

ABN AMRO CLIENTS PREDICTING THE AEX-INDEX VALUE

Two comparisons: how accurate are the expectations compared to the random walk model and the perspective on decisions of others?

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In this study we investigate to what extent the predictions made by active banking clients of ABN Amro on the AEX value are accurate. The predicted values by the respondents of the questionnaire are compared to two different scenarios: (i) approach according to the 'traditional' random walk model and (ii) what they think others will predict. Each comparison is made using three methods: the mean-squared error, the mean absolute error and the mean percentage error. In the first comparison, the random walk approach finds more support. This is not to say that the AEX follows a random, it suggests in our case that the random walk model makes more accurate predictions than the respondents do. The results of second comparison recommends that respondents are better off when they predict what they think others will predict, instead of making predictions on their own.

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The most predictable thing about the stock market is the number of experts who take credit for predicting it.” -Dave Weinbaum

1. Introduction

Making predictions on the stock markets is one of the greatest challenges an investors faces. In order to acquire high returns from stock investment, the timing of buying and selling assets is essential.

The principle of ‘equity market timing’ in finance refers to the fact that one should issue shares at high prices and repurchase the shares when their prices are low.

In addition to market timing, predicting market values is important since it is a good indicator for the investment choice. In order to make profits, it makes perfect sense that the expectations should come close to the actual values. The stereotype investor on the stock market is not considered to be clairvoyant, and makes therefore use of different tools to come closest to the actual value. The stock market involves enormous returns, which makes predictions crucial for successful investment. Naturally individuals are delighted when predicting correctly since it will lead to positive returns, though this is not always the case. In making predictions, McKenzie and Amin (2002) support several hypotheses, of which the most peculiar and important explains that incorrect predictions (whether they are from rare or from common events) are more supported than correct predictions. Making predictions on rare events are called bold predictions, and McKenzie and Amin show the importance of this boldness in the support shown to the correctness. Nevertheless, in the stock market correct predictions are preferred, whether they are supported or not. Why is predicting in the stock market so special? Stock time series have various characteristics that contribute to the fact that the prediction task is rather uncommon and calls for special concern. Hellström and Holmström (1998) explain the specific properties;

- Stock prediction is generally believed to be a very difficult exercise. The task of predicting stocks can be compared to that of inventing a *perpetuum mobile*¹.
- The process behaves a lot like a random-walk process, in the sense that the autocorrelation for day to changes is rather low.
- The fundamental process is time varying, meaning the process is ‘regime shifting’. As the stock markets move from one period to another, the level of noise and volatility change. Hence, this causes problems for traditional algorithms for time series predictions.

¹ A *perpetuum mobile* is a devise or motion that, once is has started, were to continue indefinitely.

1.1 Tools in predicting on stock market

In predicting stock market prices or values, tools are used to forecast expected values and to make trading decisions. In 1970, Fama published an article that would become of major importance for financial economists. In his “Efficient Market Hypothesis”, Fama introduced a model that states that stock markets fully reflect all information available. Stock markets assumed to follow a random walk like mentioned above, in the sense that today’s stock market prices are independent of those from yesterday. In 1990, DeLong, Shleifer, Summers and Waldmann argued that investors are exposed to sentiment. Behavioral economics soon began to show its link with making predictions in the financial world. A new generation of techniques and tools became known to intelligently support people in analyzing data, finding valuable knowledge and in some cases performing analysis automatically.

These techniques and tools include approaches like fuzzy times series (using linguistic variables to deal with the vagueness of human knowledge²) and Naïve Bayes. The Naïve Bayes uses a classifier assuming that the presence or absence of a particular property is not related to the presence or absence of any other in future time.

In spite of the traditionally enormous support for the Efficient Market Hypothesis, most market players now believe they can, at least partially, predict market values. Different sentiment indices incorporate investor sentiment into a tool for investment decisions. For example, the Nova-Ursa ratio is an indicator that uses the Rydex Nova and Rydex Ursa mutual funds to include sentiment. On the other hand, the Put/Call ratio gauges sentiment by dividing the number of traded put options by the number of traded call options. Market players buy whenever the market is ‘bullish’ and sell whenever the market is ‘bearish’; the basics of a sentiment index.

1.2 The ABN Amro sentiment index

In making predictions on the stock market, investors make use of many sources that can be helpful in predicting correctly. In addition to financial gurus and experts, a frequently used tool is a so called sentiment index. The first sentiment index was created in 1963 by the New York based Investor Intelligence. This index shows the ratio of the number of investment advisors who are bearish to the total number of advisors who are either bearish or bullish. In this context, we use bearish to name investors who drive down prices relative to the fundamental value. On the other hand, bullish investors are more optimistic; they drive up their prices. The outcome of the index tells the investor that one should buy when investment advisors are bearish and sell when advisors are bullish. A sentiment index is promoted as a contrary indicator; when the index turns bearish, the investors turn bullish.

² Dubois and Prade, 1990

The data provided by ABN Amro in this study is obtained through survey data and is incorporated into a trading index; what percentage of the respondents think the AEX value will be higher or lower than the last communicated value?

Based on the data, this study investigates to what extent the respondents were correct in predicting the AEX value. To test the accuracy of the predictions made by the respondents, two comparisons are made which include two approaches derived from: the random walk model and the phenomenon herd behavior in behavioral finance. To be able to make the comparisons between the different scenarios, various measures are used: the mean squared error, the mean absolute error and the mean percentage error. For these methods the lowest values are preferred.

Firstly, the outcomes of the respondents (scenario 1) are compared to the outcomes if the AEX value follows a random walk (scenario 2), a heavily supported theory in the field of predicting stock prices. We apply the random walk model to our study by using the actual value of the date prior to the forecast date, therefore assuming no change in the AEX value. The results indicate that the random walk approach finds more support, since the values for MSE, MAE and MPE are lower in this case than in the case with the predicted values by the respondents.

Secondly, we compare the prediction made by the respondents to the values they think that *other* respondents will predict (scenario 3). Herd behavior exist in financial decision-making because individuals think others can make better decisions than themselves. In the second comparison, we can observe whether the accuracy differs in these two cases; do the respondents make more accurate predictions for themselves or for others? The outcome of the second comparison is surprising since the respondents make more accurate predictions for others than on behalf of themselves.

The outline of this paper is as follows: in section 3 the data is described and given, followed by the methodology used in section 4. The results of the study is given in section 5. Ultimately, section 6 contains the conclusion and discussion part.

2. Relevant literature

Many theories and models have been created to investigate the changes in the stock market. These theories predict how stock prices change and what influences these changes.

2.1 Efficient Market Hypothesis and the Random Walk

Stock prices have long been assumed to reflect all information available, as is explained by the Efficient Market Hypothesis. In an efficient market, security prices fully reflect all obtained

information. When new information becomes available, prices are adjusted without any delay. Therefore, no arbitrage opportunities exist that would give investors the opportunity to gain above-average returns without accepting above-average risk.

The Efficient Market Hypothesis gives explanation to the random walk model by hypothesizing the price changes arise as a result of changes in information regarding the security in question.

The idea of the random walk model is that the flow of information is unrestrained and that information is instantaneously reflected in stock prices. The price change of tomorrow only reflects tomorrow's news and is independent of today, so no change occurs in the price. Hence, the future path of the price level of a security is no more predictable than the path of a series of cumulated random numbers (Fama, 1965). In 1973, Malkiel explained the random walk theory in an interesting and unusual way. He used blindfolded chimpanzees to throw darts at the Wall Street Journal and concluded that the animals could select a portfolio that would do just as well as the financial experts.

Nowadays, it is often believed that the stock market is at least to some extent predictable. Since the 1990s, the intellectual dominance of the EMH became less common. In the early 2000's two arguments against the EMH arose. Firstly, periods of market irrationality occurred. It became recognized that if one could avoid the psychological drawbacks that investors are prone to, then it must be possible to outperform the market. Secondly, the tendency of markets to overreact makes the stock markets at least somewhat predictable. The earliest observations of symptoms of overreaction came from J.M. Keynes, who argued that "...day-to-day fluctuations in the profits of existing investments, which are obviously of an ephemeral and no significant character, tend to have an altogether excessive, and even absurd, influence on the market" (Keynes, 1936).

In a paper by Kahneman and Tversky in 1982, it is explained that people are inclined to overweight recent information, while underweighting prior data. Individuals base their decision-making on a rule-of-thumb: "The predicted value is selected so that the standing of the case in the distribution of outcomes matches its standing in the distribution of impressions." This implies that in making predictions, the extremeness of predictions must be weakened by considerations of predictability.

The relevance of the behavior of overreaction in economic forecasting on the stock market is underlined in for example De Bondt and Thaler (1985) and Lehmann (1990).

2.2 The influence of behavioral economics on financial decision making

Like mentioned before, periods of market irrationality and overconfidence weakened the support for the Efficient Market Hypothesis. The EMH had increasing difficulty in explaining periods during for example the Dot-Com Bubble. During the Dot-Com Bubble a synthesis of increasing stock prices,

market confidence, individual speculation in stocks (speculation in the sense that it did not promise any safety), and widely accessible venture capital gave rise to an environment in which investors disregarded traditional metrics like the price-to-earnings ratio. The development of this bubble led to many bankruptcies and losses for investors.

In the financial literature, a new paradigm emerged based on behavioral economics. The alternative model is based on two assumptions;

- (i) Investors are exposed to sentiment, as mentioned first by DeLong, Shleifer, Summers and Waldmann in 1990. Not all demand changes are based on rational behavior; some responses to changes in expectations are not fully justified by information. An example of such pseudo-signals that influence investors' decisions, is advice of financial gurus and forecasters. Investors that are influenced by such sentiment, are called 'noise traders'. The essence of noise in liquid markets was already stressed out by Fischer Black in 1986, who argues that "noise trading is essential to the existence of liquid markets". Noise in this sense is information that has not appeared yet, it is the uncertainty about future demand and supply conditions within and across sectors³.
- (ii) The second assumption is laid out by Shleifer and Vishny in 1997 and it argues that betting against sentimental investors is expensive and not without a risk. Therefore, there are limits to arbitrage.

After discovering the influence of sentiment on investors, it is essential to pay attention to the effects of sentiment on stocks. Since 1980, many research has been done on the influence of investor sentiment. In these early studies, the influence of sentiment was left implicit, mainly because it was hard to differentiate a random walk from a long-lived bubble. In more current studies, the tests show stronger evidence on the influence of sentiment on investment. Two types of investors are distinguished by DeLong, Shleifer, Summers and Waldmann (1990). Firstly, there are rational arbitrageurs who are not influenced by sentiment. These traders are limited in the sense that time horizons are short and trading and short selling is costly and risky. Secondly, irrational traders are those who are in fact influenced by sentiment. Mispricing can arise when there is a combination of events; changes in sentiment on the part of the irrational traders, and a limit to arbitrage from the rational investors (because of short time horizons or from costs and risks of trading and short selling).

³ Black, F., "Noise", 1986.

The influence of sentiment on stock return is positively correlated; when sentiment increases, 'speculative' (those with higher risks involved) stocks have higher returns.

2.3 The use of a sentiment index

Despite the fact that a sentiment index is often created to advise investors, research done by Solt and Statman (1988) showed that a sentiment index is not useful as an indicator of future stock price changes. The outcome is based on the research of data of 1000 observations from the year 1963, the introduction of the used sentiment index, until 1985. The question that naturally arises afterwards, is why sentiment is still regarded to be of major importance in financial decision making. Individuals believe in the usefulness of a sentiment index because those individuals are not able to recognize patterns in random data and ignore evidence that proves their counter beliefs. A striking example in the failure to recognize randomness in data is the belief in the "hot hand" in basketball. This view is taken by coaches, players and fans and implies that one has a "hot hand" when one experiences a series of hits. People tend to believe that after scoring a hit, a player is more likely to score another hit than a miss.

Another common belief says that when people commit errors, experience leads them to recognize their faults and avoid them in the future. An appealing aspect of the belief in the "hot hand" is that its strength increases with experience.

When we link the "hot hand" theory the respondents predicting AEX values, it can be suggested that respondents who were correct in $t=1$, have a greater confidence in being correct in $t=2$. It is obvious that its strength increases with experience; assume you have (nearly) correct expected values for 5 times in a row, then you will believe you will be correct the sixth time without a doubt.

The importance of investor sentiment on the stock market has been made very clear in numerous studies. In addition, it can be questioned *how* to measure such sentiment? There many possible methods for measuring sentiment, as laid out by Baker and Wurgler (2007). Several methods are:

- Investor surveys; to gain insight into the investors, one can ask how optimistic or pessimistic investors are.
- Trading volume; liquidity can be viewed as an investor sentiment index. Trading volumes can reveal underlying differences in opinion.
- IPO (initial public offering) First-Day returns; at times IPO's earn exceptional returns on the first day of trading, that it is hard to ignore the influence of investor enthusiasm.

- Insider trading; corporate executives are better informed than outsiders concerning the performance and true value of their firms. Therefore, the portfolios of those executives unveil their opinions about mispricing of the related firm.

The data used in this paper, is obtained through the first method, namely investor surveys. ABN Amro asked their banking clients to fill in a questionnaire on, among other things, predicting the AEX value. The data derived from the questionnaire is used in this study.

3 Data

In this section the data used in this study is described. The data from ABN Amro is obtained through surveys. As discussed in the previous section, investor surveys are valid methods to measure sentiment amongst investors. For example, Pearce and Roley (1985), Brown and Cliff (2004) and Qiu and Welch (2006) all used surveys to measure sentiment in a particular market.

3.1 Data description

In this study, the data is obtained from ABN Amro. Every two weeks, for a total of twelve times, ABN Amro asked their active banking clients to fill in a questionnaire. Various topics were addressed in the questionnaire, yet the following questions were asked specifically to be of interest for this study:

- What will be the AEX value at the time of our next survey number?
- What will be the minimum and maximum value for the AEX value on our next survey number date?
- What do you expect that other ABN Amro clients will predict?

Subsequently, respondents were asked to fill in questions concerning other topics. In the appendix, the questionnaire of survey number 5 is included, which asked additional questions on the oil industry. However, due to irrelevance these additional questions are not taken into account.

Based on the obtained data, ABN Amro creates a trading index to measure the investor sentiment amongst the ABN Amro investors. The trading index contains a grade, by means of how many percent of the respondents thinks the future AEX value will be higher or lower than the current value. An overview of the average forecasted AEX value per survey and the actual AEX value can be given graphically:

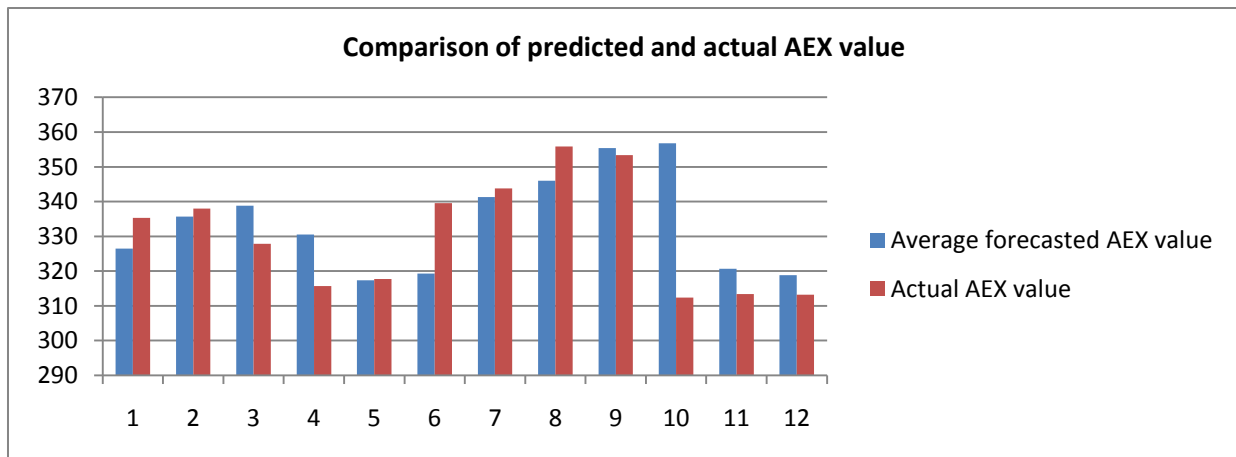


Figure 1: Bar chart with the x-axis showing the survey numbers and the y-axis showing the value of the AEX.

As can be seen in figure one, most of the survey number the forecasted value differed not greatly from the actual AEX value. However, in period 4, 6 and 10 the actual and forecasted value differed enormously. The 12 surveys cover a period of from 29th of December 2009 until the 25th of May 2010. ABN Amro asked their active banking clients⁴ to fill in the questionnaire on voluntary base. Therefore, the number of respondents differ per survey number and the respondents are anonymous. The sum of the respondents in the complete dataset is 1639.

Before the data can be used to make calculations to compare the prediction outcomes and the random walk approach, a selection is made based on the following three criteria:

- i. The respondent filled in the entire questionnaire.
- ii. The maximum value given for the AEX value is larger than the minimum value.
- iii. The predicted AEX value lies within the range given (minimum value < forecast < maximum value).

In the provided dataset, the close AEX index at forecast date was missing for survey number 12 on June the 4th 2010. The corresponded value is included and is naturally based on the actual value of the AEX Index on this date, which can be found on www.iex.nl. The actual AEX value on June the 4th of 2010 was 321,22.

After removing the 42 variables that did not follow the criteria, we end up with 1597 respondents.

Hence, an overview can be made of the data that will be used for calculations:

⁴ Active clients are considered those who have an amount of €100,000-€1,000,000 at their disposal

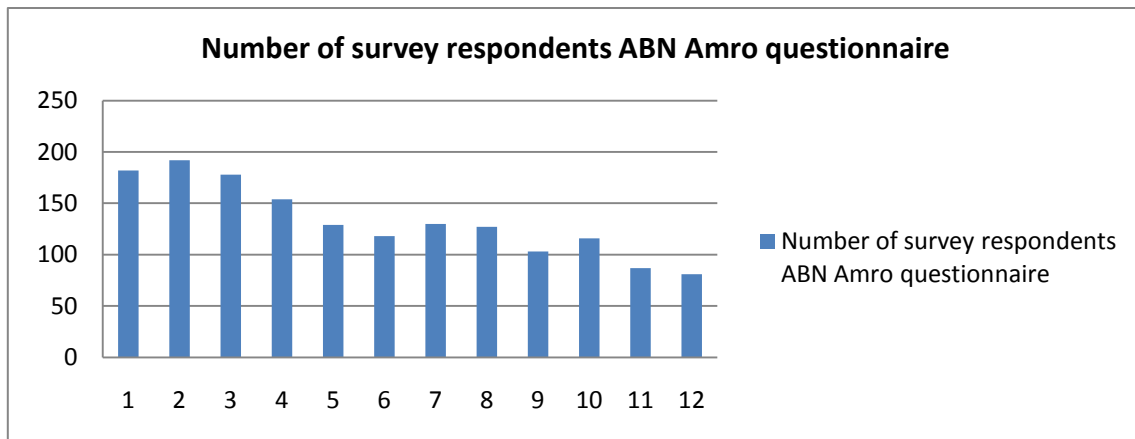


Figure 2: Bar chart with the x-axis showing the survey numbers and the y-axis showing the number of respondents per survey number.

Based on figure 1, we can calculate that the average number of respondents is 133. When looking at the shape of the bar chart, we see that total number of respondents per survey is declining. The decline in respondents can for example be due to a decreasing interest in filling in the questionnaire, but at this point there is too little information available on the respondents to make any conclusions on this part.

4 Methodology

In this chapter, the methods used in this study are explained. In order to measure to what extent the predicted values differ from the actual values, three formulas are applied to two scenarios.

Firstly the Mean Square Error (MSE), followed by the Mean Absolute Error (MAE) and finished by the Mean Percentage Error (MPE). The mean squared error is a commonly used tool to compare different outcomes. In 1981, Ohtani used a MSE comparison to test whether proxy variables are good variables to make predictions. Wolski (1998) measures the accuracy of different forecasting methods by reporting both the mean square error and the mean percentage error. Based on these previous studies we assume that using mean errors is a valid method to compare the outcomes of our respondents and the random walk model.

The mean error methods are firstly used to compare the scenarios: (i) taking the predicted AEX values from the respondents, and (ii) taking the actual AEX values on the prior date, which are the values communicated to the respondents. When the AEX values follow a random walk, it is not possible to predict future values by taking into account past patterns. Therefore, we use values that were communicated to the respondents because we assume a zero change in the AEX value. Secondly, the mean error methods are applied to compare (i) the predicted AEX values from the

respondents with (iii) the predicted values that reflect the respondents' opinion on what others will predict.

The three mean error methods are based on the error, which is explained as:

Error $e_i = f_i - y_i$, where f_i is the prediction and y_i the true value

To investigate to what extent the respondents of the survey were correct in predicting the AEX value, the following three methods are used to compare the outcomes:

A. Mean Square Error

$$MSE = \sum [(forecasted - actual)^2] / n]$$

The mean square error measures the average of the square of the error. Because of the fact we use the average forecasts, we do not sum up the squared error divided by the number and do not correct for n , but we end up having one MSE value for each survey number. Therefore, in this study the formula used is:

$$MSE = (forecasted - actual)^2$$

B. Mean Absolute Error

$$MAE = (1/n) * \sum |e| = (1/n) * \sum |f - y|$$

The mean absolute error is the average of the absolute errors. As is the case with MSE, we rearrange the formula to be able to compare the outcomes per survey number:

$$MAE = |error|$$

C. Mean Percentage Error

$$MPE = (1/n) * \sum [(f - y)/y]$$

The mean percentage error is the computed average of the percentage errors by which the predictions differ from the actual AEX values. Again, the formula we use is does not include the summation sign and correction for n :

$$MPE = [(f - y)/y]$$

Because the respondents from our survey are anonymous, we are unfortunately not able to track individuals throughout the entire survey period. The fact that the respondents are anonymous has consequences for our calculations. To calculate the MSE, MAE and the MPE we take the *average* forecasted values per survey number, instead of the forecasted value per individual. By using the

average values, we obtain a total of 12 values for the three methods. To compare the outcomes of both scenarios, the average MSE, MAE and MPE is calculated of the 12 values.

For the MSE as well as the MAE and MPE holds; the smaller the outcome, the better because this means the smaller are the differences between the predicted and the actual values. The final outcomes can be compared at the end to see which of the two scenarios is more accurate in predicting the AEX value correctly; the respondents with their predictions or the traditional random walk approach? The same method is applied to compare the respondents' predictions with the value they give on what others will predict. Furthermore, we can see if there is a learning effect whenever the values of MSE, MAE and MPE are decreasing throughout the survey period.

As pointed out before, the random walk model finds great support in literature on stock prices. In our study, we look at to what extent the ABN Amro active clients are correct in predicting the AEX value. Regarding expectations on the outcome of this study, we expect that the random walk approach finds more support than the predictions made by the respondents. This means that in at least two out of the three measures used, the scenario based on the random walk model needs to obtain lower values. Our expectations can partly be explained by the fact that ABN recently started asking their clients to make predictions, and that our data is rather limited because we have an average of 133 respondents. We can therefore suggest that the respondents have relatively little experience in making predictions on the stock market, in this manner suggesting that the random walk approach is more accurate in our case.

In addition to comparing the respondents' predictions with the random walk approach, a second comparison contains the values that respondents give each other. In this case we expect that respondents consider themselves to be better predictors than the other respondents. In order to support this view, the values of MSE, MAE and MPE need to be lower for the respondents' predicted values than for scenario in which the values are used of what respondents think that others will predict.

5 Results

In this chapter, the results of this study are discussed. Three formulas are applied to two comparisons, which will be discussed separately. Firstly, the comparison between the respondents' predictions and the random walk approach is presented. Afterwards, the comparison is discussed between the respondents and the values of what the respondents think *others* will predict.

5.1 Using predicted values: case (i)

In the first scenario the predicted values are used, which are given by the respondents through the surveys. Firstly, for calculating the three formulas MSE, MAE and MPE the absolute error is necessary, which describes the magnitude of the difference between the forecasted value and the actual value. Per survey number, the average forecast value is used, since we deal with anonymous respondents as explained earlier.

In the table on the next page, the absolute error is presented based on the average forecasted values and the actual values on the forecast dates of the twelve survey numbers:

Forecast date	1. Average forecasted value	2. Actual value	Error = (1)-(2)
(1) Dec. 31 '09	326,456044	335,33	-8,87396
(2) Jan. 15 '10	335,6510417	337,99	-2,33896
(3) Jan. 29 '10	338,758427	327,9	10,85843
(4) Feb. 12 '10	330,5324675	315,74	14,79247
(5) Feb. 26 '10	317,3643411	317,74	-0,37566
(6) March 12 '10	319,3474576	339,57	-20,2225
(7) March 26 '10	341,3	343,81	-2,51
(8) April 9 '10	345,976378	355,89	-9,91362
(9) April 23 '10	355,4310345	353,38	2,051034
(10) May 7 '10	356,8349515	312,35	44,48495
(11) May 21 '10	320,7471264	313,41	7,337126
(12) June 4 '10	318,8024691	321,22	-2,41753

Table 1: presenting per survey number the absolute error $e_i = f_i - y_i$, where f_i is the prediction and y_i the true value. The prediction is in this case the predicted value by the respondents.

The average error in scenario 1 is 10.51469⁵. This means that on average, the predicted value differed 10.5 points from the actual AEX value.

⁵ Based on the absolute values of the errors in table 1.

After calculating the absolute errors of the survey number, the mean squared error, mean absolute error and the mean percentage error can be calculated.

Forecast date	MSE*	MAE**	MPE***
(1) Dec. 31 '09	78,7471	8,873956	-0,026463353
(2) Jan. 15 '10	5,470726	2,338958	-0,0069202
(3) Jan. 29 '10	117,9054	10,85843	0,033115056
(4) Feb. 12 '10	218,8171	14,79247	0,046850154
(5) Feb. 26 '10	0,14112	0,375659	-0,001182284
(6) March 12 '10	408,9512	20,22254	-0,059553383
(7) March 26 '10	6,3001	2,51	-0,007300544
(8) April 9 '10	98,2799	9,913622	-0,02785586
(9) April 23 '10	4,206742	2,051034	0,005804048
(10) May 7 '10	1978,911	44,48495	0,142420206
(11) May 21 '10	53,83342	7,337126	0,023410633
(12) June 4 '10	5,844455	2,417531	-0,007526091

Table 2: Using the predicted values → presenting outcomes of calculating values using the following formulas:
 *MSE = (error)², **MAE = |error|, ***MPE = (error)/y

The results of the mean squared error in table 5 show that the MSE is in many cases below 1, despite the outliers of survey numbers (6) and (10). The MAE is like the MSE (and the MPE) a negatively-oriented score. The closer to zero, the better. In the results of scenario 1 all values are close to zero, with some (for example (5) and (9)) more than others (for example (10)). The mean percentage error describes the forecast accuracy as a percentage, with values close to zero indicating accurate forecasting. The MPE values in our case are very close to zero, which suggests that the forecast were accurate by the standard of this measure. Obviously a value of zero for all three methods is perfect, suggesting that the predictions are perfectly accurate. However, in the stock market, as in many other cases, making perfect predictions is only possible if one is clairvoyant.

When comparing the MSE outcomes of the first and last survey number, an improvement can be observed, since the last value is significantly lower than the with the first survey number. We cannot speak of a learning effect⁶, since the values of MSE differ greatly throughout the entire survey period. The same conclusions can be applied to the MAE and the MPE; the value for survey number 12 is smaller than for survey number 1, but we cannot mention a learning effect since the values differ to a great extent throughout the survey period.

⁶ We assume a learning effect when the values for MSE, MAE and MPE are decreasing in time.

In order to be able to compare the outcomes of the different values for MSE, MAE and MPE, the average values are calculated. After completing the same procedure for scenario (ii), a comparison can be made. The scenario that contains the lowest values for MSE, MAE and MPE, is regarded to be best in explaining the variability in observations in making predictions concerning the value of the AEX index.

Average values for case (i), based on predicted values:

MSE= 248,1174	MAE= 10,51469	MPE= 0,011120407
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5.2 Using communicated values: case (ii)

In the second scenario, we base our calculations on the well-known random walk model. Instead of using the predicted values of the respondents, the communicated value is used. The value communicated to the respondents includes the actual AEX value on the date of the previous survey number. Therefore, in scenario two we assume a zero change in the AEX value. Following the same method as used in scenario 1, we firstly obtain the absolute errors:

Forecast date	1.Communicated value	2. Actual value	Error = (1)-(2)
(1) Dec. 31 '09	324,63	335,33	-10,7
(2) Jan. 15 '10	335,33	337,99	-2,66
(3) Jan. 29 '10	337,99	327,9	10,09
(4) Feb. 12 '10	327,9	315,74	12,16
(5) Feb. 26 '10	315,74	317,74	-2
(6) March 12 '10	317,74	339,57	-21,83
(7) March 26 '10	339,57	343,81	-4,24
(8) April 9 '10	343,81	355,89	-12,08
(9) April 23 '10	355,89	353,38	2,51
(10) May 7 '10	353,38	312,35	41,03
(11) May 21 '10	312,35	313,41	-1,06
(12) June 4 '10	313,41	321,22	-7,81

Table 3: presenting per survey number the absolute error $e_i = f_i - y_i$, where f_i is the prediction and y_i the true value. The prediction in this case is the communicated value.

The average absolute error in scenario two is given by 10.68083⁷, which means that on average, the AEX value differed 10.7 points with the communicated AEX value. Subsequently, the three formulas can be applied:

⁷ Based on the absolute values of the errors in Table 3.

Forecast date	MSE*	MAE**	MPE***
(1) Dec. 31 '09	114,49	10,7	-0,031908866
(2) Jan. 15 '10	7,0756	2,66	-0,007870055
(3) Jan. 29 '10	101,8081	10,09	0,030771577
(4) Feb. 12 '10	147,8656	12,16	0,0385127
(5) Feb. 26 '10	4	2	-0,006294455
(6) March 12 '10	476,5489	21,83	-0,064287187
(7) March 26 '10	17,9776	4,24	-0,012332393
(8) April 9 '10	145,9264	12,08	-0,033943072
(9) April 23 '10	6,3001	2,51	0,007102835
(10) May 7 '10	1683,461	41,03	0,131359052
(11) May 21 '10	1,1236	1,06	-0,003382151
(12) June 4 '10	60,9961	7,81	-0,024313555

Table 4: presenting outcomes of calculating formulas:

*MSE = (forecasted – actual)², **MAE = |error|, ***MPE = [(f – y)/y]

For the values of the MSE, we see that the value differs greatly throughout the survey period. The value of the last survey is smaller than from the first survey, but a pattern of a decreasing MSE in time cannot be observed. In the case of the MAE, the values do not differ that significantly as with the MSE, but neither a learning effect can be observed. The similar story holds for the MPE, which does not fluctuate enormously but does not show a decreasing value.

Yet again as in scenario 1, the average values of the MSE, MAE and MPE are needed to make the comparison at the end.

Average values for case (ii), based on the communicated value:

MSE= 230,6311	MAE= 10,68083	MPE= 0,004338908
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5.3 Comparing cases (i) and (ii)

In the concluding table, the average values for MSE, MAE and MPE are presented to make a comparison.

Scenario	Average MSE	Average MAE	Average MPE
1 (predicted values)	248,1174	10,51469	0,011120407
2 (communicated value)	230,6311	10,68083	0,004338908

Table 5: presenting outcomes of calculating formulas with two scenarios:

- (1) Using the predicted values by the respondents
- (2) Using the communicated value

After using three measures to investigate which scenario makes better predictions concerning the AEX value, it can be concluded that scenario 2 finds more support. When analyzing the measures separately, the following conclusions can be made:

The mean squared error: scenario 2 contains a lower value, to be exact 7.6 % lower than scenario 1.

The mean absolute error: scenario 1 has a lower value for the MAE than scenario 2, with a difference of 1.6 % compared to scenario 1.

The mean percentage error: finally, the last method also shows a lower value in case of scenario 2. The average MPE using the communicated value is 70.0 % lower compared with the use of predicted values.

We expected that using the communicated value, based on the random walk model, would find more support than the predictors of the ABN Amro panel. We investigated this hypothesis by using three mean square methods. In indeed two out of the three methods, the random walk model acquires more support than the predicted values from ABN Amro clients. Our findings indicate that the traditional random walk model is in the case of predicting the AEX value more accurate than the predictions made by ABN Amro clients. Unfortunately our data is too limited to investigate whether or not the AEX values follow a random walk, but we can assume that using the principles of the random walk model leads to more accurate findings than in the case that the ABN Amro clients make predictions on their own. For the ABN investors making predictions on the AEX value, it could therefore be suggested to look at the last previous value instead of basing the prediction on other values that include their sentiment.

5.4 From the respondents' perspective: what will others predict?

Besides comparing the respondents' predictions with the random walk approach, another comparison of interest includes the expected AEX value that respondents give to other respondents. In the questionnaire respondents were asked to fill in both a prediction for themselves, as well as predictions for others. Though we assume that respondents consider themselves to predict more accurately, we will observe that this assumption is not supported in our study.

To make calculations using the same method as before, we start with the error:

Forecast date	1.Average predicted value	2. Actual value	Error = (1)-(2)
(13)Dec. 31 '09	326,4615385	335,33	-8,868461538
(14)Jan. 15 '10	338,0729167	337,99	0,082916667
(15)Jan. 29 '10	339,6235955	327,9	11,72359551
(16)Feb. 12 '10	330,6883117	315,74	14,94831169
(17)Feb. 26 '10	317,5503876	317,74	-0,189612403
(18)March 12 '10	318,4661017	339,57	-21,10389831
(19)March 26 '10	341,7076923	343,81	-2,102307692
(20)April 9 '10	345,6062992	355,89	-10,28370079
(21)April 23 '10	355,7931034	353,38	2,413103448
(22)May 7 '10	356,3883495	312,35	44,03834951
(23)May 21 '10	315,4137931	313,41	2,003793103
(24)June 4 '10	315,5925926	321,22	-5,627407407

Table 6: presenting per survey number the absolute error $e_i = f_i - y_i$, where f_i is the prediction and y_i the true value. The prediction in this case is the communicated value.

The average absolute difference between the predicted value and the actual is 10.2821215, which means that on average the predicted AEX value differs 10.28 points from the actual AEX value. This difference is lower than in the case of the respondents themselves, which is 10.5 points.

Continuing with the remaining calculations, we present hereby the outcomes of the MSE, MAE and the MPE.

Forecast date	MSE*	MAE**	MPE***
(1) Dec. 31 '09	78,64961006	8,86846154	-0,026446967
(2) Jan. 15 '10	0,006875174	0,08291667	0,000245323
(3) Jan. 29 '10	137,4426916	11,7235955	0,03575357
(4) Feb. 12 '10	223,4520223	14,9483117	0,047343738
(5) Feb. 26 '10	0,035952863	0,1896124	-0,000596753
(6) March 12 '10	445,3745237	21,1038983	-0,062148889
(7) March 26 '10	4,419697633	2,10230769	-0,006114737
(8) April 9 '10	105,7545019	10,2837008	-0,028895728
(9) April 23 '10	5,823068252	2,41310345	0,006828636
(10)May 7 '10	1939,376228	44,0383495	0,140990394
(11)May 21 '10	4,015186801	2,0037931	0,00639352
(12)June 4 '10	31,66771413	5,62740741	-0,017518858

Table 7: presenting outcomes of calculating formulas:

*MSE = (forecasted - actual)², **MAE = |error|, ***MPE = [(f - y)/y]

The values of MSE, MAE and MPE are not decreasing in time, even though the values for survey number 1 < survey number 12. Therefore, we cannot notice an obvious learning effect, just like in case as of the respondents' predictions.

Proceeding the comparison, we can evaluate the outcomes with scenario 1 (using the predictions of the respondents):

Scenario	Average MSE	Average MAE	Average MPE
1 (predicted values)	248,1174	10,51469	0,011120407
3 (what others will do)	248,001506	10,2821215	0,007986104

Table 8: presenting outcomes of calculating formulas with two scenarios:

- (1) Using the predicted values by the respondents
- (3) Using the what respondents think others will predict

The table above shows that for the MSE, MAE and MPE all values are better for scenario 3. These results suggest that respondents of the questionnaire make more accurate predictions for others than for themselves. To be precisely per method:

The mean squared error: scenario 3 contains a lower value; 4.4 % lower than scenario 1.

The mean absolute error: scenario 3 includes a lower value than scenario 1, with a difference of 2.2% compared to scenario 1.

The mean percentage error: also the last method shows a lower value in case of scenario 3. The average MPE in scenario 3 is 28.2% lower compared with the use of predicted values.

It can be assumed that respondents consider themselves to be risk-seeking if they compare themselves to other investors, in so doing willing to take more risk than what other investors would take. However, we cannot make statements on this subject for the reason that we deal with anonymous respondents of the survey. It can be concluded however that the respondents of our survey appear overconfidence when it comes to predicting the AEX value; the *confidence* in predicting the correct AEX value is greater than the actual *accuracy* of the prediction.

The recommendation conform our results is that when one wants to predict most accurately the AEX value, one should not make their own predictions, but should predict that they think others will predict.

In conclusion, we can say that in both the comparisons made in this study, the approaches based on the literature and based on what others will predict, present more accurate results than in the case of using the respondents' predictions. Therefore, support is given to the traditional random walk method and the respondents show overconfidence towards predicting. Our results confirm that making predictions on the AEX value contains more accurate values whenever one predicts the value that one thinks *other investors* will predict. What is confirmed first and foremost in this study is that making predictions on the stock market is a difficult task and involves many factors that influence decision making.

6 Conclusion and Discussion

Making predictions on the stock market involves many factors and is therefore of great interest in the financial literature. Despite the support for the traditional view that the stock market is efficient and follows a random walk, more room is made for behavioral economics in the sense that sentiment becomes more prominent in investment decision-making.

In this study a comparison is made between on the one hand predictions made by ABN Amro clients (scenario 1), and on the other hand the 'traditional' random walk model (scenario 2). Assumptions from the random walk model include a zero change in the AEX value, therefore the value of the AEX prior to the survey date is used which is communicated to the respondents. In addition, a second comparison is made between the predictions of respondents and the scenario that uses the expected AEX values that respondents give to other respondents (scenario 3).

Three methods are used to make the comparisons; the mean squared error MSE, the mean absolute error MAE and the mean percentage error MPE. To interpret the results, it counts for all methods that the smallest values indicate more accurate results and are therefore preferred.

Based on our results, in both comparisons the approach based on the literature delivers more accurate results. In both comparisons the scenarios based on the random walk model (2) and on what is thought that others will predict (3) comprised more accurate results in at least two out the three methods MSE, MAE and MPE.

It can be suggested that in the case of ABN Amro clients giving expected AEX values, using the communicated value gives more accurate results than making predictions on itself. The use of the random walk model in this study does not implicate that the AEX value follows a random walk, for the reason that we cannot make suchlike assumptions based on our data. In our comparison, the application of the random walk model basically generates more accurate outcomes than applying the predicted values. Furthermore, for the respondents to obtain more correct predictions, it can be recommended to predict the same value as what they think other respondents will predict.

Based on the results of both comparisons, it can be stated that the predictions made by the respondents do not provide the most accurate results. We investigated that by taking either the actual AEX value of the previous survey date or by taking the value the respondents think that others will predict, the respondents would make more accurate predictions on the AEX value than when they use their own prediction.

More investigation could be done with the provided dataset when it would be for example possible to follow respondents throughout the survey period. Furthermore, a greater number of respondents would lead to stronger results and more possibilities in research.

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8 Appendix