities between the two different anchors, but also some differences. I will start with the similarities of the coefficients. Both models showed a negative significant influence of the INEXPERIENCED-variable. But when we took a closer look we saw that the marginal effects were quite small (0.9% and 1.1%). Therefore I can conclude that experience is not a characteristic that matters if a forecast will be anchored or not. Next we have also seen that LNSIZE has a negative significant influence for both models, implying that when the company size gets smaller, analysts tend to use anchors in general more often for their forecasts. It seems that the smaller analyst attention for smaller companies influences the analysts to anchor in general. The last similarity found was that for both models the year 1999 was a year with more anchored forecasts than for other years.

The differences between the two models tested in this chapter consist of the significance of the LNEARNVOL-variable, the sign of the NEGATIVE variable, and the predicting abilities of the models. We have seen that the model that has anchoring on the prior year EPS is better in predicting when forecasts are anchored, and that the second model is better in predicting when forecasts are not anchored. When the volatility of earnings become bigger, analysts only tend to anchor more on the prior year EPS. This can be interpreted as follows: that the analysts think that other analysts do not know better than the analysts themselves, and therefore will not use the forecasts of others, but because of the uncertainty will use the prior year EPS. The second big difference is that when the EPS changes negatively they strongly tend to anchor on the forecasts of others, when the EPS changes positively from prior to actual, they tend to anchor on the prior year EPS. An explanation for this could be that they fail to adjust sufficiently their forecasts when they expect the EPS to be higher than the prior year, but find it more difficult to forecast when the EPS is lower than the prior year, and then tend to correct the forecasts of other analysts instead of coming up with their own forecasts.

We can thus conclude that hypothesis H1: Analysts use anchors for their EPS forecasts in the first three months after the earnings announcement under specific circumstances and fail to adjust sufficiently, is true, as this thesis finds evidence that analysts anchor more on the prior year EPS when the EPS change from prior to actual is positive, when the earnings volatility of the previous five years becomes bigger, and when the size of the company becomes bigger. I also find evidence that analysts tend to use the first consensus of three forecasts as an anchor, when the company size becomes bigger and when the change from prior to actual EPS is negative.

6 Conclusions

The goal of this thesis was not only to find evidence for anchoring among security analysts, but also to find under what circumstances this occurs most. The second goal is to investigate if different anchors are used under different circumstances. As anchoring can feature on different values, even irrelevant ones, two types that seem intuitive were tested. The first anchor tested was the prior year EPS. The second anchor is a consensus of the first three forecasts.

In most literature concerning anchoring, the results showed that anchoring and adjustment is a phenomenon that occurs both with experts and non-experts (Northcraft & Neale, 1987), (Wright & Anderson, 1989). Hence I expected that even in the group of the experts on securities, i.e. security-analysts, anchoring would be found. And indeed, as we have seen in tables 1 and 2 anchoring is a phenomenon that occurs for 50 % of all forecasts.

To proxy the difficulty of forecasting, an earnings volatility-variable was introduced, and a variable for size. As there was reason to believe that the forecasts in the year 1999 were systematically too optimistic there was a dummy variable for the year 1999 (Hong and Kubik (2003)). Literature also showed that forecasters have reasons to forecast optimistically, and thus forecasts might be different when the EPS would be bigger than the prior year EPS, or when the EPS would be smaller than the prior year EPS (Hong and Kubik (2003)). Therefore I also included a variable for a negative change from prior to actual EPS. Because inexperienced forecasters might anchor more than experienced forecasters, there was also a variable to account for this (Jacob, Lys & Neale (1999)).

The data used to test the two different anchors were obtained from the IBES database, and covered forecasts of analysts for the period that runs from 1993 until and including 2002. The samples were pooled and the forecasts that were anchored are coded one, and otherwise zero, for the two different anchors. These variables were made the dependent variables. As the dependent variables were a binary variable a generalized linear model is used to obtain the results. In this thesis the logistic-regression is used, and the parameters are chosen using Maximum Likelihood to jointly maximize a log-likelihood function.

The results showed that security analysts anchor more often on the prior year EPS when the actual EPS is bigger than the prior year EPS, when the company size gets smaller, and when the earnings volatility of the previous five years becomes bigger. The results for the regression with anchoring on the consensus of the first three forecasts pointed out something different. I found evidence that analysts anchor more often on the consensus of the first three forecasts when the actual EPS is smaller than the prior year EPS and when the company size gets smaller.

For further research I would recommend to test the two anchors in one regression, as anchoring on the prior year EPS happens more often with a negative change in EPS, and analysts anchor more often on the consensus of the first three forecasts when the change in EPS from prior year to actual is positive. In addition to this it might be interesting to investigate if the effects found in this thesis consist in period with more certainty about the EPS. That way, we could see that the amount of anchoring found in this thesis diminishes with time. A good suggestion would also be to look if one extrapolates the EPS forecasts that are bigger then the prior year EPS and see if one would obtain better forecasts. That is however beyond the scope of this thesis.

7 References

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8 Appendix

Dependent Variable: ANCHOR
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 11/01/11   Time: 20:56
Sample: 1 54347
Included observations: 54347
Convergence achieved after 4 iterations
QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0,085351	0,03758	2,271199	0,0231
LNEARNVOL	0,054078	0,00595	9,088933	0
LNSIZE	-0,020287	0,005501	-3,688024	0,0002
NEGATIVE	-0,559159	0,01162	-48,11839	0
INEXPERIENCE	-0,024741	0,011908	-2,077641	0,0377
YEAR1999	0,174727	0,018017	9,697892	0
McFadden R-squared	0,033719	Mean dependent var		0,497875
S.D. dependent var	0,5	S.E. of regression		0,488395
Akaike info criterion	1,339753	Sum squared resid		12961,95
Schwarz criterion	1,340736	Log likelihood		-36399,78
Hannan-Quinn criter.	1,34006	Deviance		72799,57
Restr. deviance	75339,96	Restr. log likelihood		-37669,98
LR statistic	2540,389	Avg. log likelihood		-0,669766
Prob(LR statistic)	0			
Obs with Dep=0	27289	Total obs		54347
Obs with Dep=1	27058			

Table 14: Eviews output of the probit-regression for the sample that tests if analysts anchor on the prior year EPS. The dependent variable is a binary variable which is 1 if a forecast is anchored, otherwise zero. LNEARNVOL is the natural logarithm of the volatility of the earnings of the company, LNSIZE is the natural logatithm of the total assets of the company. NEGATIVE is a dummy variable, which equals one if the EPS is smaller than the prior year EPS, otherwise the value of the dummy will be zero. INEXPERIENCE is a dummy variable, which equals one if the analyst who made the forecast has been active for less than three years, otherwise it equals zero. YEAR1999 is a dummy, which equals one if the forecast is made in the year 1999, if the forecast is made in any other year the value will be zero.

Dependent Variable: ANCHOR
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 11/01/11 Time: 21:02
Sample: 1 46129
Included observations: 46129
Convergence achieved after 4 iterations
QML (Huber/White) standard errors & covariance

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0,147106	0,04169	3,528598	0,0004
LNEARNVOL	-0,001126	0,006407	-0,175782	0,8605
LNSIZE	-0,030306	0,006059	-5,00159	0
NEGATIVE	0,418448	0,012437	33,64532	0
INEXPERIENCE	-0,028824	0,012783	-2,254921	0,0241
YEAR1999	0,110278	0,01955	5,640826	0
McFadden R-squared	0,018962	Mean dependent var		0,505409
S.D. dependent var	0,499976	S.E. of regression		0,493432
Akaike info criterion	1,360153	Sum squared resid		11229,78
Schwarz criterion	1,36129	Log likelihood		-31365,26
Hannan-Quinn criter.	1,360511	Deviance		62730,51
Restr. deviance	63942,97	Restr. log likelihood		-31971,49
LR statistic	1212,464	Avg. log likelihood		-0,679947
Prob(LR statistic)	0			
Obs with Dep=0	22815	Total obs		46129
Obs with Dep=1	23314			

Table 15: Eviews output of the probit regression for the sample that tests if analysts anchor on the first consensus of three forecasts. The dependent variable is a binary variable which is 1 if a forecast is anchored, otherwise zero. LNEARNVOL is the natural logarithm of the volatility of the earnings of the company, LNSIZE is the natural logatithm of the total assets of the company. NEGATIVE is a dummy variable, which equals one if the EPS is smaller than the prior year EPS, otherwise the value of the dummy will be zero. INEXPERIENCE is a dummy variable, which equals one if the analyst who made the forecast has been active for less than three years, otherwise it equals zero. YEAR1999 is a dummy, which equals one if the forecast is made in the year 1999, if the forecast is made in any other year the value will be zero.

Percentage	# of forecast	Value of Earnvol	Probability anchored
Highest	1	0.678	44.9%
5%	2,306	3.050	44.8%
10%	4,613	3.440	44.8%
15%	6,919	3.800	44.7%
20%	9,226	4.020	44.7%
25%	11,532	4.204	44.7%
30%	13,839	4.369	44.7%
35%	16,145	4.546	44.7%
40%	18,452	4.696	44.7%
45%	20,758	4.863	44.7%
50%	23,065	5.053	44.7%
55%	25,371	5.201	44.7%
60%	27,677	5.370	44.7%
65%	29,984	5.490	44.7%
70%	32,290	5.652	44.7%
75%	34,597	5.811	44.6%
80%	36,903	6.052	44.6%
85%	39,210	6.349	44.6%
90%	41,516	6.627	44.6%
95%	43,823	7.214	44.6%
Lowest	46,129	9.187	44.5%

Table 16: The probabilities generated by the regression model that has anchoring on the first consensus of three forecasts as dependent variable, for different values of the LNEARNVOL-variable. For the LNSIZE-variable the average is filled in, the variables NEGATIVE INEXPERIENCE and YEAR1999 equal 0.