ERASMUS UNIVERSITEIT ROTTERDAM

Optimism and Investor Behaviour:

Does it Persist with Feedback

Master's Thesis

Behavioural Economics

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1. Introduction

Behavioural finance has become increasingly popular with the publication of Cass Sunstein's and Richard Thaler's *Nudge* which discusses different behavioural biases and their applications. Although not all behavioural biases have been linked to irrational behaviour in the financial markets, they have been shown to exist in a large variety of environments. In this study the bias of optimism is explored, and it refers to an individual's mood that is associated with the expected desirable outcome in the future (Tiger, 1979). The optimism bias can be found for example in the context of sports. Simmons and Massey (2012) observed how NFL sports fans expect their home teams to win most of the time, even when they are incentivised to predict objectively. This effect was also shown to persist over time and experience as the fans exhibited the same optimism bias at the beginning as well as towards the end of the NFL season.

My motivation is to study optimism in financial markets and particularly whether it persists with learning. Currently, the majority of literature discusses the effects of overconfidence on investor behaviour. Although overconfidence and optimism are different concepts, they are positively correlated with one another (Ben-David et al., 2010). Therefore, I will contribute and extend the research on optimism in investor behaviour, drawing from available literature on optimism performed in different fields such as health, unemployment, and sports (Hoch, 1985; Peterson 1988; Radzevick & Moore, 2008).

The research question in this paper may be defined as:

Does optimism persist in the presence of feedback?

The research question will be answered through the combination of a literature review and survey work. Student investors participated in surveys over a six-week period during which personalised emails were sent with feedback on their progression. Their task was to predict the returns of three variables one week ahead: Apple Stocks, the AEX Index and the performance of their own portfolios. In addition, they were asked to predict their portfolios' returns two weeks ahead. Through the results, this research paper hopes to confirm the findings about the persistence of optimism by Simmons and Massey (2012).

To answer this research question, two hypotheses are derived from and developed through a literature review. I begin Section 2 by defining optimism and before discussing its drivers and effects, I delve into the influence of overconfidence in investor behaviour. This separation allows for a clearer understanding of the two behavioural biases. Afterwards, the role of experience is explored to help determine whether determines whether learning influences outcomes. Section 3 describes the methodology. Subsequently, Section 4 provides the results, and Section 5 bridges the results and the literature review and offers insights into the limitations of the research. The final part, Section 6, concludes this research paper along with the recommendations for future research.

2. Literature Review

The following section reviews literature on both overconfidence and optimism which lead, at the end, to the development of the hypotheses.

2.1. Defining Optimism

First, "optimism" should be defined so to avoid its conflation with overconfidence before initiating discussions on its drivers and evidence. Peterson (2000) delves in depth into optimism, on how it differs from person to person, and how it leads to both advantages and disadvantages to individuals and to society as a whole. He quoted a definition from anthropologist Lionel Tiger's book on optimism (1979):

"a mood or attitude associated with an expectation about the social or material future -- one which the evaluator regards as socially desirable, to his [or her] advantage, or for his [or her] pleasure" (p.18).

The above definition is what will be used for "optimism" in the context of this paper. However, while other definitions of optimism exist with different contexts – the above is deemed most appropriate. The reasoning is that this definition takes into account the individuals' desires leading to the desirability bias, which will be discussed later on. Although an individual's personality characteristics such as neuroticism and self-esteem are highly correlated with optimism, they are not part of this definition (Scheier & Carver, 1992). This implies that in the context of this research paper, optimism is measured as a factor of individuals' desirability of the social and/or material future and not the outcome of a single task.

2.2. Investor Behaviour and Overconfidence

Before explaining some of the drivers and causes of optimism, the effects of overconfidence to investor behaviour are explored. Although the behavioural biases of optimism and overconfidence are separate, they are very closely linked to one another and this division will provide a clearer understanding about their respective effects. Within the financial economics literature limited amount of research has been done into optimism with regards to stock market performance. This section looks into how overconfidence along with optimism affects investor behaviour as this provides important insights to individuals' decision-making process.

Most investors are seen as overconfident, they overestimate the quality of available information and extrapolate too much from this information (Daniel et al., 2001). In addition, Barber and Odean (2001) discuss that overconfident investors have unrealistic expectations about high returns. Interestingly, in a recent paper, it was shown that professional investors, with regards to stock price predictions, exhibit a greater overconfidence bias when compared to students (Glaser et al., 2010). This implies that greater experience does not mitigate biases. If the investors were underconfident, they would underreact to market information on low prices or high book/market rations. Separately, Glaser and Weber (2007) argue that overconfident investors underestimate the variance and the risk of assets. This is inferred from investors having too precise confidence intervals for their predictions.

The systematic over-precision of predictions is a type of overconfidence called miscalibration and it was investigated by Ben-David et al. (2010). They obtained data over a ten-year panel on different company managers and firm executives predicting the performance of various stocks. It was shown that the executives' optimism positively influences both short and long term miscalibration. This implies that optimism and overconfidence are positively correlated with one another and when the biases are observed together, they increase their respective influence over individuals' behaviour. When the company policies were analysed, it was also discovered that there was another positive relation between corporate investment and long term optimism, however in this case, short-term optimism provided insignificant results. This result proves that overall managers are overly optimistic and confident in their predictions. Similarly, Heaton (2002) shows in his research paper that managers who are overly optimistic are more likely to invest in negative net present value projects because they perceive them as good opportunities. Both of the aforementioned studies are aligned with the findings in Kahneman and Lovallo's study (1993) on how executives are both overconfident and optimistic in their skills and abilities to deal with risks.

Another form of overconfidence is the *better than average effect*, which is best described by Svenson (1981). His research about driving skills showed that 70-80% of the subjects think they are a better driver than the average. An attempt by Glaser and Weber (2007) was made to measure the better than average effect in investors by surveying a few hundred professionals about their skills and abilities in the financial markets. They showed that about half of the investors believed that they were better than the average, which do not mirror the findings of Svenson (1981). Similar findings to Glaser and Weber (2007) were obtained by Deaves et al. (2003), which used a related approach in measuring overconfidence. Although these findings imply that investors are realistic about their knowledge, the better than average effect theory assumes that a majority will believe themselves to be better than the rest. While the better than average effect and miscalibration are unrelated, they both contribute to overconfidence in individuals and irrational behaviour within the financial markets (Glaser et al. 2005, Glaser & Weber, 2007).

Finally, overconfidence has been linked to excessive trading and gender differences. According to Barber and Odean (2001), men trade 45% more than women which in turn reduces their net returns by 2.65 percentage points and 1.7 percentage points per year respectively. In addition, Barber and Odean (2008) show that individual investors are net buyers of attention grabbing stocks. The attention grabbing derives from high media exposure, unusual trading volumes as well as extreme intra-day returns. When these two studies are combined, it provides a dangerous picture of male day traders jumping at the opportunity to buy, not in making smart investments, but mediatised stocks that might perform poorly the next day, week or year.

2.3. Drivers and Effects of Optimism

As overconfidence has been explained in the previous section, I will now introduce some of the drivers of optimism in individuals that are able to explain to a certain extent our thoughts and actions as well as the observable effects of optimism in different fields.

Optimism can stem from genetics (Plomin et al., 1992), social network resources (Segerstrom, 2007) and from other socioeconomic factors (Heinonen et al., 2006). For example, parents' unemployment was shown to decrease optimism and in general, those who are living in poorer socioeconomic conditions are overall less optimistic (Heinonen et al., 2006). Alternatively, perhaps, the relation is reverse meaning that lower levels of optimism lead to lower chances of becoming successful. Thus, it is extremely difficult to evaluate the specific drivers of optimism in individuals as it may have been cultivated since childhood or due to an uncontrollable event, such as hurricane Katrina, which may have deprived of a person of their belongings, hope and optimism (Kessler et al, 2008).

Scheier and Carver's study (1992) highlighted individual differences and identified *dispositional optimism*, which can be defined as generally expecting good outcomes over bad ones. They tested this through "Life Orientation Tests", a questionnaire, and received robust results showing that dispositional optimism is linked to desirable outcomes (Carver et al., 1993; Scheier et al., 1986). This goal-oriented approach has led to a self-regulatory model (Carver & Scheier, 1981). This model enables a person to adjust their behaviour in order to perform specific actions that will allow them to achieve their desired goal. This optimism facilitates continued efforts in the face of difficulties, and conversely pessimism will lead to giving up (Peterson, 2000).

Peterson (2000) discussed how optimism is said to be part of human nature with varying degrees of optimism within a person as well as between different people. The differences within and between individuals arise from changes in lifestyles and the environment. For example, individuals who are more optimistic in their lifestyle and exercise, score higher in relevant memory recalling (Abele & Gendolla, 2007). However, it should be noted that optimism includes risks. It is possible, according to Scheier and Carver (1992) that in absence of a strong input, such as a friend who will be able to prompt the individual into action, the subject might "*simply sit and wait for success to happen" (p.19).* This phenomenon of unrealistic optimism and unproductive optimism has been documented by other researchers such as Epstein and Meier (1989) as well as by Weinstein (1984).

Another type of difference in and between individuals is the magnitude of optimism felt. Little optimism refers to the individuals' expectations about specific scenarios they are facing (Peterson, 2000). A lower magnitude of optimism could refer to finding the favourite brand of cereal at the supermarket. Whereas, big optimism refers to grander, more abstract expectations such as the future of their own country. Another strong correlate of optimism is good health (Peterson, 1988; Scheier & Carver, 1987). Limited research has been done to distinguish the differences. However, studies generally target big optimism that refers to an individual's future (Snyder et al., 1996). People, generally speaking, are overly optimistic about their health at an old age, relying on family or savings to cover the costs of care (Francesca et al., 2011). This lack of long-term care insurance is quickly becoming a worldwide problem as demographics show a larger proportion of elderly over the young, which could be easily prevented if the overly optimistic behaviour regarding health could be targeted. As such, it is essential to understand and investigate the impact of optimism on the society and explore its role in the decision-making process.

Hoch (1985) researched the effects of optimism and overconfidence in the unemployed. The subjects had to predict their search efforts nine months in advance, for example, giving a figure to the expected starting salary. What he found was that there was unrealistic optimism as all of the events involved positive outcomes. This was also documented by Weinstein (1980), through a separate experiment where he found that the levels of optimism increase with the degree of desirability. This implies that depending on the monetary incentive the degree of optimism varies over the same experiment. Therefore, if people neglect to consider failure, it may lead to poorly prepared situations as seen with the long-term care insurance example.

Moreover, two studies involve sports betting, one by Radzevick and Moore (2008) and also by Simmons and Massey (2012). Radzevick and Moore (2008) performed four studies, each about a different sporting activity with student subjects. The studies ranged from providing teams' winning probabilities in intramural soccer, predicting NBA teams' performance, betting on NCAA football games as well as NFL games. Simmons and Massey (2012) studied sports fans' predictions in the NFL league with different incentives. Overall, both studies show that an individual's prediction abilities are imperfect. The optimism bias is visible in at least one of the studies, as the fans consistently predicted home teams would win even when the odds were against them (Simmons & Massey, 2012). However, Radzevick and Moore (2008) discussed this as a possible focusing bias that the individuals are anchored to their favourite teams. The prediction accuracy as seen with these studies is able to provide the researcher valuable information. First, it allows the researcher to gauge how much people overestimate the possibility of desirable events (Coursey et al., 1987). Second, researchers can see how closely the predictions are correlated with the outcomes (Yaniv et al., 1991).

Another finding by Aspara (2013) shows that if an investor's subjective evaluation of a firm's brand increases, it also positively influences the individual's optimism about the possible future financial returns in the company's stock while decreasing the consideration of other possible stocks. This possibly stems from the investor trying to express themselves in the form of their investment decisions (Fama & French, 2007). There are other similar findings to Aspara showing how the overall affect for a company correlates with the investors' perceptions about the firm's financial prospects and as a result, suboptimal investment decisions may occur (MacGregor et al., 2000; Statman et al., 2008). These studies convey that optimism is prevalent in the simplest of investment decisions.

2.3. Wishful Thinking

The *wishful thinking effect* is part of the definition of optimism and needs to be examined as it shows that peoples' desires affect the outcomes of simple bets. This wishful thinking effect is also known as the desirability bias, and it implies that one's desires or wishes influence the outcome with certain conditions. One way to activate and to prove the effectiveness of the desirability bias is through monetary incentives with relatively simple tasks. The desirability bias is separate from the optimism bias which refers that individuals believe positive events are more likely to happen to them than negative ones (Weinstein, 1980). While desirability bias refers to how much an individual's desire influences their level of optimism and the outcome of the event (Massey et al., 2011).

The phenomenon of wishful thinking has been researched since the 1950's with mixed results. One of the classic experiments regarding the desirability bias involved a subject to predict whether a marked card will be drawn from a deck (Marks, 1951). The subjects were able to predict the marked card more often when there was a monetary incentive involved. Therefore, the subjects' desire to win the incentive influenced their outcomes to be more accurate. Similar studies have been performed by Irwin (1953), Crandall et al. (1955), as well as by Irwin and Metzger (1966). These researches have shown, within the confines of the card experiment, robust results of the desirability bias.

Windschitl et al. (2010) reviewed and improved the marked card experimental design. The researchers believed that in the previous studies, experimenter bias was affecting the results, and they wanted to prove it outside the marked cards setup. The subjects would have been able to ascertain the objective of the experimenter after repeated guesses if there was a marked card or not. As such they eliminated the experimenter bias within the marked card setup, and they went beyond the marked cards paradigm and tried to prove it through quizzes and trivia. The experimenter bias was removed by having the experimenter unaware of the value of the marked card, and the subjects had two different marks on the cards to predict from. In the traditional marked cards design the experimenter knew the values and had a single type of mark on the cards. In addition, the researchers showed that when guessing is strongly encouraged and incentivised, there were significant results for the desirability bias. In contrast, the experiments involving quizzes and trivia questions failed to show the desirability bias. This led the authors to propose that the desirability bias is driven by biased guessing rather than biased evidence evaluation, which is why the marked cards experiment provides significant results unlike quizzes.

In a separate study involving NFL betting behaviour, Massey et al. (2011) found strong evidence of the desirability bias in their research through four different tests: the favourite team, liking ratings, week to week ratings of desirability and the effect of ambiguity. This desirability bias refers that the desire for an outcome to succeed inflates individuals' optimism about the outcome. The way in which they were able to do this was by having a strong incentive mechanism in place. Each week the participants could earn a maximum of $3.50 while poor performance was punished. In addition, a $50 gift card was offered to the best performer. The sports fans exhibited persisting optimism over time through consistently predicting their favourite teams to win even when the odds were against them. Unsurprisingly, extensive experience about the NFL did not influence the fans' levels of optimism.

Another field study by Price (2000) involved two teams of students playing darts against each other, more specifically, trying to get as close as possible to the bullseye. He observed that all participants exhibited a strong wishful thinking effect which arose due to the fact that the teams thought that the opponent was less likely to hit the bullseye, whereas, their own team members had the greater likelihood. Price (2000) repeated this experiment and he was able to conclude that it was not through the team participation but rather the students' desires that created this difference in prediction. According to Price (2000) the darts experiment, with the robust results, serves to bridge the findings between purely laboratory experiments and other field studies of sports fans and voters. However, there is also research suggesting that the desirability bias does not exist.

Bar-Hillel and Budescu aptly named their paper as ''The Elusive Wishful Thinking Effect" (1995) and went even further with their follow-up chapter ''Wishful Thinking in Predicting World Cup Results: Still Elusive" (2008). They did series of experiments other than the marked card one and did not find any evidence of the desirability bias. Only when there was a monetary award on the predictability accuracy they did see some weak evidence of this by estimating the probability of an over 20-point weekly change in the Dow Jones average. Furthermore, Bar-Hillel et al. (2008) discuss that the desirability bias is ambiguous at best. They were able to replicate the results of the monetary incentives by simply making one of the outcomes in their experiment more salient. This was done by writing the option in bold and by having it specifically mentioned as the interested outcome in the experiment. Whether or not the salience affects the probability estimates, it begs the question to what extent it affects the motivational priming of individuals' outcomes. However, this does not mean that desirability bias does not exist.

Additionally, an earlier study by Kirzan and Windschitl (2007) explored the factors influencing optimism and in this case they found mixed results about the desirability bias. They concluded that they could not prove the existence of the desirability bias, and were unable to state that desires do not influence outcomes. Others, such as Bar-Hillel and Budescu (1992), provide doubts about the existence of the desirability bias. In another study, Klein (1999) showed that subjects when guessing about each other's performance within the experiment were doing it in a rational deliberate manner rather through wishful thinking.

2.4. Learning from Experience

In hindsight, it is often said that things would have been done differently than the way they were actually done. Learning from experience may sound obvious, but it is not as apparent as that.

A paper by Kahneman and Lovallo (1993) discusses inside and outside views regarding forecasts of plans and other scenarios. The inside views are often overly optimistic as the planners are anchored on the projected success rather than past cases and failures. The outside view incorporates past experiences, successes, failures and expert opinions – this generally guarantees a more level headed projection of a project's completion. Whether this also applies to investor behaviour remains to be seen.

In addition, the planning fallacy has also been investigated by Buehler et al. (1994) and they reported that individuals fail in using their past experiences when planning projects indicating that learning does not prevent optimism. They observed that the optimism bias remained in around a half of the subjects' self-predictions over future planning.

Furthermore, Kahneman (2003) discusses the concept of bounded rationality that builds the idea of attention being a scarce cognitive resource. The bounded rationality signifies that individuals are unable to take in all the available information correctly and objectively as they are influenced by a dual process system: System 1: intuition, and System 2: a judgment computer. This implies that individuals are subject to anchoring, framing effects and other heuristics within their decision-making and are unable to consciously make a fully rational choice. As seen with the overconfidence bias (Glaser et al., 2010), it is possible that these heuristics may influence professionals regardless of their experience and limit their ability to learn. Therefore, not only optimism plays a significant role in decision making.

Fraser and Greene (2005) evaluated entrepreneurs who are, at the beginning, unsure about themselves, their futures and how they learned from experience. Interestingly, they discovered that optimism diminishes with experience as the individuals become more confident in their own skills and abilities as they are able to face difficult situations accordingly rather than rely on luck. However, it could be that their level of skill did not change, rather it was a transition from under-confidence to their normal level of confidence. It is not yet certain whether the differences in experience also influence the optimism and desirability biases. This in contrast to the findings by Buehler et al. (1994) where the majority had not learned from their past experiences.

Another possibility in the failing of individuals' inability to learn from experience could derive from the fact that people persuade themselves that their predictions are nearly correct (Tetlock, 1998). This implies that the learning effect of feedback can be diminished or even possibly eliminated. Epley and Dunning (2006) showed that people are biased when predicting their own behaviour as they rely on intuitive self-knowledge, as opposed to making the appropriate base rate adjustments for the masses. In some cases, individuals are better at predicting others' behaviour than their own. However, Hart et al. (2009) demonstrated that individuals pay more attention to feedback when their own predictions are confirmed but it is difficult to evaluate how much feedback is required for this to happen and if it significantly alters their future predictions. This is similar to the confirmation bias, where individuals interpret new evidence as part of their existing beliefs (Nickerson, 1998). Therefore, there is no guarantee of feedback working if the individual upon reviewing the new information already believes it is part of his beliefs.

Through a laboratory experiment by Hussam et al. (2008) the authors could observe whether learning eliminates price bubbles by imposing restrictions on liquidity, varying dividend payment scenarios and repeating the game three times. In the first game, inexperienced investors caused a large bubble as they had not understood the fundamental value of the stock with a fixed dividend. However, in the second and third rounds in the experiment the trading price of the stock reverted to the fundamental value of the fixed dividend far more quickly indicating that learning had taken place. When the experiment was repeated with the same subjects with changes to the environment - the variance of dividend payments was increased - the evidence of learning had disappeared. The thrice experienced investors caused another large bubble mirroring the scenario of the first game. It appeared only in the third time of the rekindled experiment that evidence of learning was observed once more. This indicates that with exogenous shocks to the environment the learning process by individuals is reset and they need to experience the games twice again before changing their behaviour accordingly. Hussam et al. (2008) also conclude that depending on fluctuating market conditions experience does not play a role in eliminating bubbles, this implies that learning fails to change investor behaviour as the investment world is a continuously changing environment.

Lastly, according to the two studies of Massey et al. (2011) and Simmons and Massey (2012) it is possible that experience may have a limited influence on the optimism bias. This suggests that regardless of the feedback received the optimism may continue to persist in the individual's behaviour. Opposed to this view, List (2003) argues that market anomalies can be eliminated through market experience and that individuals' behaviour becomes more predictable.

2.5. Role of Incentives

Monetary incentives are frequently used as a method in (laboratory/field) experiments to motivate individuals and to improve their performance in both simple and complex tasks. The incentive pay-out structure needs to capture the required effort and optimise the subjects' performance. The incentive should be substantial enough for the dominance precept to apply (Smith, 1982). This means that the subjects' intrinsic motivation and any other subjective mental costs are overcome by the monetary incentive, and as such, the experimenter is able to obtain control.

For simple tasks, paying too much is a waste as the incentive cannot make a subject perform any better due to already performing at their peak and for complicated tasks, paying too little will provide sub-optimum performance from the subjects as the dominance precept is violated. Gneezy and Rustichini (2000) prove that if a monetary incentive is offered, a small amount is linked to poor performance whereas a larger amount increases performance. However, it is important to note that offering too high of an incentive will not improve the performance of an individual if they are already performing at their optimum level at a lower incentive. Therefore, it is inefficient to pay too much. Conversely, when the researchers compared the performance of two groups one with and one without an incentive, it was shown that monetary compensation is linked to a reduction in performance. As a result, introducing an incentive into the experimental design will automatically alter the subjects' behaviour in an unknown manner.

According to Kamenica (2012) there are four situations where an incentive may not work. First, when the task is inherently interesting to the subjects. Second, if the task is altruistic or noble the incentive backfires. Third, offering too high of an incentive creates anxiety and poor performance. Fourth, as already mentioned, a low incentive is deemed as insulting and provides poor results.

Therefore, as literature suggests there are chances the incentive will backfire, the incentive mechanism, in conjunction with the set task, is very important in deciding whether the subjects participating in an experiment will perform poorly or exceedingly well.

2.6. Summary and Hypothesis

Overall, the literature review suggests the following: (1) Optimism and overconfidence have been shown to have an impact in investor behaviour (2) Behavioural biases are present in the decision-making process (3) The wishful thinking effect can be significant when incentives are used in a simple game setup (4) It is difficult to learn from experience.

In addition, several of the behavioural biases have been discussed at length or highlighted: miscalibration, the better than average effect, optimism bias, framing effects, desirability bias as well as the confirmation bias. These biases provide insight into the influences over investor behaviour and how investors operate under various conditions. As the investors are always under the effect of behavioural biases, it is inconclusive whether their extensive experience allows them learn and perform better. As seen with Simmons and Massey (2012) predictions exhibited the optimism bias and experience did not play a significant role. When these points are combined in the context of financial markets I hypothesise the following:

- Optimism persists after receiving feedback
- Investors systematically predict higher than realised market returns

3. Methodology

3.3. Data Gathering

Professional traders and portfolio managers at banks were too difficult to get hold of, therefore, I approached the president of the student investment association, BNR Beurs, and was able to recruit 33 participants who would participate in the data gathering process. Every year the association organises an investment competition starting in November and ending in June. The goal of the participating teams in the competition is to generate the highest returns. Throughout this process, the

BNR Beurs board keeps track of the individual teams' performances and other benchmarks, and provides weekly updates on their website. One person can only be in a single team, and the teams operate independently and are competing against each other. The teams have near-total autonomy of its own portfolio, with a few minor restrictions regarding brokers and other factors. The teams themselves decide about what and how they will invest and where and when they will meet to discuss their investment strategy. They have access to most investment products that are available to a professional investor. Each week, starting from March 21st ending and at April 25th, a survey was sent to the subjects asking them to predict the performance of Apple stocks (AAPL:US), the AEX Index (AEX:IND) as well as their own team's returns both one and two weeks ahead. The first survey also included a question about their investment experience as some subjects are first year bachelor students while others are Master's-level students.

The Apple stocks were selected as they are widely known and the information about the company is easily accessible. Whereas, the choice for the AEX Index was motivated by the fact that the student investors belong to the same region and they should be more familiar with its performance relative to other indices. Furthermore, the one and two week ahead predictions about their own teams' performance provides information whether the student investors are able to predict rationally over time as well as observe differences in learning effects if they occur. In addition, the comparisons between the categories allow for the observation whether the students are capable to remain objective with their predictions.

BNR Beurs uploads the weekly results of the competition online at the beginning of every week. Subsequently I used the data once it was available to send personalised emails to each subject with the following feedback: (1) the performance of Apple's stock, (2) the performance of AEX Index and (3) their own group's performance in the past week. The survey itself consisted of four questions:

1. *What will be the % return for Apple stocks this week? (AAPL:US)*
2. *What will be the % return for AEX Index this week? (AEX:IND)*
3. *What will be your group's % return this week?*
4. *What will be your group's % return in two weeks?*

The subjects were not privy to information related to others' predictions, however, they were able to observe the names of the members in the same investment team. This is not a problem as the members already have this information and perhaps discuss about this with their teammates. To further clarify, members of different teams could neither see who else was participating nor anyone else's predictions. Therefore, the team oriented surveys and individualised emails for feedback created sufficient privacy between the subjects.

Rather than offer a fixed participation fee per subject at the beginning, a monetary reward based on performance was implemented. The individual who was the most accurate in predicting the returns for the Apple stocks, the AEX Index as well as their own group's performance over the six-week period received 150 euros. This performance tied incentive has been shown to be effective in inducing the desirability bias (Simmons & Massey, 2012). The single constraint in order to be eligible for the reward was that the subject was required to fill out all of the six surveys. Out of 33 who signed up, on average 20 subjects consistently filled out the surveys, however, only 13 completed each of the six surveys. The total number of participants in the surveys was 24.

Unlike Simmons and Massey (2012) only one incentive to the entire pool of subjects was offered. Furthermore, due to the small sample size the subjects were not split into a control and treatment groups. Each individual received personalised feedback, however, with such a low number of subjects it is unlikely to obtain any significant results.

The measure that is used to capture optimism is the difference between predicted and observed returns in the market. As previously hypothesised an optimist will systematically predict the returns are greater than they actually are. Therefore, there should be a constant prediction difference above zero for each of the four variables. A decreasing prediction difference over time would indicate that the feedback is providing an intervention in the decision making process, indicating that optimism does not persist or is reduced after feedback.

3.4. Data Analysis

With the survey results, the predicted returns were subtracted from the actual returns. This difference was calculated for each week for each of the four variables: Apple stock, AEX Index, their own group's return both one and two weeks ahead. For the prediction difference values please refer to **Appendix 1**. With this data the descriptive graphs of the prediction accuracy spread were created along with a linear forecast two periods ahead.

3.4.1. Page's L Test

A non-parametric test was employed to observe whether there is central tendency with the prediction differences for all of the four variables. As the data gathering process was a within-subjects design with more than three samples the options were the Friedman's Test and the Page's L Test. However, since I have a predicted sequence I am using the Page's L test. This test is more precise than simply testing for a difference in levels. As each of the six surveys is required to be completed in order for this non-parametric test to work, the total number of subjects used here is 13.

The null hypothesis is $m_1 = m_2 = m_3 = \cdots = m_{13}$ and the alternative hypothesis is that there is an ordered sequence $m_1 \geq m_2 \geq m_3 \geq \cdots \geq m_{13}$.

The stated hypothesis in this research paper is that optimism persists after feedback. Therefore, if learning takes place there will be a decreasing trend in the prediction differences over time. As such, the prediction differences are arranged in the order of weeks, meaning starting from week 1 and ending in week 6, and they are ranked accordingly from 1 to 6. The reason for this is that the smallest prediction difference should occur in the last week due to the feedback given over time and the greatest in week 1 when the feedback started. Then for each of the 13 subjects the 6 observations from each week, the prediction differences, are as well ranked through 1 to 6. The ranks are added up per column and provided a total value, which is then multiplied by the column number. This product is called *L.* The test equation can be written down as follows: $L = \Sigma cR$

Here, *c* is the column number and *R* is the column total rank. The total *L* is then compared to the Page's critical value (Page, 1963, p.221) and the null hypothesis can be rejected if *L observed* ≥ *L critical value*.

In addition, two-tailed power calculations are performed for each variable to measure relative power of the Page's L Test when using standard levels of significance. As the standard deviation is the prediction difference in percentage form, the equation is multiplied by a 100 to obtain the optimal sample size in order to observe a minimum effect size of 10% within the subjects. An additional 114 subjects should have participated in all of the surveys to obtain the required sample size of 127 in order to observe a minimum effect size of 10%.

$$\boldsymbol{n}^* = 2\left(t_{\alpha/2} + t_\beta \right)^2 * \left(\frac{\sigma}{\delta}\right)^2 * 100$$

Variable	*Alpha*	*Beta*	$t_{\alpha/2}$	t_β	*Delta*	$Std. Dev\ (\sigma)$	*N*
Apple Stocks	0.05	0.20	1.96	0.84	0.10	0.0282	125
AEX Index	0.05	0.20	1.96	0.84	0.10	0.0233	85
Team 1	0.05	0.20	1.96	0.84	0.10	0.0214	72
Team 2	0.05	0.20	1.96	0.84	0.10	0.0285	127

Table 1: Power Calculations

3.4.2. Panel Regression

The data gathered contains both time series and cross-sectional data. Rather than running a simple linear regression with each variable per each of the 24 students, who filled out at least one survey, the final level of analysis was performed through a panel regression. The panel regression model allows for simultaneous analysis of all the 24 students and provides a more comprehensive analysis of the data per variable rather than on an individual basis.

Unit Root Testing

First, the four prediction difference variables (Apple Stocks, AEX Index and the teams' one and two weeks ahead predictions) are tested for stationarity via a panel unit root test. With the panel data four different unit root tests are performed – which are: (1) The Levin-Lin-Chu Test, (2) The Im, Pesaran and Shin Test, (3) The ADF – Fisher Chi-Squared Test and (4) The PP – Fisher Chi-Squared Test. The null hypothesis for the Levin-Lin-Chu Test is that there is a common unit root in the panel data, whereas for the remaining three the null hypothesis assumes an individual unit root process within the panel data. To clarify, the first unit root tests whether the panel data as a whole is stationary, whereas the others test this on individual basis across the 24 subjects.

The unit root tests were first performed in levels and then with 1st differences to avoid spurious regressions. Each test was run three times with the following criteria about the panel data: there is an intercept, an intercept and trend, as well as with no intercept and no trend. The null hypothesis was rejected for each test across the variables as the p-values were less than 5%. Thus, proving stationarity of the panel data as a whole as well as on an individual basis. The full summary list of the unit root tests is available in the **Appendix 2.**

Model Specification

Instead of running a standard OLS regression, an EGLS panel regression is performed in order to allow for heteroskedasticity and serial correlation within the panel data. However, due to running a panel regression, each of the models needs to be tested via the Hausman Test for exogeneity of the unobserved error component. This test defines whether to run the panel regression with a Fixed Effect model or a Random Effect model. The difference between the two effects is that the Fixed Effect allows for heterogeneity between the subjects, but the intercept is time invariant. Whereas the Random Effect Model assumes that the subjects can be viewed as a random sample from a large population and the subjects have a common mean value for the intercept. The null hypothesis suggests that $H_O : \hat{\beta}_{RE} = \hat{\beta}_{FE}$ which implies that the unobserved effects are exogenous, that the FE and RE are asymptotically equivalent. If the null hypothesis is rejected, we can conclude that the Random Effect is inconsistent and the Fixed Effect model should be used.

Five different models are considered as the best fit model for each of the four variables. The Hausman Test showed that the Random Effects was best for every variable per each model and this can be seen in **Appendix 3**. The equations for the five different models with the Random Effects are shown below.

1. $Prediction\ Difference_{it} = \beta_0 + \beta_1 \exp_{\mathrm{i}} + \beta_2 Diff_{it-1} + \varepsilon_i + u_{it}$

$$Prediction\ Difference_{it} = \beta_0 + \beta_1 \exp_{\mathrm{i}} + \beta_2 Diff_{it-1} + w_{it}$$

2. $Prediction\ Difference_{it} = \beta_0 + \beta_1 \mathrm{exp_i} + \beta_2 Diff_{it-1} + \beta_3 Diff_{it-2} + \varepsilon_i + u_{it}$

$Prediction\ Difference_{it} = \beta_0 + \beta_1 \mathrm{exp_i} + \beta_2 Diff_{it-1} + \beta_3 Diff_{it-2} + w_{it}$

3. $Prediction\ Difference_{it} = \beta_0 + \beta_1 \mathrm{exp_i} + \beta_2 Diff_{it-1} + \beta_3 Dummy\ G_{i1} + \beta_4 Dummy\ G_{i2} + \ldots + \beta_{13} Dummy\ G_{11} + \varepsilon_i + u_{it}$

$Prediction\ Difference_{it} = \beta_0 + \beta_1 \mathrm{exp_i} + \beta_2 Diff_{it-1} + \beta_3 Dummy\ G_{i1} + \beta_4 Dummy\ G_{i2} + \ldots + \beta_{13} Dummy\ G_{11} + w_{it}$

4. $Absolute\ Prediction\ Difference_{it} = \beta_0 + \beta_1 \mathrm{exp_i} + \beta_2 week\ nr_i + \varepsilon_i + u_{it}$

$Absolute\ Prediction\ Difference_{it} = \beta_0 + \beta_1 \mathrm{exp_i} + \beta_2 week\ nr_i + w_{it}$

5. $Cumulative\ absolute\ Prediction\ Difference_{it} = \beta_0 + \beta_1 \mathrm{exp_i} + \beta_2 Diff_{it-1} + \varepsilon_i + u_{it}$

$Cumulative\ absolute\ Prediction\ Difference_{it} = \beta_0 + \beta_1 \mathrm{exp_i} + \beta_2 Diff_{it-1} + w_{it}$

The *i* stands for the *i*[th] cross section unit, *i = 1 , … , N* which in this case refers to the subjects that participated in the survey.

The error term w_{it} consists, only for the Random Effect Model, of two parts, and the assumptions about the components are:

$$\varepsilon_i \sim N\,(0, \sigma_\varepsilon^2)$$
$$E\,(\varepsilon_i \varepsilon_j) = 0 \quad for\ i \neq j$$
$$u_{it} \sim N\,(0, \sigma_u^2)$$
$$E\,(u_{it} u_{is}) = E\,(u_{it} u_{it}) = (u_{it} u_{js}) = 0 \quad for\ i \neq j \quad t \neq s$$
$$E\,(\varepsilon_i u_{it}) = 0$$

This provides us further assumptions about the expected error, variance and covariance:

$$E\,(w_{it}) = 0$$
$$Var\,(W_{it}) = \sigma_\varepsilon^2 + \sigma_u^2$$
$$Corr\,(w_{it}, w_{is}) = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_u^2}$$

Model 1 is a simple AR(1) model that uses the months of experience the subjects have in investing within the financial markets and the first lag of the prediction difference.

Model 2 builds on the first model and estimates the prediction difference with two lags. It is an AR(2) model.

Model 3 is an AR(1) model and it uses the subjects' teams as a dummy variable $Dummy\ G_1 \ldots Dummy\ G_{11}$ in order to estimate the effect of participating in the same team against the prediction error.

Model 4 measures the impact of the continuous feedback over the weeks against the absolute prediction differences.
Model 5 measures the impact of Model 1 on the cumulative absolute prediction differences, that being the total prediction error over time.

Subsequently the best out of the five models is presented below for each variable and the full summary of the selection criteria is available in **Appendix 3.** The best fit models per variable are then analysed in the ensuing *Results* section.

Variable	***Chosen Model***	***Fixed/Random Effect***
Apple Stocks	Model 1	Random Effect
AEX Index	Model 1	Random Effect
Teams 1	Model 1	Random Effect
Teams 2	Model 1	Random Effect

Table 2: Model Selection

The reason why Model 1 is chosen for each of the variables is that it takes into consideration the past week's prediction difference, which is under the influence of the feedback loop. Although Model 2 does provide some more insight, adding another independent variable will automatically make the regression more significant and as such, it is discounted. Finally, Models 3 through 5 either use too many dummy variables and/or use absolute prediction differences which are unable to show the direction of the possible learning effect.

4. Results

4.1. Descriptive

Over the six-week period, there is a large variation in the prediction differences for Apple stocks as shown in *Table 3.* In four out of the six weeks, the subjects predicted higher than realised market returns, which may indicate optimism bias. Furthermore, in week 4 it is shown that an individual had a prediction difference of 20.19%, however, it is likely that this subject was inattentive rather than expecting Apple to perform better in a week relative to the previous year. The prediction difference volatility changes over time and is quite large, conveying that subjects have clearly different expectations for the returns.

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Max	9.25%	1.24%	5.68%	20.19%	6.21%	2.42%
Min	-4.75%	-5.76%	0.36%	-2.81%	-2.05%	-3.08%
Median	2.18%	-2.76%	3.09%	0.19%	3.20%	-0.78%
Mean	1.94%	-2.60%	2.99%	0.78%	2.72%	-0.26%

Table 3: Apple Descriptive Statistics

With regards to the prediction differences for AEX Index the subjects were more uniform with their predictions as per *Table 4*. There are no large spikes as for Apple Stocks and instead of having two weeks with a negative mean the prediction differences for AEX Index are negative only once. This implies that the subjects are consistently predicting above market returns for the Index. The only standout figure in *Table 4* is the Week 4 mean figure at -3.48%. It is possible that the discussion of Brexit within the student investment body influenced their predictions in a negative manner while the markets did not react as much.

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Max	6.64%	8.69%	3.07%	0.22%	7.19%	5.59%
Min	-0.56%	-0.41%	-1.96%	-5.78%	-6.15%	-0.41%
Median	2.14%	1.69%	0.57%	-3.63%	1.35%	1.99%
Mean	2.26%	2.23%	0.45%	-3.48%	0.98%	2.05%

Table 4: AEX Index Descriptive Statistics

When reviewing the descriptive statistics for the prediction differences for their own teams' performance one week ahead, it can be seen that the mean values are overall more accurate relative to the predictions on Apple stocks and the AEX Index as shown in *Table 5*. It is interesting to note as this shows that the subjects are on average better at guessing their own teams' performances rather than those of a large multinational firm or of an index comprising of many different stocks. This does not, however, prove either optimism bias or the desirability bias.

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Max	6.32%	3.63%	3.85%	4.92%	3.21%	7.15%
Min	-3.40%	-2.60%	-0.59%	-4.36%	-7.22%	-2.08%
Median	1.00%	0.95%	1.79%	-1.52%	0.06%	1.95%
Mean	1.43%	1.02%	1.38%	-0.80%	-0.29%	2.29%

Table 5: Teams' 1 Week Ahead Descriptive Statistics

When comparing the descriptive statistics of the subjects' predictions of their own teams' returns two weeks ahead in *Table 6* with those shown in *Table 5*, it becomes clear that the individuals are not able to predict accurately two weeks ahead. The volatility in prediction differences increases sharply and individuals, according to the mean, only expect positive returns.

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Max	7.22%	8.85%	14.64%	29.01%	9.35%	6.37%
Min	-7.60%	-6.55%	-3.74%	-6.22%	-0.05%	-5.83%
Median	1.81%	1.84%	-1.27%	0.47%	4.55%	3.02%
Mean	1.76%	1.66%	0.06%	1.28%	4.22%	2.46%

Table 6: Teams' 2 Weeks Ahead Descriptive Statistics

Overall, the mean values per variable fluctuate around 0% for the prediction differences. To see this more clearly, refer to **Appendix 4**. In addition, when the graphs are compared, the prediction differences per variable per week fluctuate and do not follow a similar pattern. AEX Index shows a significant slump in week 4, whereas Apple stocks and their own teams' predictions one week ahead do not. Furthermore, a two steps ahead linear trend line is plotted for each variable according to their respective means. The only graph that shows a decreasing trend is the AEX Index, this indicates that there may be a learning effect taking place while for the others there is none.

4.2. Page's L Test

When the Page's L Test for a predicted ordering sequence is run on the four variables the null hypothesis is rejected for AEX Index at a 5% confidence interval and for the subjects' predictions of their own portfolios two weeks ahead at each level of significance. Therefore, according to the alternative hypothesis, AEX Index and Team's two week ahead predictions have a predicted ordering sequence that decreases over time whereas the other variables have the same central tendency with every significance level as per *Table 7*. The AEX Index was shown to have a decreasing trend line with regards to its prediction differences that supports this finding. Conversely, the trend line for Team's two weeks ahead predictions was flat, seeming to be contradictive of the below findings.

		Is Null Rejected?		
	L score	0.1%	1.0%	5.0%
Apple	924	No	No	No
AEX	1015	No	No	***Yes***
Team 1	918	No	No	No
Team 2	1056	***Yes***	***Yes***	***Yes***

Sig. level	Critical Values
0.1%	1044
1.0%	1022
5.0%	1003
m=	13
n=	6

Table 7: Page's L Test Results

However, since these tests were run with 13 subjects, this test has extremely little power as per the power calculations several thousands of individuals are required to participate to observe a 10% change in behaviour.

4.3. Panel Regressions

The below table is the summary of the panel regressions performed per variable. AEX Index, and subjects' predictions both one and two weeks ahead for their own teams show zero significance and as a result cannot be analysed further. The prediction difference for Apple is negative and significant at 1% with a p-value of 0.0042. The coefficient -0.2897 indicates a 0.29bp decrease from the previous week's prediction difference. Therefore, during each period the prediction difference decreases by 0.29bps which indicates that the subjects are learning from their feedback.

Although the AEX Index showed a decreasing trend line and had a predicted decreasing trend, according to the Page's L test at a 5% confidence interval this is not statistically significant in the panel regression. It may be that the patterns were random noise, or that by chance a few subjects influenced the results in such a great manner to show a trend. The same can be said about the subjects' predictions two weeks ahead for their own portfolios. There may have been a trend according to the Page's L test, however no learning takes place according to the panel regression analysis.

Furthermore, another contradictory finding within the panel regression is that the months of investment experience across the subjects is insignificant throughout the different models. This implies that more experienced investors perform similarly as unexperienced investors. These findings are inconsistent to the significance found in the prediction difference for Apple stocks. Therefore, it could be that past experience does not play a role. However, it may be that some measure of learning did take place within the six-week period.

Summary Regression Results

Variable	*Apple Stocks*	*AEX Index*	*Team 1*	*Team 2*
Intercept	0.0100*** (0.0042)	0.0061 (0.1331)	0.0080*** (0.0318)	0.0198*** (0.0002)
Inv. experience	-0.0000 (0.6762)	-0.0000 (0.9329)	-0.0000 (0.8050)	-0.0001 (0.5742)
Prediction diff (-1)	**-0.2897*** (0.0000)**	0.0519 (0.6261)	0.0607 (0.5774)	0.0664 (0.3881)
R-squared	0.1588	0.0029	0.0048	0.0110
Sum Squared Resid	0.0533	0.0670	0.0514	0.1081
Durbin-Watson stat	1.9880	2.1943	2.0169	2.0347

Table 8: Summary Regression Results

The Durbin-Watson statistic evaluates the presence of autocorrelation in the residuals. This is an important statistic to observe as with panel data there are greater chances of autocorrelation occurring. As the Durbin-Watson statistics for each model are close to 2, this indicates that there is almost no autocorrelation in the sample. Values near 0 have positive autocorrelation and values near 4 have negative autocorrelation. Therefore, the EGLS model was used correctly across the four models to take into consideration the autocorrelation and heteroscedasticity.

The best model is the one for *Team 1* as it has the smallest sum of squared residual value. It is the measure of how much the dependent variable's variation the model did not explain, therefore, the larger the value, the poorer the model fits the data. However, as no significance is found with *Team 1* the best model is with *Apple Stocks* as it has a smaller sum of squared residual value at 0.0533 relative to *AEX Index* and *Team 2*. In addition, when comparing the R-squared values between the different models it is unsurprising that AEX Index, Team 1 and Team 2 models have the lowest – near 0% explanatory power. Apple Stocks, on the other hand, due to it having the only significant variable has a 15.88% explanatory power over the prediction differences. However, this is unusually large within financial regression models and may be an indication of model misspecification.

4.4. Summary of Results

When looking at the descriptive statistics, Page's L Test, and the panel regression altogether they both support and contradict each other with their respective findings.

The AEX Index shows a decreasing trend in both the descriptive and Page's L test. This may be due to the students' predictions in week 4 for the index which weighs the rest of the data down into a visible pattern that is then confirmed by the non-parametric test. The panel regression, on the other hand, proves the model to be insignificant, indicating that the observable trends were false.

The Page's L Test result for the teams' two week ahead predictions that showed a decreasing pattern is an indication of learning. It is possible that the students were able to learn through the feedback what realistic weekly returns are. However, as no trend was observed in the descriptive statistics and the model having insignificant results in the regression, it is unlikely that learning took place. Alternatively, the results may be due to random noise, or from a few students guessing wildly inaccurate returns as seen in **Appendix 1**.

Finally, when reviewing Apple stocks and the teams' predictions one week ahead they are quite similar. Neither exhibits a trend or a predictive in either the descriptive statistics or the Page's L test respectively. However, Apple stocks did have significant results in the panel regression which sets it apart from all of the other variables. Consequently, the following section analyses, explains and discusses these similarities and differences.

5. Discussion

Overall, the obtained results about learning and experience are inconsistent and this may be due to a plethora of reasons working either together or independently of one another. Each of these factors is explained and discussed in relation to the observed results as well as the examined literature.

First, it is important to address whether or not the optimism can be observed through the results. Although the panel regressions are unable to provide this evidence, the non-parametric test and the descriptive statistics together are able to convey, to an extent, the existence of optimism. Section 4.1 indicates that the subjects had positive prediction differences over time which is indicative of an optimism bias. When coupled with the results of the Page's L test where the null hypothesis of a central tendency was not rejected, it indicates that optimism persists over time. The notable exception to the central tendency are the prediction differences for the AEX Index and the subjects' predictions of their own teams' portfolios two weeks ahead, whereupon, it was shown that the predicted pattern of decreasing prediction differences exists.

As the patterns indicating a decreasing prediction difference were observed with two variables (AEX Index and portfolio predictions two weeks ahead), it cannot be said that learning occurs across the board. Investment experience for each of the models is insignificant. Possessing more knowledge or acumen of the financial markets and investments does not increase the accuracy of predictions. This may be due to the constant change in the markets, for example, Apple issued a press release where they announced a new mobile device. Issuing dividends also changes the behaviour due to an increase in liquidity (Hussam et al. 2008). Several companies issued dividends in the AEX Index as well as Apple during the data gathering process. However, including a dummy variable for this would not resolve the problem as it is unknown whether the stocks within the teams' portfolios also issued dividends. Furthermore, as only some firms issue dividends in the AEX Index, it would be impossible to segregate them accordingly. In addition, assuming everyone has the same access to information the student subjects should behave similarly, but this is not the case. This is in line with the findings of Hussam et al. (2008), that learning fails to change investor behaviour due to changing market conditions.

Therefore, the null hypothesis that individuals systematically predict higher than realised market returns is not rejected. This is consistent with the evidence from the studies by Radzevick and Moore (2008) as well as the Simmons and Massey (2012). Both of the studies explained that individual's prediction abilities are imperfect, and as shown in **Appendix 4** the spread of the prediction differences is largely visible for each of the variables. It is also possible that the subjects were under the influence of miscalibration or the above average effect. As per Ben-David et al. (2010), the individuals' optimism positively affects the miscalibration, which is the over-precision of the outcomes. This implies that the student subjects were inadvertently predicting the weekly returns with an insufficient consideration of a larger range of outcomes due to the irrational belief deriving from optimism and overconfidence.

Another aspect influencing an investor's perceptions is the feeling of affect towards a company, more specifically the investor's perceptions about their financial prospects (MacGregor et al., Statman et al., 2008). The participants in the data gathering process are also subject to this. As the students are freely allowed to pick and choose their own investments for their portfolios, it is plausible that the subjective value of a firm's brand influences their optimism about future financial returns (Aspara 2013). As per the panel regression analysis the previous week's prediction differences are insignificant implying that the past predictions do not explain the present predictions. Therefore, because the students have selected their portfolios with overly optimistic expectations of future returns they are unable to predict accurately both one and two weeks ahead.

The wishful thinking effect is not able to clearly explain the results. This is generally observed when there are two different types of incentive mechanism in place. Regardless of this fact, as the subjects are requested to predict weekly returns for a stock, an index and for their own portfolios it is no longer within the context of a simple game like the marked cards. There are too many different changes in the environment and the predictions of weekly returns do not fall within a binary choice category. Therefore, unlike the card experiments, no proof of the desirability bias is evident. It could be that the student subjects were not motivated enough, or thought that it was too unlikely for them to win. As such the desire, the wish to win the 150 euros was not sufficient enough to alter their behaviour as only 13 subjects out of 33 fully completed all of the six surveys. This is contrary to the findings of Massey et al. (2011) and Price (2000) who were able to prove evidence of the desirability bias in sport betting. Additionally, Bar-Hillel and Budescu (2008) were only able to see weak evidence in the prediction accuracy when estimating the probability of over 20-point weekly change in the Dow Jones average. This may indicate that it is more complex and inconclusive to prove the existence of wishful thinking in the financial markets.

The fact that only the Apple prediction differences model showed any significance may be explained by Klein (1999). The subjects are more rational when guessing outside their own portfolios. However, as the AEX Index did not indicate any significance, this may be construed as a coincidence. Alternatively, it is possible that predicting the performance of a stock is easier than that of an index or a portfolio as there are less variables to consider. It is also possible that the student investors had strong knowledge about the technology industry and were able to consistently predict accurately. Therefore, the students were better able to predict the returns for Apple than for the rest of the variables, or it was a matter of being fortunate.

Alternatively, as the panel regression models for the teams' one and two week predictions ahead showed no significance it could be due to the inside vs outside views (Kahneman & Lovallo, 1993). The subjects are anchored on the projected successes rather than the past realised returns of their portfolios. This inside thinking prevents them from addressing the predictions rationally as they are part of the owners of the portfolio. As they are outside of the decision making process of Apple the subjects are able to act more rationally and as such obtain an outside view of their future returns. As such the prediction difference for the previous week is significant for Apple unlike for the rest of the models. This does not apply to the AEX Index, as that comprises of dozens of companies and the outside view of that is far more complex to achieve.

Furthermore, subjects' bounded rationality reveals more insights as to the reason why the results are insignificant. As the subjects process the market and sectoral level information, this overloads their capacity to analyse further information and as a result provide inaccurate weekly predictions. Attention is a scarce resource and once depleted, the subjects make suboptimal decisions (Kahneman 1973). This is reflected in the results of the Page's L test as two variables showed a decreasing pattern in the prediction differences. Had the subjects been capable of using the information provided in the feedback, the same predicted trend would have been observed for the other two variables as well.

Therefore, the null hypothesis of optimism persists after receiving feedback cannot be rejected. There simply is not enough evidence to indicate that prediction differences decrease over time.

5.1. Limitations

One of the main limitations is the quality of the data obtained. As per the power calculations around a few hundred are required to observe a 10% change in behaviour, therefore, the 20 subjects who consistently filled out the surveys are clearly not sufficient for meaningful and robust results. In addition, the surveys were sent out via email, so there is no control over the environment in which the subject completes it. There is no guarantee that the students predict the weekly returns with thoughtful consideration. In addition, the student body in charge of the investment game uploaded the results at the beginning on a Sunday, but then changed to Monday mid-mornings or later on in the week after the markets had been open for a day or two. This was extremely unfortunate as the individuals who immediately responded to the survey were predicting the weekly returns in a more honest manner than those who had to be sent reminders to complete the survey on a Tuesday or a Wednesday. These individuals who had not filled the survey immediately could have biased results as they were able to observe the markets longer, and as such predict with greater information available. These should be controlled for in later experiments. However, with regards to the late data, the entries did not influence the results as they still remained insignificant. Otherwise the late entries would show greater accuracy and possibly provide greater significance in the panel regression analysis.

In addition, it is unknown how much feedback and for how long it must continue before a change in behaviour is observed (Hart et al., 2009). Sending personalised emails with the last week's returns made bold to increase its saliency may not be enough for the students to react appropriately. Therefore, instead of an online medium, the students should be invited to complete the survey at a previously specified location and handed the information out at the same time on every Monday morning in order to eliminate tardiness and unequal access to information. Alternatively, professional investors should also be invited to join the experiment in order to observe differences in behaviour and investment knowledge. Moreover, the data gathering process should be extended for a longer period of time, such as a year, to have more data points across the subjects. Not only should the time period be extended but also the number of companies and indices to predict the weekly returns for. The period of the year should have dummy variables for important news releases as well as for dividend payments. This way the prediction differences will reflect more accurately the subjects' decision making behaviour.

Finally, the incentive mechanism that was selected was suboptimal. Only a third of the subjects fully reacted to the incentive and completed each survey. Subsequently, the study should be performed with two separate incentive mechanisms. Rather than have the winner take it all after the six weeks, intermediary winners should be announced as per Simmons and Massey (2012) experimental design. This way the subjects are more enthused and willing to participate in later stages as they are able to win weekly prizes rather than one prize after six weeks. By having two different incentives in place it will allow the researcher to extrapolate whether the wishful thinking effect is present outside the context of sports betting and the marked card experiments.

In general, with these changes both the panel regression and the Page's L test will become more powerful and more robust. With such differences, it is expected that greater significance is found and the economic costs of optimism are able to be calculated. This could be obtained by using the panel regression coefficients to forecast several weeks ahead and then calculate the differences between predicted and realised market returns.

6. Conclusion

The goal of this research paper was to observe whether optimism persists in the presence of learning with regards to investor behaviour as Simmons and Massey (2012) had found it to persist with sports fans. The performed study involved a literature review, primary data gathering, a non-parametric test and a panel regression analysis. Although the results are not significant, perhaps this was due to the small sample size of student investors who agreed to participate in the surveys, they do suggest about the persistence of optimism and that experience does not influence the outcomes. Overall, these inconclusive findings have laid down the groundworks for future research that is able to continue and prove that optimism persists both over time and through feedback within investor behaviour in the financial markets.

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Appendix

1. Prediction Differences

1.1. Apple

Apple Returns Prediction Differences									
Team Nr.	Subject Nr.	Gender	Inv. Exp. (months)	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
1	1	Male	18	-1.75%	-1.76%	2.59%	0.19%	3.95%	-1.08%
2	2	Male	5	6.25%	-2.86%	1.09%	-1.81%	2.15%	-0.58%
2	3	Male	18	-1.75%	-3.26%	3.09%	-0.31%	3.45%	-0.58%
2	4	Male	7	6.28%	-2.80%	4.79%	0.19%	4.15%	0.92%
3	5	Male	42	3.25%	-2.76%	#N/A	1.19%	2.95%	-3.08%
3	6	Male	7	#N/A	-2.70%	5.68%	1.49%	6.21%	-0.97%
3	7	Male	21	#N/A	-3.46%	1.59%	-0.11%	3.95%	0.92%
4	8	Male	24	9.25%	1.24%	#N/A	20.19%	-2.05%	-1.08%
5	9	Male	9	3.00%	-3.91%	5.64%	-0.46%	3.63%	-1.83%
6	10	Male	12	2.10%	#N/A	0.36%	-1.84%	4.32%	-1.28%
6	11	Male	48	-4.75%	1.24%	3.59%	1.19%	0.95%	-1.08%
6	12	Male	36	1.25%	-2.76%	#N/A	0.19%	3.95%	0.92%
6	13	Male	28	2.75%	-1.26%	3.59%	#N/A	-0.05%	2.42%
7	14	Female	5	2.25%	-3.26%	4.09%	-1.31%	4.45%	0.42%
8	15	Male	4	3.75%	-2.76%	2.59%	-1.81%	1.95%	-1.08%
8	16	Male	120	-1.75%	-3.26%	1.59%	0.19%	3.75%	0.92%
9	17	Male	18	1.75%	-2.76%	#N/A	-2.81%	-0.05%	#N/A
9	18	Male	24	8.25%	-2.76%	3.59%	0.69%	2.45%	-1.43%
9	19	Male	28	2.25%	-2.76%	#N/A	#N/A	#N/A	#N/A
10	20	Male	20	3.25%	-1.76%	3.09%	0.19%	3.95%	1.92%
10	21	Male	30	-1.75%	-3.76%	1.59%	0.19%	1.95%	1.42%
10	22	Male	15	-1.75%	-5.76%	3.59%	#N/A	1.95%	#N/A
10	23	Male	5	1.25%	#N/A	3.59%	#N/A	#N/A	#N/A
11	24	Male	30	-0.75%	-3.26%	1.09%	0.19%	1.95%	-1.08%
			Participants:	22	22	19	20	22	20

1.2. AEX

AEX Returns Prediction Differences									
Team Nr.	Subject Nr.	Gender	Inv. Exp. (months)	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
1	1	Male	18	-0.56%	0.69%	-0.93%	-3.68%	-0.65%	0.59%
2	2	Male	5	2.64%	4.69%	-0.93%	-4.98%	1.85%	4.59%
2	3	Male	18	2.14%	2.69%	0.77%	-3.28%	0.35%	2.59%
2	4	Male	7	3.71%	-0.41%	-0.38%	-3.58%	3.70%	1.79%
3	5	Male	42	1.84%	1.69%	#N/A	-3.78%	1.85%	2.59%
3	6	Male	7	#N/A	3.77%	-1.96%	-1.98%	7.19%	1.46%
3	7	Male	21	#N/A	1.14%	1.37%	-4.78%	0.85%	3.09%
4	8	Male	24	6.64%	8.69%	#N/A	0.22%	-6.15%	5.59%
5	9	Male	9	1.79%	-0.07%	-0.68%	-3.75%	0.60%	1.94%
6	10	Male	12	4.76%	#N/A	-0.52%	-4.65%	2.72%	0.59%

6	11	Male	48	-0.36%	3.69%	0.57%	-2.78%	-2.15%	-0.41%
6	12	Male	36	0.64%	1.69%	#N/A	-2.78%	1.85%	0.59%
6	13	Male	28	2.49%	4.69%	1.57%	#N/A	-0.15%	-0.41%
7	14	Female	5	2.14%	0.89%	0.57%	-3.81%	1.85%	2.59%
8	15	Male	4	3.64%	2.69%	-0.43%	-4.28%	3.35%	4.59%
8	16	Male	120	-0.36%	0.99%	0.07%	-3.38%	1.85%	1.99%
9	17	Male	18	3.84%	2.69%	#N/A	-5.78%	1.85%	#N/A
9	18	Male	24	2.64%	2.19%	1.07%	-3.28%	0.50%	2.47%
9	19	Male	28	1.64%	1.69%	#N/A	#N/A	#N/A	#N/A
10	20	Male	20	0.44%	2.79%	2.07%	-2.78%	1.85%	1.99%
10	21	Male	30	1.64%	1.19%	0.07%	-3.78%	-0.15%	2.09%
10	22	Male	15	3.64%	-0.31%	2.07%	#N/A	-1.15%	#N/A
10	23	Male	5	3.64%	#N/A	3.07%	#N/A	#N/A	#N/A
11	24	Male	30	1.14%	1.19%	1.07%	-2.78%	-0.15%	0.59%
			Participants:	22	22	19	20	22	20

1.3. Team's own portfolio predictions one week ahead

Team_1 Returns Prediction Differences									
Team Nr.	Subject Nr.	Gender	Inv. Exp. (Months)	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
1	1	Male	18	0.55%	-0.16%	-0.31%	4.92%	-0.74%	1.74%
2	2	Male	5	1.70%	2.81%	0.42%	-3.01%	0.06%	6.04%
2	3	Male	18	1.20%	1.31%	-0.43%	-1.46%	0.06%	2.04%
2	4	Male	7	2.65%	0.46%	-0.48%	0.09%	2.02%	1.02%
3	5	Male	42	6.32%	3.22%	#N/A	-0.65%	-0.42%	0.95%
3	6	Male	7	#N/A	-0.24%	2.00%	2.25%	-1.45%	1.97%
3	7	Male	21	#N/A	3.32%	-0.59%	0.55%	1.08%	1.45%
4	8	Male	24	-3.40%	-2.60%	#N/A	4.65%	-2.99%	3.18%
5	9	Male	9	3.41%	1.12%	2.05%	-2.70%	2.86%	2.60%
6	10	Male	12	4.30%	#N/A	2.39%	-3.89%	-4.32%	1.99%
6	11	Male	48	-0.02%	3.63%	3.85%	-1.74%	-7.22%	1.11%
6	12	Male	36	4.98%	1.63%	#N/A	-2.74%	-5.22%	0.11%
6	13	Male	28	0.48%	2.63%	2.35%	#N/A	-2.22%	2.11%
7	14	Female	5	0.53%	0.78%	0.35%	-1.92%	2.44%	1.74%
8	15	Male	4	0.72%	0.76%	1.79%	0.50%	3.17%	-2.08%
8	16	Male	120	-3.21%	-0.24%	0.79%	0.00%	1.17%	1.92%
9	17	Male	18	2.83%	2.42%	#N/A	-4.36%	3.21%	#N/A
9	18	Male	24	3.83%	1.62%	2.35%	0.64%	2.11%	4.07%
9	19	Male	28	1.83%	1.42%	#N/A	#N/A	#N/A	#N/A
10	20	Male	20	0.29%	-0.05%	2.67%	-1.57%	2.23%	7.15%
10	21	Male	30	-0.21%	-0.62%	1.37%	-3.07%	0.23%	6.35%
10	22	Male	15	0.79%	-1.62%	2.37%	#N/A	-0.77%	#N/A
10	23	Male	5	1.69%	#N/A	2.37%	#N/A	#N/A	#N/A
11	24	Male	30	0.16%	0.78%	0.83%	-2.39%	-1.65%	0.40%
			Participants:	22	22	19	20	22	20

1.4. Team's own portfolio predictions two weeks ahead

Team_2 Returns Prediction Differences									
Team Nr.	Subject Nr.	Gender	Inv. Exp. (months)	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
1	1	Male	18	0.84%	0.29%	5.42%	-1.74%	4.74%	1.24%
2	2	Male	5	1.81%	1.82%	-1.51%	-0.94%	7.04%	1.17%
2	3	Male	18	1.81%	0.57%	-1.71%	-0.04%	5.04%	-2.83%
2	4	Male	7	4.31%	0.28%	-2.21%	1.36%	7.93%	-5.83%
3	5	Male	42	7.22%	-2.29%	#N/A	-2.42%	-0.05%	2.15%
3	6	Male	7	#N/A	-2.14%	14.64%	3.18%	1.18%	4.49%
3	7	Male	21	#N/A	3.51%	2.35%	0.58%	1.95%	3.65%
4	8	Male	24	-7.60%	-6.55%	#N/A	29.01%	5.18%	2.70%
5	9	Male	9	3.57%	3.45%	-3.30%	3.63%	4.90%	6.37%
6	10	Male	12	2.40%	#N/A	-2.62%	-5.63%	1.61%	3.99%
6	11	Male	48	2.63%	8.85%	-0.74%	-3.22%	1.11%	4.33%
6	12	Male	36	0.63%	1.85%	#N/A	-6.22%	0.11%	3.33%
6	13	Male	28	0.63%	4.85%	-3.74%	#N/A	6.11%	4.33%
7	14	Female	5	4.28%	2.30%	-0.42%	2.94%	3.24%	5.98%
8	15	Male	4	2.69%	3.79%	3.00%	3.17%	3.92%	0.11%
8	16	Male	120	1.76%	1.29%	0.00%	1.17%	3.92%	2.11%
9	17	Male	18	5.42%	5.85%	#N/A	-2.29%	7.27%	#N/A
9	18	Male	24	3.42%	2.81%	-1.36%	2.71%	5.87%	5.81%
9	19	Male	28	1.42%	2.85%	#N/A	#N/A	#N/A	#N/A
10	20	Male	20	0.88%	2.27%	-1.27%	1.73%	9.35%	3.49%
10	21	Male	30	-2.52%	0.87%	-3.07%	-1.77%	6.85%	0.99%
10	22	Male	15	0.38%	-0.63%	-0.07%	#N/A	4.35%	#N/A
10	23	Male	5	2.38%	#N/A	-0.07%	#N/A	#N/A	#N/A
11	24	Male	30	0.38%	0.73%	-2.19%	0.35%	1.20%	1.68%
			Participants:	22	22	19	20	22	20

2. Unit Root Testing

Apple Prediction Differences						
	P-Values					
	In Levels			1st Differences		
Test	Intercept	Intercept & Trend	None	Intercept	Intercept & Trend	None
Levin, Lin Chu	0	0	0	0	0	0
Im, Pesaran and Shin	0	0		0	0	
ADF - Fisher Chi-Squared	0	0	0	0	0	0
PP - Fisher Chi-Square	0	0	0	0	0	0

AEX Prediction Differences						
	P-Values					
	In Levels			1st Differences		
Test	Intercept	Intercept & Trend	None	Intercept	Intercept & Trend	None
Levin, Lin Chu	0	0	0	0	0	0
Im, Pesaran and Shin	0	0		0	0	
ADF - Fisher Chi-Squared	0	0	0	0	0	0
PP - Fisher Chi-Square	0	0	0	0	0	0

Team Prediction Differences One Week Ahead						
	P-Values					
	In Levels			1st Differences		
Test	Intercept	Intercept & Trend	None	Intercept	Intercept & Trend	None
Levin, Lin Chu	0.0002	0.0004	0	0	0	0
Im, Pesaran and Shin	0.0008	0.0341		0	0	
ADF - Fisher Chi-Squared	0.0006	0.0171	0	0	0	0
PP - Fisher Chi-Square	0	0.0002	0	0	0	0

Team Prediction Differences Two Weeks Ahead						
	P-Values					
	In Levels			1st Differences		
Test	Intercept	Intercept & Trend	None	Intercept	Intercept & Trend	None
Levin, Lin Chu	0	0	0	0	0	0
Im, Pesaran and Shin	0	0		0	0	
ADF - Fisher Chi-Squared	0	0	0	0	0	0
PP - Fisher Chi-Square	0	0	0	0	0	0

3. Model Selection

Apple

Hausman Test		
Model	p-value	Fixed/Random Effect
1	0	Random
2	0.0001	Random
3	0.0001	Random
4	0.5777	Fixed
5	0	Random

Summary Stats			
Model	Sum squared resid	Durbin-Watson stat	R - Squared
1	0.053332	1.988034	0.158829
2	0.014464	1.45454	0.458208
3	0.049481	1.992063	0.217374
4	0.048692	2.409117	0.26299
5	0.15699	0.663819	0.056141

AEX

Hausman Test		
Model	p-value	Fixed/Random Effect
1	0.0009	Random
2	0.0037	Random
3	0.002	Random
4	0.1924	Fixed
5	0	Random

Summary Stats			
Model	Sum squared resid	Durbin-Watson stat	R - Squared
1	0.066959	2.194256	0.002869
2	0.028764	2.445826	0.339719
3	0.063493	2.275495	0.054497
4	0.028311	2.377824	0.019077
5	0.101218	0.991735	0.153695

Teams 1 week ahead

Hausman Test		
Model	p-value	Fixed/Random Effect
1	0.0145	Random
2	0.0046	Random
3	0.1484	Fixed
4	0.8996	Fixed
5	0	Random

Summary Stats			
Model	Sum squared resid	Durbin-Watson stat	R - Squared
1	0.051362	2.016926	0.004782
2	0.033993	2.290199	0.111635
3	0.046589	2.127858	0.097252
4	0.028316	1.961687	0.022976
5	0.100407	0.766642	0.108473

Teams 2 weeks ahead

Hausman Test		
Model	p-value	Fixed/Random Effect
1	0.0006	Random
2	0	Random
3	0.0004	Random
4	0.6954	Fixed
5	0	Random

Summary Stats			
Model	Sum squared resid	Durbin-Watson stat	R - Squared
1	0.108072	2.034675	0.01101
2	0.061797	2.009686	0.025451
3	0.097722	2.240555	0.105729
4	0.11734	1.889735	0.024049
5	0.295623	0.71259	0.207164

4. Descriptive Graphs