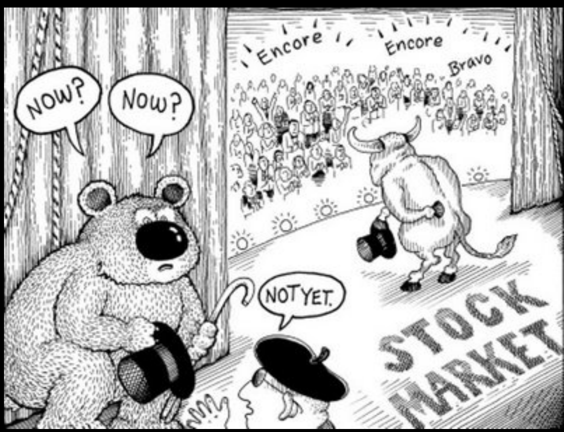

INVESTOR FORECASTING BEHAVIOR IN BULL AND BEAR MARKETS

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Abstract

This research examines the forecasting behavior of investors in bull and bear markets. I find that investors forecast the AEX index positive in bull and bear markets, which is a novelty in academic research. These positive forecasts are hedged by negatively skewed confidence intervals, which contradicts with previous research. Studying the volatility expectations of investors resulted in a confirmation of previous literature: investors forecast volatility higher in bear markets than in bull markets. Finally, the forecasts of the expected price change of other investors are studied. It resulted in positive forecasts in bull and bear markets, which significantly differ in magnitude from the expectations of investors' own forecasts in bear markets, however are equal to the expectations of investors' own forecasts in bull markets.

Keywords:

Market trend; Return forecast; Confidence intervals; Asymmetry; Volatility forecast, Individual investor; Return forecast other investors.

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1. Introduction

In my study Economics and Business Economics, Various different financial disciplines were discussed. Having attended the bachelor seminar Corporate Finance and having written my bachelor thesis about the sentiment of ABN AMRO investors, I decided to continue in the field of 'Financial Economics'. It was my bachelor thesis, supported by the course 'Advanced Behavioral Finance' in my master, which motivated me to write my master thesis in the discipline of behavioral finance.

Behavioral finance differs in a number of ways from classical finance. In classical finance, beliefs are formed through fundamentals and revolve around two basic assumptions. The first assumption is that financial markets are informationally efficient (Efficient Market Hypothesis), meaning all available market information is reflected in the asset prices. If prices reflect all information in the market, prices will always be equal to their fundamental value, leaving no room for trading. The second assumption states that market participants are rational, which is in line with the Efficient Market Hypothesis. In decision-making, investors will incorporate all information available and will react instantly on any new available information. Hence, irrational investors will be eliminated from the market.

In real life, there are limits to arbitrage in financial markets and the investors that participate in these markets tend to be far from perfect. Real life cannot be explained by classical finance, which urges a behavioral explanation. Behavioral finance can explain decision-making with models that are much more flexible than classical finance models. Studying investor behavior has become an important topic in academic financial literature. One of the popular topics in investor behavior studies is the forecasting of stock markets. Once the stock market can be forecasted, positive returns can be generated and profits can be obtained. The question that arises is whether the stock market can be foreacasted? De Bondt (1989) states that stock markets are not a random walk, but predictable in a certain way.

Stock markets are a good representation of the economic climate; they tend to mirror the business cycle of the economy (Han, Lee and Suk, 2009). If the economic climate has a high return and a low volatility it is called a bull market. If the economic climate has low or negative returns with high volatility it is called a bear market (Traustason, 2009). Previous research found (Gonzalez, Powell, Shic and Wilson (2005), Han et al. (2009)), that people tend to behave differently in bull and bear markets.

The purpose of this paper is to combine the investor forecasting with its economic climate, i.e. studying investor forecasting behavior in different bull and bear markets. An unique dataset with data of individual ABN AMRO investors will be used to test different hypotheses around the forecasting behavior of investors. This research is based on different previous studies concerning the behavior of investors in bull and bear markets like De Bondt (1993), O'Connor, Remus and Griggs (2001), Glaser, Langer, Reynders and Weber (2007) and Grobys (2012)

This paper is organized as follows. In section 2, previous literature will be discussed. The studies named in the previous paragraph will be discussed in detail and at the end of the chapter the hypotheses will be defined. Section 3 provides the methodology that is used to offer solutions to the hypotheses. Section 4 presents the empirical results, obtained by different tests. Section 5 offers the concluding remarks and section 6 presents a discussion concerning further research.

2. Literature review

In this chapter, theories of investors forecasting behavior and bull and bear markets will be discussed. Previous literature by De Bondt (1993), O'Connor et al. (2001), Glaser et al. (2007) and Grobys (2012) are compared. In these studies, investor forecasting behavior under different market conditions are described and tested.

First, the literature of the classification of bull and bear markets will be studied (2.1), followed by theories around the forecasted expected price changes (EPC) of investors (2.2). Thirdly, the symmetry of forecasted confidence intervals will be studied. (2.3). The next thing that will be discussed is the forecasted volatility of investors expect in the market (2.4). Finally, the forecasted price changes of other investors are discussed (2.5).

2.1 Classification bull and bear markets

While it is relatively easy to explain what bull and bear markets imply, it seems to be more difficult to define them within a dataset, as a general definition for the two market trends are not at hand. One explanation could be that both bull and bear markets incorporate a lot of different factors, i.e. the volatility, the degree of the movement, the historical trend and the market price of risk (Traustason, 2009). De Bondt (1993) simplifies the two terms, as the author defines bull and bear markets as two market trends with respectively a positive and negative return.

In order to identify and predict the state of equity markets, two fundamentally different types of methods arise: non-parametric and full-parametric methods. The former are based on rules whereas the latter are based on models. According to Kole and van Dijk (2010), the advantage of rules-based methods is that these will be more transparent and robust to misspecification. However, the authors state that model-based techniques are statistically more efficient, as these handle the identification and prediction of the business cycles in one step, whereas the rules-based models are two-step approaches. Finally, a fully defined model for the price process on the equity market provides more insight and the quality of the model can be evaluated through statistical techniques, whereas rules-based methods typically call for some arbitrary, subjective settings. If the input values change, different bull and bear markets can be obtained. Hence, one must be certain of the underlying assumptions of the model.

Examples of ruled-based methods are business cycle algorithms. These are models originally explored by Bry and Boschan (1971). They generated a monthly-based algorithm to obtain peaks and throughs in stock index series. The National Bureau of Economic Research (NBER) has a business cycle committee, which publishes turning points in stock index series. The Bry and Boschan algorithm tends to give turning points almost exactly as those published by the NBER (Gonzalez et al., 2005)[1]. An extension to the Bry Boschan model has been performed by Harding and Pagan (2002). They adjusted the algorithm rules so that it can be applied to quarterly data series.

Another example of rules-based methods is an intuitive classification, where the graphical trend is used as a decision basis. Periods of positive returns can be named bull markets; periods with negative returns can be named bear markets. This method is widely used in previous literature (e.g. de Bondt (1993), Shefrin (2000) and Glaser et al. (2007)).

As stated above, the main disadvantage of the ruled-based methods is their subjectiveness. If the input values change, different bull and bear markets can be obtained. Hence, one must be certain of the underlying assumptions of the model.

An alternative to non-parametric methods, is the parametric Markov Switching Regime. This method is based on the notion that bull and bear markets influence the behavior of certain economic variables. Furthermore, low frequency events are visible, as the Markov Switching regime does not take minimum lengths for the different phases into account. Also short peaks and crashes are certified as respectively bull and bear markets. Grobys (2012) uses this econometric method to obtain the bull and bear markets in his research.

2.2 Expected Price Change (EPC)

To study the EPC, it is important to examine previous literature involving investor behavior. For the forecasting behavior of investors, previous literature is divided in two different streams, that is those involving short- and long-term behavior.

[1] The NBER requires a cycle (peak-peak or through-through) to be minimal 15 months and a phase (peak-through or through-peak) to be mimimal 5 months. These requirements are used in the Bry Boschan algorithm

Previous papers found that markets to be mean reverting on the long term (e.g. Kahneman and Tversky, 1973; de Bondt and Thaler, 1985; Daniel, Hirshleifer, and Subrah-Manyam, 1998 and Hong and Stein, 1999) and trend continuing on the short-term (Jegadeesh and Titman, 1993 and Cooper, Gutierrez Jr., and Hameed, 2004).

On the short run, investors are following the trend of the economic business cycle. This short-term trend continuation, also known as momentum trading, is caused by overconfidence and a self-attribution bias (Daniel Hirshleifer and Subrahmanyam, 1998). Overconfident investors attribute successes more to their own private information than that of the market and overreact to it. Thereby generating momentum on the short run. The self-attribution bias states that investors attribute successes to their own skills and attribute failures to bad luck. If the news is in line with their expectations, investors will overreact to it and generate momentum on the short run as well. The overreaction will be corrected in the future whenever investors realise they were too optimistic, which results in mean-reverting stock markets on the long run (Daniel Hirshleifer and Subrahmanyam, 1998).

In 'Betting on trends: Intuitive forecasts of financial risk and return', De Bondt (1993) studied the investor forecasting behavior in bull and bear markets using an experimental setting. He found in previous literature that people on the short-term, discover trends in past prices and expect their continuation. He found positive expected price changes in bull markets and negative expected price changes in bear markets. This result is consistent with the theory of short-term trend continuation.

O'Connor et al. (2001) also examined the market trend in an experimental setting and found negative forecasts in bull markets and positive forecasts in bear markets. They found in previous literature opposite information as De Bondt (1993), namely that people have the tendency to dampen the trend with forecasts in the opposite direction of the market. Therefore, their results are consistent with their expectations.

In addition to the analysis of the forecast placement by looking at the market trend, they suggest that there should also be a focus on the immediate last movement in the series and the last actual value when forecasting the stock market. This analysis found in periods that the market trend was flat or upward trending, there was a strong tendency to place the forecast below the last actual and vice versa for a downward trending series.

Glaser et al. (2007) researched the difference between forecasting future price *levels* and future price *changes*. They find that studies asking for future price levels provide mean reverting results, whereas studies asking for future price changes give trend-continuing results. They refer to Andreassen (1987, 1988) and argue that the forecasting behavior depends on how they look at past prices: "He argues that the most representative price of the time series "35, 37, 39, 41, 43, 45" is lower than the final price. Thus, making a forecast while thinking in terms of price levels leads to mean reverting expectations. In contrast, the most representative change of the time series "+2, +2, +2, +2, +2" is "+2". Thus, thinking in terms of changes leads to a belief in trend continuation." (Glaser et al. 2007, pp. 3-4). An exception on the theory above is de Bondt (1993). He asks for future price levels, but in combination with a forecast of future confidence intervals. Despite of asking for future price levels instead of future price changes, the results lead to trend-continuing results oudcomes instead of mean-reverting outcomes.

In 2012, Grobys performed research in investor forecasting behavior in bull and bear markets as well. The main difference with other papers is that the author studied the change in bull and bear markets over time. He found that the forecasted returns are trend-continuing in bull and bear markets in all time periods and that there are differences in magnitudes over time in bull markets. The expected price change in the bull market of 1982-2011 is significantly higher than in the bull market of 1954-1982. Because the paper only has one bear market, = no difference can be observed.

In Table 1 below, a summary of the forecasted expected price changes in previous literature is stated.

Table 1: Forecasted Expected Price Change in previous literature

	Bull	Bear
De Bondt (1993)	+	-
O'Connor et al. (2001)	-	+
Glaser et al. (2007)	+	-
Grobys (2012)	+	-

2.3 Asymmetry of confidence intervals

For a better understanding of the investor forecasting behavior, examining the forecasted index alone is not enough. Confidence intervals forecasted by investors, can reflect extra information. If one looks at the width of the predicted confidence interval, it might be possible to detect overconfidence. Overconfidence can be found in a too narrow prediction of the confidence interval (e.g. Shefrin, 2000 and O'Connor et al., 2001).

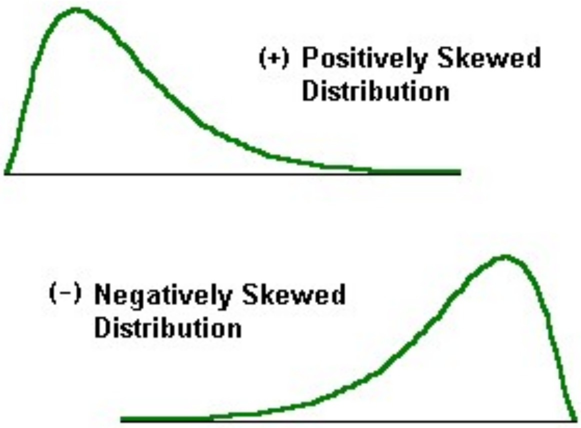
In addition, the symmetry of confidence intervals is another characteristic that can be studied. If confidence intervals are symmetric, the investor predicts the index to grow or to shrink in similar proportions: a forecast would be rational if the estimate is exactly situated in the middle of the upper and lower limit of confidence intervals (Taylor& Bunn, 1999).

Existing literature shows that confidence intervals are not symmetric, thereby providing information about the expectations of the investor. For example, if an investor believes that there is a greater probability that a time series will fall instead of maintaining flat or rise, the investor will create a confidence interval that is downwardly biased where there is greater probability that the series would turn down than other wise.

De Bondt (1993) suggests that when subjects fit a trend line (bull or a bear market) the *expected price change* is not the only important characteristic to examine. There should be a focus on the *past price levels* as well. According tot the momentum theory, in a bull market prices are expected to keep rising on the short-term. However, taking the past into account, the average of the past price levels is lower than our expectation. People will incorporate this when predicting a confidence interval and forecast the interval not to be symmetric around the expected price change. The representative low price drags the confidence interval down, resulting in a left-skewed (negative) confidence interval. The opposite happens in bear markets: the average of past price levels is higher than our expected price change, resulting in a asymmetric confidence interval. The confidence interval is pulled up and gives a right-skewed (positive) confidence interval.

De Bondt (1993) refers to this theory as 'The hedging theory of confidence intervals', predicting that the average skewness to be negative in bull markets and positive in bear markets. Although investors expect a bull market, they are still aware of a great downside potential, thereby creating a left-skewed interval. De Bondt (1993) confirms in his results the asymmetric confidence intervals: he found left-skewed confidence intervals in bull markets and right-skewed confidence intervals in bear markets

Figure 1: Skewness



O'Connor et al. (2001) also studied the symmetry of confidence intervals. In their hypotheses the authors state that the results could be a biased forecast with a symmetric confidence interval, an unbiased forecast with an asymmetric confidence interval or a combination: a biased forecast with an asymmetric confidence interval. It resulted in the latter: they found negative confidence intervals both in negatively biased bull and positively biased bear markets. This leads to a rejection of the 'Hedging theory of confidence intervals'.

Despite O'Connor et al. (2001) rejected the 'Hedging theory of confidence intervals' the authors invented another theory. They suggest the placement of confidence intervals is related to the placement of the forecast. In bear markets, their forecasts were positive containing negative confidence interval. In bull markets, forecasts are negative with a negative confidence interval as well, but a relatively more positive one than in bear markets.. The authors suggest the placement of the confidence interval must be considered together with the expected price change.

In Glaser et al. (2007), the symmetry of confidence intervals is not their main purpose of the paper: only the 'Hedging theory of confidence intervals' is described and tested. The authors found negative skewness, irrespective of the market climate, whereby the 'Hedging theory of confidence intervals' can be rejected. If the new theory of O'Connor (2001) is applied to the results of Glaser et al. (2007), the results do not confirm the theory that the confidence interval hedges the expected price changes.

An experiment from Grobys (2012) in two bull markets and one bear market, shows left ánd right skewed confidence intervals in the bull markets and right skewed confidence intervals in bear markets. Grobys did his research in two bull markets, 1954-1982 (left-skewed) and 1982-2011 (right-skewed) and one right skewed bear market.

2.4 Measuring volatility

In addition to the EPC and the hedging theory of confidence, the volatility is important to examine as well. Many articles have been published concerning volatility forecasting over the last thirty years. One of them is Granger and Poon (2003), in which volatility forecasting and its problems are discussed. Volatility can be explained as uncertainty in the stock market, but it is not similar to risk.[2]

There are some common mistakes about volatility. Many people use the standard deviation as a measure of volatility, thereby forgetting that this is only meaningful with a normal distribution and some other distributions. Also the presence of extremes can influence the standard deviation.

A solution to these problems lies in the Parkinson volatility estimate. The Parkinson volatility estimate measures the volatility perspective of individual investors. It is based on the predictions of the highest and lowest bound of the forecasted confidence interval and therefore corrects for the presence of extremes. Huisman, van der Sar and Zwinkels (2011) use the Parkinson volatility estimate in their research about overconfidence. They estimated the volatility expectations and compared these to the VIX-implied volatility benchmark, resulting the investors to be significantly overconfident.

[2] "While standard deviation is a measure of absolute volatility that shows how much an investment's return varies from its average return over time, beta is a measure of relative volatility that indicates the price variance of an investment compared to the market as a whole. The higher the standard deviation or beta, the higher the risk, according to the theory. In a rising market, however, high volatility can boost the return potential of an investment. Volatility, in other words, is essentially a double-edged sword, and does not measure what an investor intuitively perceives as risk.", Keppler (1990).

Many authors studied stock market volatility in bull and bear markets and found that the volatility is higher during bear than bull markets (Cuñado, Gil-Alana and Perez de Gracia, 2008). Cuñado et al. (2008) studied the difference in volatility in bull and bear markets in the United States. Their conclusion is similar to previous literature, stating volatility to be significantly higher in bear than in bull markets. Grobys (2012) studied the volatility in bull and bear markets as well and found that the volatility in bear markets is almost twice as high as in bull markets.

Two possible explanations for higher volatility during bear markets are given by Jones, Walker and Wilson (2004). The first states that in volatile markets equity values decline, reflecting a higher risk in the market, which is associated by an increased uncertainty. Second, investors react more quickly to news in times of uncertainty, which increases the stock price volatility. Chordia, Roll and Subrahmanyam (2001) argue that declining markets attract less investors, which leaves the markets to be subject to falling liquidity and therefore more uncertain and volatility.

2.5 Expected Price Change (EPC) of other investors

From an investor perspective, it would be nice if the stock market could be forecasted accurately. Hence, it is not only the investors' own forecast that matters. It can be also important to 'forecast the forecasts of other investors (others)', as prices in the stock market depend on the beliefs of all investors.

Previous research[3] found that in efficient markets, higher order beliefs do not have to be taken into account. Observed prices give a signal to participants in industry: all the information held by the participants in the market. This means that people forecast the forecasts of others the same as their own forecasts.

However, in a rational world there is no perfect information and forecasts have to lie on the whole hierarchy of investor beliefs. Romer (1993) states that investors put little weight to their own private information, because they think that other investors have superior information. This difference in information between investors themselves and other investors, means that investors predict the forecasts of other investors different than their own forecasts.

[3] Singleton (1987), Kasa (2000) and Sargent (1991)

Makarov and Rytchkov (2011) state that investors forecast the expected price change of other investors on a trend-continuing way. This theory agrees with the theory of the expected price change, forecasted by the investors themselves.

2.6 Research hypotheses

In the previous paragraphs, different theories about the forecasting behavior of investors are studied. Different topics as the expected price change, the symmetry of confidence intervals, the volatility expectations and the expectations of the forecasted price changes of other investors can be tested to gain a more clear insight in the investor forecasting behavior in bull and bear markets. A unique dataset with data of individual ABN AMRO investors will be used to test different hypotheses about the forecasting behavior of investors.

The first hypothesis that will be tested, is about the forecasted expected price change of investors. Related to previous theory and research, it is likely that the expected price change forecast on the short-term follows the continuation of past trends, because there is asked for future price levels, in combination with a forecast of future confidence intervals. This implies that the expected price change will be higher in bull than in bear markets.

Hypothesis 1:

$$H_0: EPC_{bull} = EPC_{bear}$$

$$H_1: EPC_{bull} > EPC_{bear}$$

The expected price change is defined as 'EPC'. EPC_{bull} is the expected price change in bull markets. EPC_{bear} is the expected price change in bear markets.

The next hypothesis that will be tested is the hypothesis about the symmetry of forecasted confidence intervals. Previous research shows that confidence intervals are not likely to be symmetric. Investors predict asymmetric confidence intervals to hedge themselves. This asymmetry is measured by skewness (Δ). Related to previous research, the presence of skewness in bull and bear markets is expected. I expect the skewness to be significantly more negative in bull than in bear markets:

Hypothesis 2:

$$H_0: \Delta_{bull} = \Delta_{bear}$$
$$H_1: \Delta_{bull} < \Delta_{bear}$$

Skewness is defined by the variable 'Δ'. The Δ_{bull} is the expected skewness in bull markets. The Δ_{bear} is the expected skewness in bear markets.

Thirdly, a hypothesis involving the volatility perspective of investors will be tested. The expectation in relation to previous literature is that investors are expecting more uncertainty in bear than in bull markets. This leads to a higher expected volatility (σ) higher volatility in bear than in bull markets:

Hypothesis 3:

$$H_0: \sigma_{bull} = \sigma_{bear}$$
$$H_1: \sigma_{bull} < \sigma_{bear}$$

The expected volatility of investors is defined by the variable 'σ'. The σ_{bull} is the expected volatility in bull markets. The σ_{bear} is the expected volatility in bear markets.

Finally, three hypotheses about the expected forecast of other investors are stated. The first concerns the direction of forecasting. Because previous research tells that investors forecast the stock market to be trend continuing, I assume investors know that other investors dispose of the same trend-continuing information. Therefore, I expect the expected price change of others to be, just like their own forecast, trend-continuing[4]. Specifically, the expected price change in bull markets will be higher than in bear markets:

Hypothesis 4:

$$H_0: EPC_{others,bull} = EPC_{others,bear}$$
$$H_1: EPC_{others,bull} > EPC_{others,bear}$$

The expected price change is defined by EPC. $EPC_{others,\ bull}$ and $EP_{others,\ bear,}$ are the expected price changes in bull resp. bear markets markets for other investors.

The following hypothesis according other investors lies in the difference between the forecasts of others and the investors' own forecast. As discussed in the literature review it is important to know what other investors think, as prices in the stock market depend on the

[4] Related to Hypothesis 5a and 5b, I expect the forecast of other investors to be in the same direction as the own forecast of investors, but having different magnitudes of amount.

beliefs of all investors. Hypothesis 5 is divided in two sub-hypotheses. The first sub-hypothesis is about the difference between the forecast of other investors and the own expectation of investors in bull markets. The second sub-hypothesis is about the difference between the forecast of other investors and the own expectation of investors in bear markets. According to previous research, I believe that investors think that other investors have more information than they do. Therefore, I expect the expected forecast of other investors to be different from the own forecast of investors bull markets and in bear markets:

Hypothesis 5:

A) $H_0: EPC_{bull} = EPC_{others,bull}$

$H_1: EPC_{bull} \neq EPC_{others,bull}$

B) $H_0: EPC_{bear} = EPC_{others,bear}$

$H_1: EPC_{bear} \neq EPC_{others,bear}$

The expected price change is defined by EPC. EPC_{bull} and EPC_{bear} are the expected price changes in bull resp. bear markets markets. $EPC_{others, bull}$ and $EPC_{others, bear}$ are the expected price changes in bull resp. bear markets, forecasted for other investors. Hypothesis 5a tests the difference between the forecast of other investors and the own forecast of investors in bull markets. Hypothesis 5b tests the difference between the forecast of other investors and the own forecast of investors in bear markets.

3. Methodology

In this chapter the dataset and methodology that will be used to obtain the results, will be discussed. This chapter shows how we can calculate how investors forecast the AEX index in bull and bear markets. The difference between this research comparing to the papers of De Bondt (1993), O'Connor et al. (2001) and Glaser et al. (2007), is that the other authors used an experimental setting. In this research, and in Grobys (2012) as well, are the results directly tested.

3.1 Data

The dataset that is going to be used is obtained from a repeated biweekly survey, dated from December 2009 through June 2012. Describing the data, the method of Huisman et al. (2011) is used.

The respondents of the survey are private investors of the Dutch ABN Amro bank, one of the biggest Dutch Banks. These private investors are active investors who trade at least multiple times per week. ABN Amro bank runs a specific operation for these investors; they therefore know that they are part of a specific group within the ABN Amro clientele. The group is referred to as ABN Amro Trading clients. There is no additional insight in other client specific information. Biweekly on Friday after the close of the exchange the investors are invited by email to participate in a survey, an online questionnaire. Each survey consists of two sets of questions. One set of questions is designed by the Erasmus University and is the same over all surveys. Our set of questions starts with the observation (translated from Dutch): "Today, the AEX Index closed at XXX.", with XXX replaced by the exact closing price of the AEX Index. Then, the investors are asked to answer the following questions (translated from Dutch and in the exact order of questioning):

1. "On what level will the AEX Index end on dd-mm-yyyy?"
2. "On what level will the AEX Index end maximally on dd-mm-yyyy?"
3. "On what level will the AEX Index end minimally on dd-mm-yyyy?"
4. " How do you think that other investors forecast the AEX Index?"

With dd-mm-yyyy being a specific date of the Friday two weeks after the survey (or a Thursday if the specific Friday is a holiday)

The outcomes of this set of questions are used as the data. Because we specifically ask for both the expected level and confidence bounds, this survey can give us a good insight to the forecasting behavior of the ABN Amro Trading Clients.

The second set of questions is designed by ABN Amro bank and varies each survey. These would be open questions such as “What do you think that 2010 will offer you?” or “What is currently your favorite stock?”. After the forecasts were received, ultimately on Sunday, a report is send back to the ABN Amro Trading clients with a summary of the outcomes and a sentiment index derived from the results. Table 3.1 contains a summary of the surveys and shows that the number of respondents decreases over time and more or less stabilized from survey 11. Survey 11 had 87 respondents and the number of respondents stays approximately at this level in later surveys. There is no apparent reason why the number of respondents decreased, perhaps some investors lost interest (Huisman et al., 2011).

Table 3.1: Summary of surveys

Survey t	**N**	**Survey Date**	**Forecast date**	**St**	**Average Et(St+1)**	**Average E(s(t+1),others)**
1	180	18-12-09	31-12-09	324,63	326,49	326,49
2	192	31-12-09	15-01-10	335,33	335,65	338,07
3	175	15-01-10	29-01-10	337,99	338,76	339,65
4	154	29-01-10	12-02-10	327,9	330,53	330,69
5	129	12-02-10	26-02-10	315,74	317,36	318,33
6	118	26-02-10	12-03-10	317,74	319,35	318,47
7	129	12-03-10	26-03-10	339,57	341,26	341,63
8	126	26-03-10	09-04-10	343,81	346,16	345,65
9	116	09-04-10	23-04-10	355,89	356,29	356,66
10	103	23-04-12	07-05-12	353,38	356,83	356,39
11	87	07-05-10	21-05-10	312,35	320,75	315,41
12	81	21-05-10	04-06-10	313,41	318,80	315,59
13	81	04-06-10	18-06-10	321,22	319,85	318,86
14	87	18-06-10	02-07-10	336,06	337,44	336,92
15	68	02-07-10	16-07-10	308,2	312,26	310,26
16	87	16-07-10	30-07-10	323,99	323,99	324,38
17	83	13-08-10	27-08-10	323,92	326,45	324,57
18	103	27-08-10	10-09-10	317,04	322,04	320,54
19	85	10-09-10	24-09-10	334,96	338,73	337,81
20	88	24-09-10	08-10-10	337,85	340,00	338,99
21	83	08-10-10	22-10-10	336,49	341,64	339,90
22	81	22-10-10	05-11-10	341,07	346,70	343,60
24	105	19-11-10	03-12-10	344,58	348,11	347,11

Survey t	N	Survey Date	Forecast date	St	Average Et(St+1)	Average E(s(t+1),others)
25	111	03-12-10	17-12-10	342,19	347,47	345,30
26	105	17-12-10	31-12-10	352,05	354,38	354,21
27	108	31-12-10	14-01-11	354,57	355,07	356,66
28	111	14-01-11	28-01-11	361,32	363,41	363,42
29	100	28-01-11	11-02-11	361,16	361,00	361,77
30	101	11-02-11	25-02-11	369,65	370,81	370,92
31	105	25-02-11	11-03-11	366,77	367,16	365,95
32	86	11-03-11	25-03-11	359,07	358,78	358,77
33	82	25-03-11	08-04-11	364,65	367,50	366,96
34	79	08-04-11	22-04-11	366,94	368,42	368,81
35	83	22-04-11	06-05-11	359,01	363,22	362,04
36	71	06-05-11	20-05-11	359,12	360,96	360,38
37	79	20-05-11	03-06-11	348,24	349,67	349,65
38	75	03-06-11	17-06-11	340,24	342,40	341,77
39	65	17-06-11	01-07-11	333,11	335,26	334,38
40	55	01-07-11	15-07-11	342,82	349,64	347,55
41	77	15-07-11	29-07-11	329,49	332,31	332,05
42	61	29-07-11	12-08-11	329,22	331,41	330,38
43	66	12-08-11	26-08-11	291,9	300,85	300,92
44	56	26-08-11	09-09-11	276,6	279,82	280,14
45	59	09-09-11	23-09-11	276,1	279,51	276,85
46	68	07-10-11	21-10-11	288,31	285,82	288,13
47	65	21-10-11	04-11-11	305,7	305,95	306,34
48	72	04-11-11	18-11-11	301,97	303,39	303,72
49	81	18-11-11	02-12-11	288,01	286,73	289,40
50	82	02-12-11	16-12-11	300,77	310,06	306,05
51	89	30-12-11	13-01-12	312,47	311,88	312,56
52	78	13-01-12	27-01-12	309,28	309,10	309,49
53	76	27-01-12	10-02-12	319,36	320,70	319,58
54	71	10-02-12	24-02-12	320,09	320,30	321,25
55	79	24-02-12	09-03-12	324,91	325,35	325,94
56	73	09-03-12	23-03-12	326,03	328,34	327,37
57	77	23-03-12	06-04-12	326,19	327,84	327,12
58	75	06-04-12	20-04-12	314,91	317,63	316,55
59	92	20-04-12	04-05-12	309,2	311,53	311,22
60	69	04-05-12	18-05-12	300,95	300,48	303,28
61	65	18-05-12	01-06-12	288,77	287,45	286,98
62	72	01-06-12	15-06-12	283,77	281,82	285,49

This table shows for each survey the survey number (t), the number of respondents (n), the date on which the survey invitation was send (survey date), the indicated forecast date (forecast date), the close price of the AEX Index as mentioned in the survey invitation (St), the average forecast of the price at the forecast date over the respondents (average Et(St+1) and the expected average forecast of others of the price at the forecast date over the respondents. The total number of responses (obtained from all the surveys) is 5560.

The first survey (t = 1) was sent out on December 18, 2009 and the last was send out on June 1, 2012 (t = 62) resulting in 61 surveys[5]. Survey 23 has been removed, because question 4 about the forecast of others, was not filled in by the respondents. In survey 1, one respondent has been removed, because the respondent did not answer question 4: "How do you think that other investors forecast the AEX Index".

3.2 Bull and bear markets

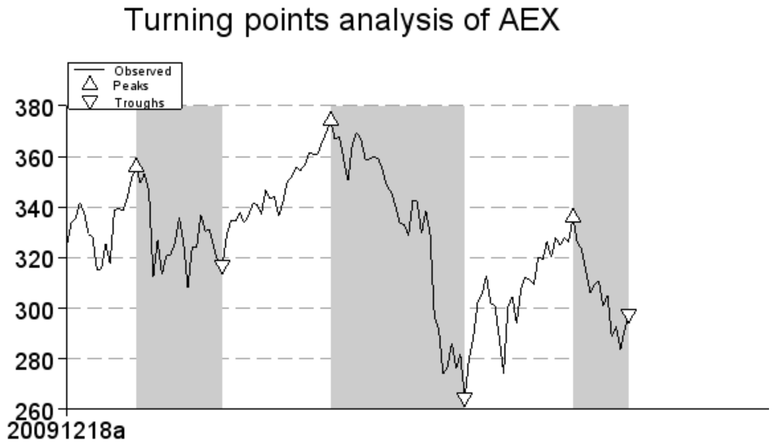
3.2.1 Main results

Hence, when comparing the non-parametric and full-parametric method, the non-parametric rules-based method fits the ABN AMRO dataset the most. The short crashes or peaks, which are present in the Markov Switching regime, are not welcome as long bull and bear markets are needed to obtain valid results. In this research, a rules-based method is chosen. Because our dataset is very small and the Bry Boschan algorithm (1971) has rules that require cycles from minimal 15 months and phases from at least 5 months, the Bry Boschan algorithm will obtain solely a few bull and bear markets. Since that would lead to diminished significance, the graphical trend method is chosen. Based on a graph, bull and bear markets are chosen. Periods where the AEX increases are defined as bull markets, periods of a decreasing index as bear markets.

In the period from December 18th, 2009 and June 1, 2012, three peaks and three troughs can be obtained which correspond with three small bull and three small bear markets. The bull markets correspond to survey 1-9, 19-30 and 46-56, with returns of respectively +9,6%, 10,4% and 13,1%. The returns of the bear markets are -10,3%, -24,7% and -13,0%, corresponding to respectively survey 10-18, 31-45 and 57-62.

[5] The surveys send out on July 30, 2010 about the forecast for August 13, 2010, on 23 September 2011 about the forecast for 7 October 2011 and on 16 December 2011 about the forecast for 30 December 2011 are missing. The first one due to a technical error because of which the survey results were not saved. There is no specific reason why the second and third one miss. Survey 23 is removed, because it was not completely filled in by the respondents.

Graph 3.1: Classification of the different bull and bear periods in the dataset for the main results



This graph dates from 18-12-2009 until 01-06-2012. It shows the bull and bear markets obtained by the graphical trend method. The white areas are the bull markets, ending with a peak (Δ). The grey areas are the bear markets, ending with a through (∇).

3.2.2 Robustness check

The Bry Boschan algorithm (1971) is used as robustness check, as it can be extended by transforming the monthly towards biweekly dataseries.

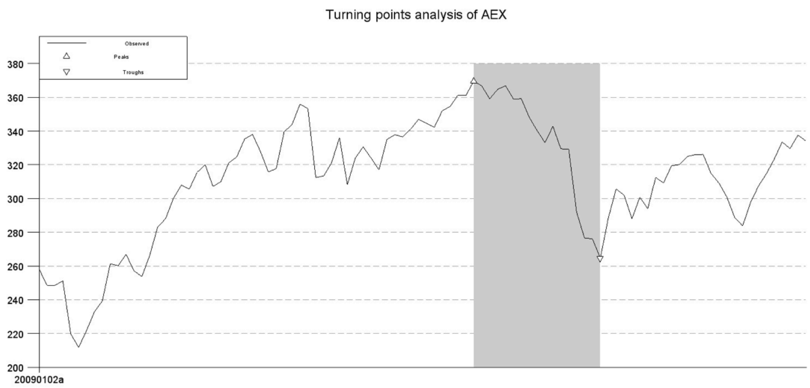
Different periods of peaks and troughs in the stock market must be determined. These peaks and troughs are obtained by estimating the parameters of the algorithm. The values for the minimum length of a business cycle from peak to peak or trough to trough must be inserted (M), the minimum length of one phase from peak to through or vice versa (m), the minimal number of periods separating a turning point from the borders (e) and the number to determine the local minimum or maximum (k) must be inserted.

As the Bry Boschan algorithm is originally created for monthly time series, the biweekly dataset must be multiplied by two, thereby mimicking monthly time series. According to Gonzalez et al. (2005), the NBER requires a minimum value for phases between extraction and expansion (m) to be equal to 5 months. Moreover, the NBER states that the minimum length of the cycle (M) must be 15 months. Gonzalez et al. (2005) states that if these phases are less than 5 months, the results will be of little economic and statistical significance.

Because our ABN AMRO-dataset is small (18-12-2009 until 01-06-2012), we enlarge the AEX-dataset to 02-01-2009 until 21-09-2012 to obtain the bull and bear markets. On this way, we can see the bull and bear markets in a broader perspective.

Subsequently, after the parameters have been set and the business cycle algorithm has been executed, two bull markets and one bear market are obtained. This results in the classification of the following periods for the bear and bull markets. The bull markets correspond to survey 1-30 and 47-62 yielding average returns of respectively +13,87% and -7,17%[6]. The returns of the bear market is -21,39%, corresponding to respectively survey 31-46.

Graph 3.2: Classification of the different bull and bear periods in the dataset for the robustness check



This graph shows the bull and bear markets obtained by the Bry Boschan algorithm (1971). The white areas are the bull markets, ending with a peak (Δ). The grey areas are the bear markets, ending with a through (∇).

3.3 Expected price change and the expected price change of others

To measure the expected price change and the expected price change of others, the method of de Bondt (1993) is used. De Bondt (1993) calculated the expected price changes in absolute terms. The forecast (F) minus the last known level of the AEX (P_0) is calculated in the different bull and bear markets. A weighted average is calculated for all the bull and bear markets, so that there is one result generated for the bull markets and one result generated for the bear markets. This is called the mean expected price change.

[6] Because the bull and bear markets are determined in a broader perspective, the part which falls in our dataset can be negative.

In addition to the absolute value of de Bondt (1993), the relative expected price change in percentages will be calculated. This is a valuable standard, because it is independent on the chosen standard.

The expected price change of others is calculated on the same way.

3.4 Asymmetry of confidence intervals

To measure the asymmetry of confidence intervals, skewness will be used to see whether there is asymmetry. Skewness gives an insight into the asymmetry in the distribution of the expectations of investors. Once there is negative skewness, the left tail of the distribution is more pronounced. This is a sign of dominant negative sentiment. If positive sentiment is dominant, the distribution is positively skewed: the right tail of the distribution is more pronounced.

In the dataset, respondents answered questions about the forecasted value of the AEX index. The forecasted value of the AEX Index and the forecast of the maximum and minimum level of the AEX Index[7] are needed to calculate the skewness. The formula below shows how skewness (Δ) in the dataset can be calculated:

Formula 3.1: Calculating Skewness

$$Skewness\ (\Delta) = \frac{(H + L - (2F)}{(H - L)}$$

In this formula, skewness is defined as 'Δ'. Let H be the 'maximum' forecast of the AEX, L the 'minimum' forecast of the AEX and F the forecasted value of the AEX index.

[7] "On what level will the AEX Index end maximally on dd-mm-yyyy?" and "On what level will the AEX Index end minimally on dd-mm-yyyy?".

3.5 Measuring volatility

To measure the expected volatility of the AEX forecasted by investors, the Parkinson measure (1980) will be used. The Parkinson volatility measurement, measures the expected price volatility or uncertainty, forecasted by investors, in the AEX index in two weeks. The volatility can be measured with the following formula:

Formula 3.2: Calculating Volatility with the Parkinson Volatility Estimator

$$\sigma_{i,t} = \sqrt{\frac{\ln\left(\frac{H_{i,t}}{L_{i,t}}\right)^2}{4\ln(2)}}$$

In this formula, the volatility is defined as 'σ'. The survey number is t, n_t will be the number of respondents for survey t. The forecasts of investor 'i' in survey t, about the closing price of the AEX Index on date t + 1 equals $E_{i,t}(St+1)$. $H_{i,t}$ and $L_{i,t}$ are the respondent i's estimates for the maximum and minimum value that the AEX will obtain two weeks after the survey date. Given $H_{i,t}$ and $L_{i,t}$, the Parkinson measure method can be used to estimate the expected uncertainty (volatility), $\sigma_{i,t}$, of respondent 'i' in survey 't', regarding the price of the AEX Index over two weeks.

In this research, the Parkinson volatility estimate can be calculated for the bull and bear markets, which is earlier provided in the research of Grobys (2012).

4. Results

In the next paragraphs the results will be presented. With the graphical trend method, three peaks and troughs can be obtained which correspond with three bull and three bear markets. The results in this chapter are based on this classification of bull and bear markets. An alpha-level of 5% is used for all statistical tests.

Table 4.1: Main Results

	Bull	Bear	Bull -/- Bear
Mean (EPC)	1,783	2,544	-0,760
T-value	10,316	13,335	-2,953
P-value	0,000	0,000	0,002
Mean (EPC%)	0,534%	0,790%	-0,003
T-value	8,796	13,010	-3,122
P-value	0,000	0,000	0,001
Mean (Δ)	-0,220	-0,176	-0,043
T-value	-32,181	-23,411	-4,263
P-value	0,000	0,000	0,000
Volatility (σ)	3,636%	3,902%	-0,266%
T-value	89,827	87,360	-4,413
P-value	0,000	0,000	0,000
Mean (EPCothers)	1,709	1,814	-0,105
T-value	13,928	13,395	-0,573
P-value	0,000	0,000	0,284
Mean (EPCothers%)	0,516%	0,569%	-0,052%
T-value	13,401	13,377	-0,913
P-value	0,000	0,000	0,182

4.1 Forecasted EPC

Table 4.1 shows the forecasted AEX Index changes in bull and bear markets. The expected price changes (EPC) equal the forecast (F) minus the last known level of the AEX index (P_0). As can be seen are the expected price changes on average positive, +1,783 or 0,534% in bull markets (EPC_{bull}: $t(60)=10{,}316$, $p<0{,}001$ and $EPC\%_{bull}$: $t(60)=8{,}796$, $p<0{,}001$) and +2,544 or +0,790% in bear markets (EPC_{bear}: $t(60)=13{,}335$, $p<0{,}001$) and $EPC\%_{bear}$: $t(60)=13{,}010$, $p<0{,}001$). Comparing the scores for the expecting price changes in bull and bear markets, a significant difference is observable. The value of the expected price change in bear markets, is significantly larger in bear than in bull markets ($t(60)$=2,953, p = 0,002 for the Mean EPC and $t(60)$= -3,122, p = 0,001 for the Mean EPC%).

These results are remarkable, since they contradict with previous literature. De Bondt (1993), Glaser et al. (2007) and Grobys (2012) found that the expected price changes follow the trend of the market. O'Connor (2001) found it in opposite way: negative forecasts in bull markets and positive forecasts in bear markets. The results in this research, positive forecasts in bull and bear markets and in bear markets even higher forecasts are not previously shown.

4.2 Symmetry of confidence intervals

In Table 4.1, the symmetry of confidence intervals can be seen in the row 'Mean Δ'. Both in bull and bear markets a asymmetric confidence interval is observed: there is a significant negative skewness in both markets: -0,220 in bull and -0,176 in bear markets (Δ_{bull}: $t(60)$=-32,181, p<0,001, (Δ_{bear}: $t(60)$=-23,411, p<0,001). Comparing the negative skewness in bull and bear markets, there can be concluded that there is a significant difference observable between bull and bear markets. There is significantly more negative skewness noticeable in bull than in bear markets ($t(60)$=-4,263, p < 0,001).

Regarding previous research[8], the expected asymmetry in confidence intervals can be confirmed. The results are contradicting to de Bondt (1993), who set out the 'Hedging theory of confidence intervals' and found that confidence intervals hedge the market state: there should be negative skewness in bull markets and positive skewness in bear markets. The results of Grobys (2012) are partly confirmed: he found negative and positive skewness in two bull markets and, but positive skewness in bear markets.

The results in this study are most consistent with the results of O'Connor et al. (2001), who found that confidence intervals hedge the forecasted expected price change. In his research negative skewness is found in bear markets with positive forecasted expected price changes and positive skewness is found in bull markets with negative forecasted expected price changes. This concurs whith our results: positive expected price changes in bull and bear markets, hedged by negative confidence intervals in both markets.

[8] De Bondt (1993), O'Connor et al. (2001), Glaser et al. (2007) and Grobys (2012).

4.3 Volatility

The results in the row 'Volatility (σ)' in Table 4.1, contain the expected volatility or uncertainty in the AEX in two weeks, measured by the Parkinson volatility estimator. There is a significant volatility of +3,636% found in bull markets ($t(60)$=89,827, p<0,001) and also a significant volatility noticeable of +3,902% in bear markets ($t(60)$=87,360, p<0,001). The volatility is significantly higher in bear than in bull markets ($t(60)$=-4,413, p<0,001).

The higher inged expected volatility in bear markets, is in line with previous literature (e.g. Cuñado et al., 2008). In a similar dataset, Grobys (2012) measured the volatility as well and found just like this research higher volatility in bear than in bull markets. However, he found twice as high volatility in bear than in bull markets, which is not the case in this research.

4.4 Forecasted EPC of others

4.4.1 Direction of forecasted expected price change

Looking at the expected price change for others, there was a significant positive effect for the expected price changes of others of +1,709 or 0,516% ($t(60)$=13,928, p<0,001 resp. ($t(60)$=13,401, p<0,001) in bull markets and +1,814 or 0,569% ($t(60)$=13,395, p<0,001 resp. $t(60)$=13,377, p<0,001)in bear markets. Comparing this results, there is no significant difference noticeable between the positive forecasts in both bull and bear markets (EPC $t(60)$=-0,573, p=0,284 and EPC% $t(60)$=-0,913, p=0,182) on a 5% significance level. This means that the magnitude of the EPC and EPC% is similar in bull and bear markets.

In previous researches about the forecasting behavior of investors in bull and bear markets, investors are in general following the prevailing consensus (De Bondt, 1993, Glaser et al., 2007 and Grobys, 2012) or forecasted in opposite direction of the prevailing consensus (O'Connor et al., 2001). In all those studies the magnitude of the forecast in bull and bear markets differ from each other. Our results contradict with both: positive forecasts in bull and bear markets are not following the prevailing consensus and there is no difference observable between bull and bear markets.

4.4.2 The difference between the forecast of others and the own forecast of investors.

As can be seen in Table 4.2, there is an observable difference between the own forecast of investors and the forecast of others in bear markets, but not in bull markets. In bear markets a significance difference can be seen between the own forecast of investors (+2,544 or +0,790%) and the forecast of others (+1,814 or 0,569%) (Difference EPC and EPC others in bear markets: $t(60)=13{,}188$ $p<0{,}001$ and difference EPC% and EPC% in bear markets: $t(60)=12{,}153$, $p<0{,}001$). Investors forecast the forecast of others significantly lower in bear markets than their own forecast.

In bull markets there is no significant difference between investors' own forecast (+1,783 or +0,534%) and the forecast of others (+1,709 or 0,516%), which means that investors expect others to forecast the same as they do (Difference EPC in bull markets: $t(60)=1{,}484$ $p=0{,}14$ and EPC% in bear markets: $t(60)=1{,}087$ $p=0{,}281$).

It is remarkable that investors forecast their own forecast (+2,544 or +0,790%) significantly higher than the forecast of others (+1,814 or 0,569%) in bear markets, but in bull markets they forecast the same. Romer (1993) states that other investors have superior information, which results in the fact that investors think that the expectations of others are superior. Therefore, the forecasts of other investors are expected to be different than the own expectations of investors. This is confirmed in bear markets: investors forecast the expected price changes different for themselves than for others. In other words, investors think that other investors have different information than they have in bear markets. But in bull markets, investors forecast the same for themselves and others, which suggest that investors think that other investors have the same information in bull markets.

Table 4.2: Results own forecasts compared to forecasts others

	Mean EPC	Mean EPC others	Mean EPC -/- Mean EPC others
Bull	1,783	1,709	0,074
T- value	10,316	13,928	1,484
P-value	0,000	0,000	0,14
Bull%	0,534%	0,516%	0,018%
T- value	9,706	13,401	1,087
P-value	0,000	0,000	0,281

	Mean EPC	Mean EPC others	Mean EPC -/- Mean EPC others
Bear	2,544	1,814	0,730
T- value	13,355	13,395	13,188
P-value	0,000	0,000	0,00
Bear	0,790%	0,569%	0,222%
T- value	13,010	13,377	12,153
P-value	0,000	0,000	0,000

5. Robustness check

The results in the previous chapter are based on the classification of bull and bear markts with the graphical trend method. Because this is a subjective rules-based method, a robustness check will be performed to control for the subjectiveness of the bull and bear markets. The robustness check will be done by classifying bull and bear markets with the Bry Boschan algorithm (1971). The parameters of the Bry Boschan method are set based on literature. The Bry Boschan Method generates two bull and one bear market (as stated in chapter 3, paragraph 3.2.2), whithin the EPC's, volatility and skewness will be calculated. The methods of calculation of the mean EPC's, the calculation of the volatility and the skewness do not change.

Table 5.1: Results robustness check

	Bull	**Bear**	**Bull -/- Bear**
Mean (EPC)	1,993	2,571	-0,578
T-value	12,759	5,851	-1,239
P-value	0,000	0,000	0,110
Mean (EPC%)	0,607%	0,794%	-0,186%
T-value	4,334	5,666	-1,254
P-value	0,000	0,000	0,107
Mean Δ (All)	-0,202	-0,190	-0,012
T-value	-34,171	-11,415	-0,692
P-value	0,000	0,000	0,246
Volatility (σ)	3,773%	3,735%	0,037%
T-value	105,869	37,270	0,351
P-value	0,000	0,000	0,363
Mean (EPCothers)	1,647	2,072	-0,424
T-value	13,906	6,217	-1,199
P-value	0,000	0,000	0,118
Mean (EPCothers%)	0,504%	0,647%	-0,144%
T-value	13,325	6,089	-1,273
P-value	0,000	0,000	0,104

5.1 Forecasted EPC

Table 5.1 shows the forecasted AEX index changes in bull and bear markets, where the expected price changes (EPC) equal the forecast (F) minus the last known level of the AEX index (P_0). As can be seen are the expected price changes on average positive, +1,993 or +0,607% in bull markets and +2,571 or +0,794% in the bear market. There was a significant effect for expected price changes in bull markets: $t(60)=12{,}759$, $p<0{,}001$ for the Mean EPC and $t(60)=4{,}334$, $p<0{,}001$ for the Mean EPC%. Also in bear markets was a significant effect for expected price changes: $t(60)=5{,}851$, $p<0{,}001$ for the Mean EPC and $t(60)=5{,}666$, $p<0{,}001$ for the Mean EPC%. Looking at the positive values in bull and bear markets, there is no significant difference observable between the expected price changes in bull and bear markets ($t(60)=-1{,}239$, $p=0{,}110$ for the Mean EPC and $t(60)=-2{,}254$, $p=0{,}107$ for the Mean EPC%). The forecasted price changes have the same magnitude in terms of amount in bull and bear markets.

These results that there is a positive forecast in bull and bear markets, confirm our main results. The difference is that there are higher positive results in bear than in bull markets in the main results and equal magnitudes in the robustness check.

5.2 Symmetry of confidence intervals

In Table 5.1, the symmetry of confidence intervals can be seen in the row 'Mean Δ'. The mean skewness is negative (left-skewed confidence intervals), -0,202 in bull and -0,190 in bear markets ($t(60)=-34{,}171$, $p<0{,}001$) and bear ($t(60)=-11{,}415$, $p<0{,}001$) markets. There is no significant difference observed in the values of the bull and bear markets ($t(60)=-0{,}692$, $p=0{,}246$).

The negative skewness confirms our main results: the confidence intervals both in bull and bear markets are negatively skewed. However, it differs in the magnitudes of the forecasts. In the main results, there is significantly more negative skewness in bull than in bear markets where in the robustness check is no significance difference observed.

4.3 Parkinson volatility estimate

The results in the row 'Volatility (σ)' in Table 5.1, contain the expected volatility or uncertainty in the AEX in two weeks, measured by the Parkinson volatility estimator. The measured volatility in bull markets is 3,773% ($t(60)=105{,}869$, $p<0{,}001$) and in bear markets

3,735% *(t*(60)=37,270, *p*<0,001). This is no significantly different result observed: investors expect the same uncertainty in bull and bear markets *(t*(60)=0,351, *p*=0,363). This is a remarkable result, because the existing literature and our main results find more volatility in bear than in bull markets.

5.4 Forecast others

5.4.1 Direction of forecasted expected price change in robustness check

In table 5.1, the forecasted expected price change of investors can be seen in the bottom row. The forecasted expected price change of others (EPC_{others}) equal the forecast of others (F_{others}) minus the last known level of the AEX index (P_0).

It results in a significant effect of positive forecasts. The expected price change of others is +1,647 or 0,504% *(t*(60)=13,906, *p*<0,001 resp. *(t*(60)=13,325, *p*<0,001) in bull markets and 2,072 or 0,647% *(t*(60)=6,217, *p*<0,001 resp. *t*(60)=6,089, *p*<0,001)in bear markets. There is no significant difference noticeable between the positive forecasts in both bull and bear markets (EPC: *t*(60)=-1,199, *p*=0,118 and EPC%: *t*(60)=-1,273, *p*=0,104) on a 5% significance level.

The significant positive results from a same magnitude of amount confirm the main results. It contradicts like the main results, with the previous literature.

5.4.2 The difference between the forecast of others and the own forecast of investors in the robustness check

Comparing the forecasts of others forecasting the AEX Index to the forecasts of the investors themselves, both in bull and bear markets a significance difference can be observed (EPC_{bull}: *t*(60)=7,354, *p*<0,001, $EPC\%_{bull}$: *t*(60)=8,620, *p*<0,001, EPC_{bear}: *t*(60)=4,704, *p*<0,001 and $EPC\%_{bear}$: *t*(60)=4,332, *p*<0,001). Investors forecast the expected price change of others significantly lower in bull and bear markets than their own forecast.

The bear market' result is in line with the main results, the bull market' result contradicts with the main results. In the main results, the bull market observations do not differ between the own forecasts and forecasts of others. The results in the robustness check agree with Romer (1993): other investors are expected to have other information, whereby investors forecast the expectations of others different than their own expectations.

Table 5.2: Results own forecasts compared to forecasts others

	Mean EPC	Mean EPC others	Mean EPC -/- Mean EPC others
Bull	1,993	1,647	0,288
T- value	12,759	13,906	7,354
P-value	0,000	0,000	0,00
Bear	2,571	2,072	0,499
T- value	5,851	6,217	4,704
P-value	0,000	0,000	0,00

	Mean EPC%	Mean EPC% others	Mean EPC% -/- Mean EPC% others
Bull	0,607%	0,504%	0,104%
T- value	12,190	13,325	8,620
P-value	0,000	0,000	0,000
Bear	0,794%	0,647%	0,146%
T- value	5,666	6,089	4,332
P-value	0,000	0,000	0,000

6. Conclusion

The purpose of this thesis is to get a better insight in the forecasting behavior of investors in bull and bear markets. Until so far, de Bondt (1993), O'Connor et al. (2001), Glaser et al. (2007) and Grobys (2012) paid attention to how investors forecast in bull and bear markets. The difference between the previous literature and this study is the experimental setting that is used in the previous studies (except from Grobys, 2012) and the dataset with real Dutch investors in this research. Three hypotheses about the expected price change of investors, the expected asymmetry in the confidence intervals and the expected volatility in the AEX index, and two hypotheses about the expectations related to the forecasts of others investors were tested.

Starting with the *mean expected price change* in bull and bear markets, we found that the mean expected returns are positively forecasted in bull and bear markets. This is remarkable, because it is never found before and contradicts with the expected trend following expectations of investors in previous literature. Another striking result according the positive results of the expected price change, is that the expected price changes in bear markets are forecasted significantly higher than in bull markets. This would mean that investors have more positive expectations in bear than in bull markets. However, this is not confirmed in the robustness check. Summarizing this paragraph, we can reject the first hypothesis, that the mean expected price change is higher in bull than in bear markets.

Looking at the *symmetry of confidence intervals*, asymmetric confidence intervals are found. Both in bull and bear markets, these asymmetric confidence intervals are negatively skewed, confirmed by the robustness check. In the main results there is a difference observed in the magnitude of skewness in bull and bear markets, but this is not found in the robustness check. These results concerning skewness, are contradicting with 'The Hedging Theory of Confidence Intervals' (de Bondt, 1993), therefore we reject our second hypothesis.

Combining the results of hypothesis one and two, the theory of O'Connor et al. (2001) can be applied. This theory suggested that the placement of a confidence interval is related to the earlier asked forecast of the index and that there may be an association between the first question about the expected price change of the AEX and the next questions about the confidence interval. This theory explains our results, since our positive forecasts are hedged by negative confidence intervals.

Our third hypothesis is about the *volatility expectations* of investors. The hypothesis that there is more volatility expected in bear markets than in bull markets, can be accepted according to our main results. This agrees with previous literature that there is a higher volatility in bear than in bull markets. However, the higher volatility cannot be confirmed by the robustness check.

As can be seen in the results of the *expected price changes of other investors*, are the forecasts positive and equal in bull and bear markets. This means that the magnitude of the EPC_{others} and $EPC\%_{others}$ is not different in bull and bear markets. So, the fact that expected price changes do not follow the trend confirms their own forecasts, but it is different that the expected price changes of others are equal in magnitude in bull and bear markets. These results reject hypothesis 4, where is stated that the expected price change is higher in bull than in bear markets.

If the own forecast of investors about the expected price change is compared to the *expected forecast of other investors*, it results in different expectations in bear markets. In bull markets, investors forecast their own forecast the same as the forecast of others. This confirms hypothesis 5b that the forecast of others differs from the own forecast of investors in bear markets. However, it rejects hypothesis 5a: the forecast of others differs from the own forecast of investors in bull markets. It is remarkable that investors expect other investors to have the same knowledge in bull markets, but different knowledge in bear markets. They themselves are much more positive in bear markets than they expect other investors to be. The robustness check would accept both hypotheses: the results confirm significant differences in expectations between own forecasts and the forecast of others both in bull and bear markets.

7. Discussion

In finalizing this thesis I will look back at the results of this study. Not all results directly point in the direction of my hypothesis and are therefore not directly in line with previous literature. In this chapter, there will be a look at possible explanations and possibilities for further research.

The basis of this study lies in the *classification of bull and bear markets*. This is a quite subjective classification, because there is not one definition or approach to obtain bull and bear markets in a dataset. In this research is chosen for the non-parametric graphical trend method. To control for subjectiveness a robustness check was done with the Bry Boschan algorithm (1971). Different periods can result in different results. In this research some results are equal in the main results and the robustness check, other results differ from each other. Therefore, I think it is more valid to use two classification methods for bull and bear markets instead of one. Results that are verified by both methods are more valid for your research. Therefore, I would recommend other researches to look for bull and bear markets on two methods and not only one, subjective method.

Going back to investors' forecast of the AEX, the *expected price changes* resulted in a more positive AEX forecast in bear than in bull markets. There is no direct explanation for this phenomenon, but a possible way to explain the higher forecasts of investors in bear than in bull markets can be with psychological theories about being positive in bad periods. If it is a negative situation, the only way out is the desire of better times. One wants to believe better periods will come soon. This is confirmed in the book of Frankl (1978), where people in concentration camps during the Second World War were studied. It occurred to him that people were too happy than they were ought to be. He calls it logotherapy, which is based on the fact that even in the most unbearable situations, there is a goal and therefore the suffering has a meaning.

Another way to study the expected price changes is to look at the immediate last movement in the index and the last actual value (O'Connor et al., 2001). By studying the expected price change forecasted by investors, we assumed the investors looked at the bull or bear market trend to forecast their expected price change. Studying results in relation to the last price movement before the forecast date can extend this research. Then can be looked whether investors follow the trend of the last price movement.

Looking at the symmetry of confidence intervals in our research and previous research, it can be said that the ‘Hedging theory of confidence intervals’ does not hold in forecast situations[9]. But the theory found in O’Connor et al. (2001) about the hedging of the earlier forecast of the index, can be confirmed in this research. There can be suggested that investors hedge their own forecast independent of the market state. There is room for further research to test this ‘Hedging Theory of Expected Price Changes’ in new datasets and periods.

That the *expected volatility* is equally forecasted in bull and bear markets in the robustness check is remarkable. This can be possibly explained with a short run and long run approach: it insinuates that investors base their volatility expectations more on the short run than on the long run. In the robustness check are within the large bull (bear) markets small falling (increasing) periods noticeable. Investors notice these small falling (increasing) periods and do not recognize it as a bull (bear) market anymore. Further research can be done on the short-term and long-term volatility.

It is remarkable that there is a difference between investors’ own forecasts and the *forecasts of others* in bear markets, but not in bull markets. This means that investors expect that other investors have the same information in bull markets as they have, but other information in bear markets. Because investors forecasts the index more positive for themselves than for others, it could indicate over-optimism in bear markets. Frey and Stutzer (2012) define over-optimism as "Overoptimism, according to which people in identifiable situations believe that the outcomes of events are better for them than for others.” (pp. 22-23).

[9] Only in de Bondt (1993) this theory is completely confirmed, other literature of O’Connor (2001), Glaser (2007) and Grobys (2012) and this research reject the theory.

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