

A Work Project, presented as part of the requirements for the Award of a Master Degree in Finance
from the NOVA – School of Business and Economics



NSP Work Project

How does Behavioural Finance affect Portfolio Management decisions?

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Nº2299

A Project carried out on the Master in Finance Program, under the supervision of:

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January 2017

Abstract

The main objective of this paper is to study how Behavioural Finance affects Portfolio Management decisions and performance by studying a real case - the Nova Students Portfolio (NSP) course. To do so, this paper explored the main topics in the Behavioural Finance theory as well as the most common behavioural biases and applied the theory to the NSP fund. There was found evidence in the NSP of 10 well known biases in literature as well as some of their consequences. Recommendations were then proposed in order to avoid them. Furthermore, the investor sentiment was studied but it was found no evidence of weekly predictive power of investor sentiment on the short-term asset prices.

Keywords: Behavioural Finance; Biases; Decision-making; Investor Sentiment

1. Introduction

“The investor’s chief problem – even his worst enemy – is likely to be himself.”

Benjamin Graham

The purpose of this Work Project is to understand how the human nature of investor’s behaviour affects his decision-making process and impacts his performance. The analysis of the Nova Students Portfolio (NSP) will constitute a practical example to understand how the field of Behavioural Finance influences the decisions taken and the fund’s performance. The aim of the paper is then to introduce this emerging area of Finance as well as to apply it to a real case, while taking conclusions that can be useful and applicable in the following years of the course as well as to other funds. Standard finance models assume investors as being rational but the human condition makes humans susceptible to some cognitive biases while making decisions. Indeed, Warren Buffet states that: *“The fact that people will be full of greed, fear or folly is predictable. The sequence is not predictable.”* This paper plans to ‘give some predictability’ to this behaviours by trying to find these biases in practice, show their possible consequences and provide recommendations for investors to be less affected by them while investing.

The structure of this Work Project will be as follows: Section 2 will describe the NSP fund and its performance. Section 3 will function as a literature review by providing some relevant theory of Behavioural Finance, including how it appeared, what developments has it experienced and what are its main principles and as well as the well known biases affecting investors. Section 4 will analyse the data from the fund to find some of the biases described in the previous section and their consequences but also present some recommendations to avoid these biases. Finally, section 5 will analyse the market sentiment to understand its predictive power and its impact on the NSP decisions.

2. Nova Students Portfolio (NSP)

2.1. NSP description

The Nova Students Portfolio is a long only portfolio managed by a group of around 15 students from the Masters in Finance of Nova School of Business and Economics, under the supervision of two professors. It was launched in November 2014 (this was its second year) with an inception net asset value (NAV) of \$310,000, sponsored by a Portuguese bank. The portfolio invests in stocks and bonds in the US market and starts with a 60/40 allocation in bonds and equities, respectively, by investing in the following ETF's: BOND US Equity¹ and SPY US Equity. The students are supposed to change the allocation and have two options to do so: change the weights on a maximum of 10% up or down or change to risk parity, depending on whether they are more bullish or bearish on the market. Students should also present stock picks that may be added to the portfolio. The performance is evaluated against a fixed 60/40 benchmark composed by two indexes: LBUSTRUU Index² (bonds) and SPX Index (equities).

2.2. NSP Performance and Statistics

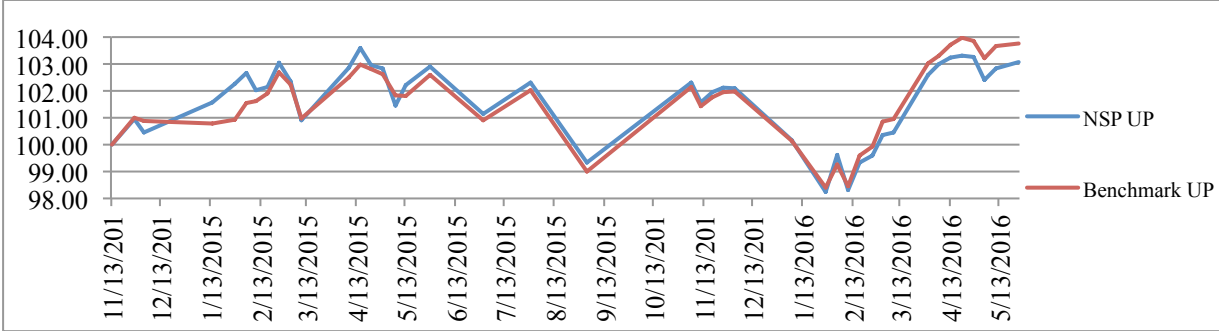
Firstly, some general performance measures of the whole NSP (2 years) will be presented but then this work project will only be focused on the last year's fund. Considering the whole NSP performance, the fund underperformed the benchmark with an annualized return of 2.16% against 2.57% with info sharpes of 0.26 and 0.33, respectively (annualized volatilities of 8.43% and 7.73%, respectively). In value, the NSP ended up, at the end of May, with a NAV of \$319,528 while the benchmark ended up with a theoretical \$321,688. This is translated in an Information ratio of -0.17 that shows the underperformance of the NSP. (Table of overall general performance in appendix 1 and weights allocation in appendix 2).

¹ BOND US Equity: PIMCO Total Active Return ETF is an actively managed ETF that invests in fixed income instruments.

² LBUSTRUU Index: Bloomberg Barclays US Aggregate Bond Index is an index that measures the investment grade bonds with a fixed-rate taxable bond market.

The graph below shows the evolution of the UP of the NSP against the one of the benchmark, since the inception of the fund.

Graph 1. NSP UP vs Benchmark UP



Considering the performance of this last year of the NSP course, after a period of investment of around 6 months (from mid November until the end of May), the portfolio registered a total return of 1.56% (2.90% annualized) against 2.35% for the benchmark (4.37% annualized). This was calculated based on the UPs on the first Investment Committee (IC) 101.57 and 101.44, respectively for the NSP and the benchmark, and the UPs on the last IC, 103.07 and 103.77, respectively. In terms of risk, the NSP portfolio had an annualized volatility of 7.29% against 6.57% of the benchmark and a beta of 0.39 against 0.36 of the benchmark, showing that NSP was more sensitive to changes in the market than the benchmark. Also, the NSP average total VaR was 0.78% of the NAV, being 0.80% from equities and 0.18% from bonds (VaR graph can be found in appendix 3). The lower return and higher risk of the NSP fund resulted in an Info Sharpe of 0.40 against 0.67 of the benchmark and in an Information ratio³ of -0.54. If one looks to each month performance, one concludes that the NSP underperformed the benchmark in all the months, except November (Table with monthly performance in appendix 4).

The following table has a summary of the general performance against the benchmark for the last year’s fund performance with the descriptive statistics mentioned before.

³ Information ratio: Ratio of the portfolio returns in excess of the returns of the benchmark relative to the volatility of those returns. It measures a portfolio’s ability to generate excess returns relative to a benchmark.

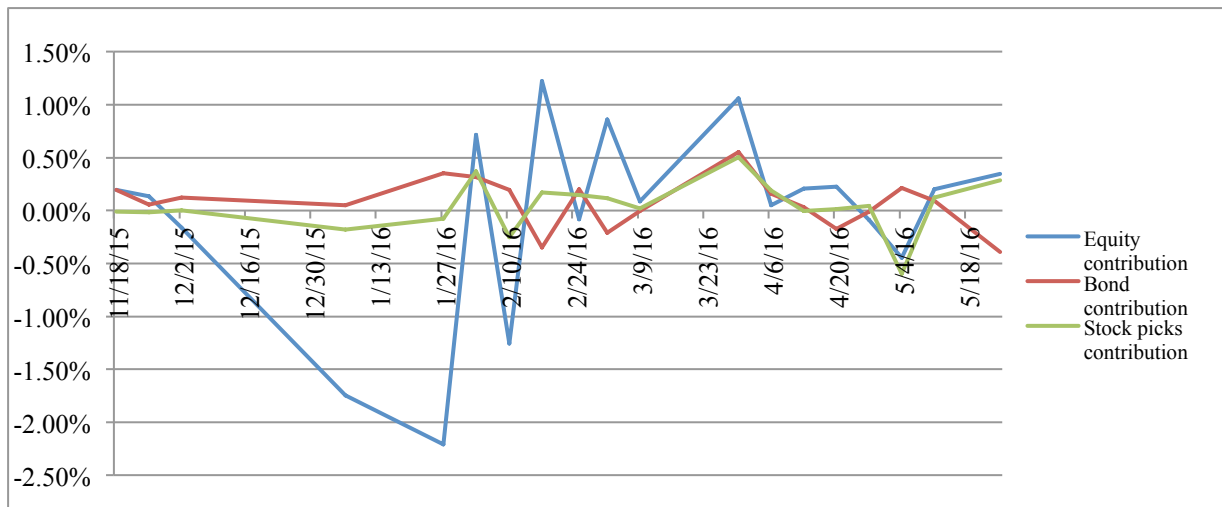
Table 1. General Performance of the NSP vs Benchmark (last year)

	NSP	Benchmark
Total Return	1.57%	2.35%
Annualized Return	2.92%	4.37%
Annualized Volatility	7.28%	6.57%
Info Sharpe	0.40	0.67
Max Drawdown	-3.84%	-3.54%
Beta	0.40	0.36
Skew	-0.43	-0.47
Kurtosis	0.67	1.19
Max Return	2.12%	2.04%
Min Return	-1.93%	-1.79%
NAV - Inception	\$ 314,853.03	\$ 314,467.83
NAV - Final	\$ 319,527.89	\$ 321,687.57
Information Ratio		-0.54

Throughout the 19 ICs, there were 50 stock picks presented, 36 approved and 14 rejected what gives an approval rate of 72%. From the 36 approved, there were 33 different picks as 3 stocks were bought twice. Also, there were 16 stocks approved in the first half of the investment period (44%) and 20 approved in the second half (56%). 53% of the stocks obtained a positive absolute return while 47% had a negative absolute return. In terms of relative returns, half of the stocks outperformed the S&P 500 while the other half underperformed. The weighted average return of the stocks when compared to the S&P 500 was -0.35%. In relative terms, the best stock pick was KORS US Equity with a return of 31.55% and the worst was DAL US Equity with -18.82% (graph with stocks picks performance can be found in appendix 5).

In terms of weekly P&L it is also important to understand the impact of each of the asset classes: equities (without stock picks), bonds and stock picks. The asset class with the best performance was bonds followed by the stock picks and finally by the equities. They presented an average contribution to the weekly P&L of respectively 0.07%, 0.04% and -0.04% and a total cumulative return of 2.93%, 0.60% and -0.23%, respectively. The graph below presents the weekly P&L contribution of each asset class.

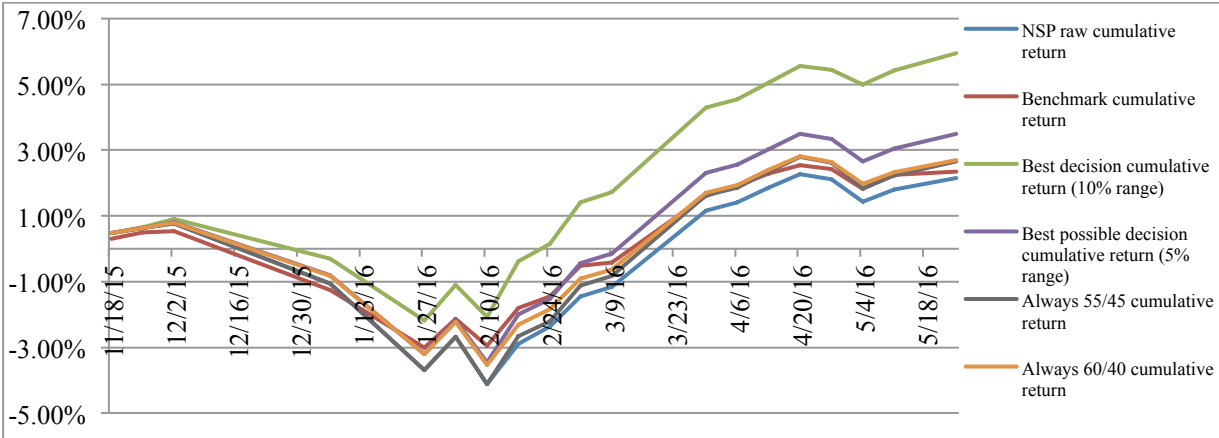
Graph 2. Weekly P&L contribution by asset class



The allocation decisions are also very important for the fund's performance and they are decided based on whether students are more bullish or bearish on the market performance for the following week. In retrospective, one can conclude when the decisions were good or bad in the 19 ICs as one has now the information of what happened after the decisions being made. From those 19 allocation decision, 37% were good decisions and 63% were bad, meaning that in only 37% of the time the students were able to "guess" were the market was going by analyzing several factors as for example the main events and news in the previous and next week, the market performance and the market sentiment. Despite this, the NSP fund was still able to beat the benchmark in 53% of the times. By analyzing the cumulative returns on different allocation decision paths, one has that the NSP performance was 1.91% against 2.35% of the benchmark. This means that despite beating the benchmark most of the time, the cumulative performance was still lower. Furthermore, this analysis demonstrates that if NSP students opted for maintaining always the same allocation, either 60/40 or 55/45, the performance would always be better than the one achieved and the fund would have beaten the benchmark as the cumulative returns would have been 2.46% and 2.41% respectively. If one take the case where the best decision was always taken (inside the range of 10% up or down), the cumulative performance would have been 5.72%. If one takes the case where

students ended up making the best decisions but just between 60/40 and 55/45 (60/40 when bearish and 55/45 when bullish), the cumulative return would have been 3.25%. This analysis has three main conclusions: the first is that if choosing always one allocation scheme, it is somehow indifferent on which one to choose as they end up with approximately the same results, in the period mentioned. The second is that if the decisions were bad most of the time (as happened), it would have been better to keep always the same allocation. Finally, on the other hand, if the allocation decisions were good most of the time, both the fixed allocation scheme and the benchmark would be beaten. The graph of the cumulative returns of the allocation decisions mentioned before can be found below.

Graph 3. Comparison of the cumulative returns on different allocation decisions



But how can one infer what would be the best decision for the next week? Market sentiment can be a good hint on that as investors’ expectations may have a huge impact on their trading behavior and consequently on the market performance. This is why this topic on market sentiment is important and will then be analyzed further on in this work project.

In conclusion, the NSP fund underperformed the benchmark with a difference of -1.47% annualized return. This underperformance can be explained by 3 main factors: i) underperformance of the bond ETF, ii) bad allocation decisions and iii) not very good stock picks relative to the S&P 500.

3. Behavioral Finance

3.1. Background and Evolution

Are markets rational? Does the Efficient Markets Hypothesis (EMH) hold in practice? These questions are a good starting point to discuss Behavioral Finance Theory and how it appeared.

Authors defending the EMH state that stock price fluctuations are independent of each other (Kendall, 1953), the market and stocks could be just as random as flipping a coin (Malkiel, 1999) and that stock prices approximately describe random walks through time and so, price changes are unpredictable (Shiller, 2000). Fama (1998) argues that irrational behavior is not sufficient for market inefficiency, as arbitrage by rational investors would push prices to their correct value. But this might not be true because, as Keynes said, *“Markets can remain irrational longer than you can remain solvent”* (Prast, 2004). The idea behind Behavioural Finance is then very simple and easy to understand: Humans are not always rational in the way equilibrium models assume us to be. (Ricciardi and Simon, 2000). This happens because human decisions are subject to cognitive illusions. This topic of market efficiency has been widely discussed throughout the time with Behavioural Finance trying to solve what neoclassical finance fails in explaining.

Howard (2014) states that the capital market theory has passed mainly through two paradigms to explain the movements of market prices and is now experiencing the rise of a third one. It all started in the mid 30's when Graham and Dodd (1929) tried to explain market movements just based on fundamental analysis. It lasted until mid 70's when a second paradigm emerged, the Modern Portfolio Theory (MPT), introduced by Markowitz (1952) and followed by other authors as Sharpe (1964). This one, on the other hand, stated that markets were efficient as they could fully incorporate all the available information. Despite agreeing that investors made cognitive errors, they argued that there were also rational

investors arbitraging pricing inefficiencies. This standard finance model where rational investors would always make prices equal to the present value of its future cash flows was not able to explain some market anomalies [eg: stocks with low price-to-earnings (PE) ratios outperformed high PE stocks studied by Basu (1977)], crashes, bubbles and other phenomena (Howard, 2014)]. Warren Buffet even mentions the following about bubbles: *“Like most trends, at the beginning it’s driven by fundamentals, at some point speculation takes over.”* Due to these problems facing MPT, the study of how investors actually make decisions emerged, as this decision-making process under risk is in fact less simple than what was described in the assumptions of the standard finance theories. This was the genesis of the third paradigm that became known as Behavioral Finance.

3.2. Behavioural Finance Theory

In the words of (Shefrin, 2009): *“Behavioural finance, as a field, is the application of psychology to financial decision making and financial markets and, as a process, is about the transformation of the financial paradigm from a neoclassical based framework to a psychologically based framework”*. Thaler (2005) describes Behavioural Finance even in a simpler way by saying: that *“it is simply open-minded finance”*.

In other words, it is a field of finance that tries to fill the existent gap in the efficient markets theory by studying psychological biases that cannot be captured in models based on perfect investor rationality and proposing psychological theories to explain market anomalies. It surged in the 80’s with contributors as the financial economists Robert Shiller, Hersh Shefrin, Werner De Bondt and Richard Thaler, and the psychologists Daniel Kahneman, and Amos Tversky, some of them cited in this paper (De Bondt et al., 2008). Literature in Behavioural Finance is then based on two main assumptions: firstly, investors are subject to sentiment, meaning that each investor has a certain belief about risk and future cash flows that

is not only derived by the existent facts and, secondly, there are limits to arbitrage, meaning that betting against sentimental investors is risky and costly. (Baker and Wurgler, 2007).

Besides the two main assumptions just mentioned, this field of finance has two main pillars: the Prospect Theory and the irrational use of information. (Prast, 2004). The first pillar of Behavioural Finance is what became known as the Prospect Theory which was developed in 1979 by Daniel Kahneman and Amos Tversky in the paper: "Prospect Theory: An Analysis of Decision under Risk". Its main point is that the theory of expected utility maximization does not hold in practice. This theory is based on the already mentioned idea that people do not always behave rationally and that there are biases influencing people's choices under conditions of uncertainty (Ricciardi and Simon, 2000). Actually, Kahneman and Tversky (1979) found in their studies that people most of the time did not choose the option that maximised their expected utility and, also, that people's decision weights do not correspond to objective probabilities. The second pillar is focused on how people often process and use information in an irrational way. Information is not used in an objective manner by the investors, as human beings suffer from some biases and heuristics (Prast, 2004). Indeed, Jason Zweig (the editor of the revised edition of Benjamin Graham's *The Intelligent Investor* and the writer of one of the first books exploring the neuroscience of investing) has a sentence that describes well the human behaviour biases and investing: *"Investing isn't about beating others at their game. It's about controlling yourself at your own game"*.

3.3. Biases and Heuristics

After discussing the main topics on this recent field of Finance, one will now present some of the well-studied heuristics (mental shortcuts) and consequent biases in literature that will be used further on to explain the behaviour of NSP students and some of their decisions:

Loss Aversion: As the name suggests, this bias is the tendency for people to be more frustrated with a given loss than happy with a gain of the same size. It is one of the biases

described in the Prospect Theory and states that an investor is more prone to risk when faced with the prospect of losses, but more risk-averse when faced with gains people prefer avoiding losses to making gains (Kannadhasan, 2006). Some studies state that investors consider the loss of \$1 twice as painful as the pleasure got from a \$1 gain (Singh, 2012).

Cognitive Dissonance: *"Cognitive Dissonance is the mental conflict that people experience when they are presented with evidence that their beliefs or assumptions are wrong."* (Montier, 2002). It is the tendency for people to feel internal anxiety in the presence of two conflicting cognitive elements, namely, an opinion and new information. Normally, investors try to reduce this cognitive dissonance as they have difficulty to realize their initial opinion was wrong. At some point in time, as more information is released, people will realize that their initial decision was wrong and if one thinks in the aggregate market, it may lead to a sudden change of direction of the market (Prast, 2004).

Disposition effect: Disposition effect refers to the tendency for people to realize small gains but avoid realizing small losses. The result is the closing of several positions with small gains and few with small losses. For example, few people would sell a stock for \$18 that was bought at \$20 but that has already dropped to \$15. Most people do not want to sell it until it is above \$20 again (Singh, 2012).

Regret Aversion: Regret aversion arises from the fact that investors avoid feeling guilty for a poor decision and regret the pain of being responsible for it (Zeelenberg et al., 1996). Hence, one of its consequences is that people will have the tendency to hold poor performing stocks.

Mental Accounting: Mental accounting is the tendency that people has to separate financial decisions into different mental accounts despite the fact that would make more sense to consider them together in the same portfolio decision. When making two investment

decisions, investors tend to consider them separately in practice while portfolio theory states that it would be optimal to integrate them (Prast, 2004).

Overconfidence: Overconfidence is the investor's tendency to overestimate its ability. *"Overconfidence can be summarized as unwarranted faith in one's intuitive reasoning, judgments, and cognitive abilities"* (Pompian, 2006). It is higher among investors than among people from other professions as in this particular case they can easily blame unforeseen circumstances for their mistakes (Nofsinger 2001). Two of the causes of overconfidence are the self-serving bias (tendency that people has to interpret and process information in a way more favourable to him/her) and the biased self-attribution (tendency that people have to attribute the success to its own ability and attribute failures to others).

Availability: Availability is a cognitive heuristic in which a decision maker relies upon knowledge that is readily available (Sewell, 2007). People tend to overweight information that is easily accessible (De Bondt et al., 2008). For example, people will now be more cautious in investing in structured products, as the 2008 financial crisis is still present in their minds, despite the fact that the objective probability of this event happening has not changed. Then, this caution is not because of a objective high probability of a financial crisis but then due to a subjective increase of that probability.

Anchoring: is the tendency for people to make estimates based on a reference value or an initial value and make adjustments to find the final answer (Kahneman and Tversky, 1979). Most of the times adjustments are insufficient (Lichtenstein and Slovic, 1971). People usually rely to much on an "anchor" when making decisions and then tend to change slowly when presented with new information. It is normally a logically irrelevant reference point that investors use while making an investment decision (Pompian, 2006). Anchoring can be then one of the causes of conservatism that can then lead to underreaction.

Gamblers Fallacy: Gamblers Fallacy is the tendency that people have to think that a tendency will revert despite the fact that the probabilities are the same (Singh, 2012). When flipping a coin, for example, after seven “heads”, people will be more willing to bet on “tails” despite the fact that the probability of each outcome is always 50%.

Herding Behaviour: Herding behaviour is the tendency for people to follow the trend or to “go with the crowd” (Banerjee, 1992). Hence, investors trade more based on emotion and sentiment than in objective facts or fundamentals as investors are most of the time concerned of what others think of their investment decisions (Stein and Scharfstein, 1988). This behaviour is an example of extreme market sentiment as either in market bubbles or crashes, investors follow others in a rush to enter or exit the market (Caldwell and Dolvin, 2012).

In conclusion, there are some well-accepted facts among Behavioural Finance literature, but this is still an emerging field where no unified theory exists at this time (Kannadhasan, 2006). Also, it has still some weaknesses mainly in modelling the patterns found empirically. From now on, it is essential to address this weakness to continue the process of “behaviouralizing finance” (Shefrin, 2009). In this way, Shefrin (2009) believes that the future of finance will somehow be a mix of standard finance and behavioural finance as a logic evolution would be to combine the more realistic assumptions of behavioural finance with the rigorous methodology and analysis used by neoclassical finance models.

4. Behavioural Finance impact's on NSP decision making process and performance

4.1. Biases within the NSP

After presenting and explaining the biases and heuristics studied in the Behavioural Finance literature, one can now go further on and try to find them within NSP students' decisions and evaluate their impact in the NSP performance.

The first three biases mentioned in section 3 were Loss Aversion, Cognitive Dissonance and Disposition Effect. They are very similar, and the first two can be seen as causes for the third. The loss aversion presented by investors will make them reluctant in closing positions with small losses while cognitive dissonance will make people to try to ignore information that goes against its belief or that suggests they made a wrong decision. It has two immediate consequences: firstly, investors will be more reluctant in realizing losses, what can be translated in even higher losses and secondly, investors may be willing to take more risk to offset the losing position (e.g.: an "all or nothing" bet on a stock or increase the exposure to more risky assets). NSP data was analysed to find these patterns of no realization of small losses and "all or nothing bets" when losing. What was observed was that from the 7 negative positions closed by students, 6 were closed by the stop loss (most of the time around -10%) and only 1 was closed with a small loss (lower than 5%). Here is clearly present the pattern of loss aversion has students always expect the tendency to revert and their stocks to end up performing well. Furthermore, by taking the beta and volatility of all the stocks, one can infer that from the 12 stocks presented in the last 4 ICs, 4 of them were in the top 5 of the most risky stocks presented and 5 of them in the top 10 of the most risky stocks presented. This implicitly shows a high percentage of "nothing to lose" bets when reaching the end of the investment period. From the top 5 volatile stocks, just 1 of them had a positive return (curiously the most volatile one). Another analysis that can contribute to test these biases is the average holding period of the stocks. By looking at this, what is seen is that the average

holding period, taking into account all the 33 approved stocks, is 42 days. But if one computes the average of the 10 best performing stocks and the 10 worst performing stocks, the conclusion is that students on average hold losing stocks (47 days) much more time than winning stocks (37 days), what also confirms these biases. The results found are in accordance with Feng and Seasholes (2005) study where is mentioned that experience eliminates the reluctance to realize losses (Glaser and Weber 2007), but on the other hand, it contradicts a study on another students' managed fund, where it was found that students were more likely to sell losing stocks and keep winning stocks than vice-versa (Kranner, Stoughton, and Zechner 2014).

The fourth bias presented was Regret Aversion and it is also related with the previous three, as it can also be a cause for disposition effect. The wish to avoid this regret can affect new investment decisions with investors avoiding sectors or stocks that performed bad recently in an anticipation of the sentiment of guilt they would feel if they made the investment there and lost money. Furthermore, this regret aversion and consequent "run" from poor performing sectors/stocks can lead investors to invest more in hot or well established companies, encouraging the herd behaviour as they think that if they lose money, so will a lot of other people, and therefore they will not feel so bad about it (Singh 2012). To test this bias, the presence of momentum stocks in the portfolio as well as hot stocks was analysed. Hot stocks were measured based on the fact that they are present in the S&P 500 and on analyst recommendations. Firstly, it was found that from the 32 different stocks approved (they are 33 but one was an ETF so it was not considered), 78% (25 stocks) were in the S&P 500. From the 14 stocks rejected, only 50% were in the S&P 500 what shows a tendency to approve or to vote more positively in stocks with more recognizable names. Additionally, based on analyst recommendations, 72% of the approved stocks had more than 50% buy recommendations, 50% had more than 2/3 of buy recommendations and 13% had

more than 80% buy recommendations. This shows a clear preference for choosing well known and well-recommended stocks that can possibly be justified by regret aversion.

The fifth bias mentioned was Mental Accounting. When looking at NSP, there are only 3 decisions in each IC: vote on the allocation, vote on others' stocks picks and present a stock pick (if the case). Then, it was analysed how students behaved on these 3 topics because the fact that the behaviours were not in accordance with each other or that there is not a rational reasoning or pattern might be a sign that they were probably considered separately, and so students were affected by mental accounting. One sign of mental accounting is that from the 10 students presenting the top 10 riskier stock picks, 5 of them voted for a bearish allocation in that IC and the other 5 voted bullish in that IC, showing mixed behaviours. There were two hypotheses: or they were very bullish and it would make sense to present them if they were bullish on the market performance and then they would vote more bullish on the allocation as well, or they had the intention of diversifying and so they would vote the opposite (bearish) in the allocation. What one can observe is that the behaviours differ with half (50%) doing one thing and the other half doing another. This shows that probably the decisions were not considered together as there was not a pattern and a clear desire for diversification, as it would have happened if students considered both decisions together. On the other hand, from the students voting in favour of buying these stocks, there was 9 times (90%) that more than 80% vote bearish in the allocation showing in this case less propensity to mental accounting. Furthermore, this bias impacted NSP's performance negatively as from the 10 stocks mentioned, 7 had a negative return. (70%). Students, mainly stock pickers, did not present a consistent reasoning when making decisions, sometimes making decisions in accordance, but sometimes making the complete opposite decisions as just explained. This type of behaviour can be caused by mental accounting as students probably did not considered the decisions together, but instead as separate ones, making irrational choices as a consequence.

The sixth bias mentioned in section 3 is Overconfidence. The main and immediate consequence of this bias is excessive trading. When people are overconfident, they tend to trade more. To test overconfidence one can infer if students traded more when performing well in their first stock pick, and how was their performance after that. From the 14 students that had stock picks approved, 10 had a positive return on their first pick (71%). From these 10, 8 decided to present another stock pick (80%). From the ones that presented this second stock pick, 5 had a negative return meaning that 63% had a negative performance in the second pick after having had a positive return in the first stock pick. This can be due to overconfidence, as the fact that they performed well in the first pick made them trade less rationally and cautiously in their second stock pick, what led to a negative performance. Also, Barber and Odean (2001) found that men are on average more confident than women and consequently tend to trade more. Despite the fact that there were only two women in the NSP fund, what happened is that the average number of stock picks for men was 3.8 while for women was just 2, confirming somehow what the study mentions.

The seventh bias mentioned above is Availability. One way to test the availability bias is to analyse if there was a tendency to approve or vote more positively on more popular stocks. What one verifies is that from the 32 stocks bought, 7 are not from the S&P 500. From those 7, 2 were only approved at the second time they were presented and from the other 5, 4 have an approval rate lower than 80%. If one compares this approval rate with the average approval rate of all stocks this bias becomes clearer. The average approval rate of the 32 stocks is 84%, but if one takes out these 7 stocks, it increases to 86% (the average of the 4 previously mentioned stocks is “just” 71%). The impact on the performance is mixed with 4 of the 7 stocks that are not in the S&P 500 having negative returns. Furthermore, one can also take into account the stocks that were not approved and one found that 50% of the stocks rejected were not in the S&P 500. This behaviour can be explained by the availability bias, as

people tend to invest in stocks that are more familiar to them and are more available in their heads mainly because they recognize and know the business and not due to the company's fundamentals or other rational reasons. This bias is somehow related with Regret Aversion, as the consequence is the same that is to invest more in hot stocks, despite their fundamentals.

The eighth bias explained before is Anchoring. Investors tend to rely too much on a reference value. It can be the price that a stock exhibited before starting to drop or for example the price at which it was bought. The main consequence of this bias is conservatism as people will only gradually adapt to new information and that it would take some observations to change their opinion. Another consequence is that investors tend to invest in stocks that have fallen considerably in the short term as they will be anchoring on a recent high of the stock and will expect it to mean revert, seeing this as an opportunity to buy the stock at discount. To test the presence of Anchoring, it was analysed the percentage of stocks approved that were dropping more than 5% in the last week and in the last month. The results are that from the stocks that were approved and were dropping, 36% were dropping more than 5% in the last week and 58% were dropping more than 5% in the last month. This shows a preference for either stocks that are going up or instead, for stocks that dropped a lot recently.

The ninth bias that can be found in the NSP fund is the Gamblers Fallacy. It is somehow related with the previous one as both lead investors to buying stocks that are dropping. The two main consequences of this bias are regarding market performance and regarding stock picking. The first is a tendency to vote on the allocation against what happened in the previous week as investors think the tendency will revert. The second is the tendency for people to buy stocks that have been dropping just because they think the "bad luck" is about to change. The first consequence can be easily found and confirmed as the allocation votes were against the market performance in 65% of the times (if it increase/decreased the previous week the votes would be more bearish/bullish). The second can be found by

studying number of stock picks presented that were dropping before. Considering periods of 1 year and 1 month, there is evidence of a considerable percentage of Gamblers Fallacy as 36% of the stocks approved and 33% of stock rejected had a negative return on the previous month and 48% and 58% respectively had a negative return on the previous year. This bias was found in a moderate way, specially in what stock picking is concerned, but the findings are consistent with the literature as Kannadhasan (2006) found that more experienced investors have more tendency to commit gamblers fallacy and in this case the students are inexperienced investors. Furthermore, the impact in the performance is mixed as by analysing one can infer that, in this sample, this bias affects positively the performance when stocks were dropping month to date, as 58% had positive returns while it affects negatively in the case that the ones dropping year to date, as 44% had a positive return.

Finally, Herding behaviour, that is the tenth and last bias that will be analysed, can be found either in allocation votes and stock picking votes as people might have the tendency to follow the others in both voting processes. By analysing the votes on the allocations, in the 18 IC there were 78% of them with 2/3 of the votes in the same direction (either more bullish or bearish), 61% of them with 75% of the votes in the same direction and 44% of them with 85% of the votes in the same direction and, finally, there were even 5 ICs (28%) with 100% of the votes in the same direction. This clearly shows herding behaviour in the allocation votes by the NSP students. Regarding stock picks, an analogous reasoning was made. From the 47 stock picks presented (they were 50 but 3 of them were bought twice so they were not considered), 70% were approved and 30% were rejected. From the ones approved, 91% were approved with at least 2/3 of the votes, 67% were approved with at least 80% of the votes and 21% with 100% of the votes. On the other hand, from the ones rejected, 50% were rejected with at least 2/3 of the votes, 29% with at least 80% of the votes and, finally, just one (7%) with 100% of the votes. The main conclusion is that herding behaviour in stock picking seems

to be present when approving stocks but not when rejecting stocks. This is in accordance with some studies about student managed investment funds that state that these type of funds due to the social environment of the class and the fact that students are investing real money, in many cases for the first time, tend to exhibit this type of bias (Caldwell and Dolvin, 2012). According to this study, there are specific situations where herding is more likely to occur. Three of them were analysed: if herding decreases over time, if herding increases with stocks held before and if herding increases in days with many SP presented. The findings were firstly that the percentages of major approvals in allocation and in stock picks were similar but with a slight advantage for herding in the 1st half of the course. Secondly, by analysing the three stocks held twice, one can observe that their second approval rate was above average for all of them: 100%, 93% and 87%, respectively, against an average of 84%. Thirdly, the fact that herding increases with the number of picks presented was found, but not significantly, as the average approval rate in days with 4 or more stock picks was 86% against a total average of 84%. The results are somehow in line with the ones found by Caldwell and Dolvin (2012): student managers do not change their herding behaviour over the course time, trades held before will be easier to get approved and days with more trading are associated with a higher approval rates on the stocks presented.

The main question now is if this type of behaviour has a negative impact on the performance. Oddly, the answer is yes in the case of the NSP. For the stocks approved with 100% of the votes, 57% had a negative return, which is counter intuitive because if they are approved so unanimously, they should perform well. Similarly, from the ones approved with more than 2/3 of the votes (except the ones with 100% approval), 52% had a negative performance. For example, the worst performing stock (DAL US Equity) was approved with 93% of the votes. This is once again in accordance with Caldwell and Dolvin (2012) study, as it states that herding, especially when it is more pronounced, tend to result in lower returns.

4.2. Recommendations to avoid these biases

In the specific context of the NSP fund, what can be done to avoid some of these biases and heuristics from happening? Both the allocation votes and the stock picking votes should be done secretly (through paper or online) to avoid herding. Caldwell and Dolvin (2012) found that this measure decreases the overall approval rate. In terms of allocation votes, these should account for the final grade, as it happens with votes in stock picks. In terms of stock pick presentation, there must be a maximum time for each SP and students should be required to clearly specify its investment reasoning as well as some predefined fundamentals. Also, each stock pick should have tighter stop losses and students should be obliged to have at least one SP in the first half of the course. There should be also a maximum number of SP presented per IC. The course may also include a class about Behavioural Finance as it would make students aware of this area and, more specifically, of the behavioural biases mentioned and how they can impact their decisions and performance.

Finally, to avoid biases from occurring, students in the NSP should: be patient, try not to be overconfident, look for accurate information before making a decision, not follow the crowd (other students) blindly in their decision making process and always bear in mind that past events are independent and not correlated with the probability of happening in the future.

5. Measuring Investment Sentiment

After having explained what Behavioural Finance is, how it contributes to financial literature and how behavioural biases affect investment decisions, one can easily understand that its theories are becoming well accepted. Indeed, as Baker and Wurgler (2007) state: *“Now, the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather how to measure investor sentiment and quantify its effects.”*

This section plans to measure the market sentiment during the period of the NSP portfolio, from mid November until the end of May, and assess if it had any impact in our allocation decisions and what would have been the performance if for example students have always followed the market sentiment or have always gone against it. The goal is to assess the returns predictability based on market sentiment indicators and try to find a good investment strategy recurring to market sentiment, to help students on the NSP fund to decide better in terms of allocation. But what is then investor sentiment? Beer and Zouaoui (2013) define it as *“a belief about future cash flows and investment risks that is not warranted by fundamentals”*, meaning that it is like a subjective aggregate belief of the investors about the market direction. In appendix 6 one can find a figure describing investors emotions during a market cycle. There are several studies in financial literature that attempted to measure investor sentiment. This measure can be done through direct and indirect sentiment measures (Brown and Cliff, 2004). The first one is based on surveys, so it directly asks investors how they feel about the market or about economic conditions. The second one is based on financial or economic variables that can somehow translate the investors' expectations on the market, for example: volatility, trading volume, put/call ratio and mutual funds cash positions [(Beer and Zouaoui, 2013) and (Feldman, 2010)]. After a deep research on sentiment indicators⁴, three were chosen. The first one is the SPX Index, the market itself, as the direction of the

⁴ The other sentiment indicators considered were: University of Michigan Consumer Sentiment Indexes (CONSSSENT Index, CONSCURR Index, CONSEXP Index), Bloomberg New Highs and Lows (NWHLSSENY Index), Bloomberg Trade Sentiment (TRADSENI Index and Sentix Indexes (SNTEUSGX Index, SNTEUSH6 Index).

market at some moment in time is a good proxy for investors' expectations. The second one is the AAIIBULL/AAIIBEAR Index that is a direct sentiment measure based on the AAI Survey⁵, used in several studies of market sentiment as Verma and Soydemir (2009) and Brown and Cliff (2005). Finally, the last sentiment indicator used is the VIX Index⁶ that is an indirect measure as it is based on the volatility. But how does it measure market sentiment? Large investors try to hedge their portfolios and to do so they usually use options. If these investors think the market will go down, as it is difficult to sell large amounts of stocks, the way they have to hedge their portfolios is to buy put options contracts at the market to offset some of the expected losses. On the other hand, if they are bullish, they increase their leverage by buying call options. This will be reflected in the market volatility, captured by the VIX. Hence, Baker and Wurgler (2007) suggest the VIX as an alternative market sentiment measure because it increases when investors buy put options to insure their portfolios against losses, meaning that they are more bearish. This is why the VIX is sometimes referred as the fear index.

By knowing what would be the best decision at each IC (already presented before), the objective is, first, to compare the best decision with the one predicted by the market sentiment indicators and second, compare our decision with the one "recommended" by the market sentiment indicator. As one is trying to assess the impact on the NSP, all the returns will be on a weekly basis calculated from Wednesday to Wednesday (day before the ICs). In this way, the assessment of short term predictability in stock returns was done similarly on what was done in several studies, for example, Brown and Cliff (2004).

Starting by the S&P 500 as a proxy for market sentiment, 4 rules were tested to predict the best decision. The first rule⁷ consists in increasing the equity weights to 55/45 (going bullish) if the market was positive in the previous week and keep the base weights at 60/40

⁵ AAI Survey consists in asking a random poll of investors, on a weekly basis, their expectations on the market direction for the next 6 months (up, down or the same) and it is obtained the percentage that is bullish, bearish or neutral.

⁶ VIX Index was created by the Chicago Board of Options Exchange (CBOE) to track the implied volatility of the S&P 500 Index options.

⁷ Intuition rule 1: Always go with the market.

(or decrease if the case) (going bearish) if the market was negative in the previous week. The second rule⁸ consists in going bullish if the return of the previous week was between $-\infty$ and -1% and between 0 and $+\infty$ and bearish if the return in the previous week was between -1% and 0 . The third rule⁹ is similar to the previous one but one would go bearish between -1% and 1% . The fourth and final rule¹⁰ is to go bullish if the market return in the previous week was between $-\infty$ and -1% and between 0 and 1% and to go bearish in the other cases. The rule that gave the best results to the sample period of the NSP was the fourth one. The results are that 84% of the time, the market sentiment was right, meaning that the signal given by the market returns was able to correctly predict the behaviour of the market in the following week. However, the decisions made in the NSP were only 45% of the times in accordance with market sentiment, what resulted in an underperformance in 53% of the times. Investing according with this rule, in this period, would generate a cumulative return of 3.18% against the 1.91% generated by the NSP (taking into account only allocations). Secondly, one takes the AAIIBULL/AAIIBEAR Index and calculates the Bull-Bear Spread¹¹. This measure is widely used in literature with Brown and Cliff (2005) even saying: “*our preferred sentiment variable is the bull-bear spread*”. The rule¹² here is to go bullish when the Bull-Bear Spread is positive and bearish when it is negative. In this case, the market sentiment was right 42% of the times and the NSP decisions were 55% of the times according to market sentiment. Thus, in this case, it would be more valuable to invest against the market sentiment, as it would generate a cumulative return of 3.09% (against 2.27% if investing with market sentiment), but both would be better than the 1.91% of the NSP. Here applies the advice of Warren Buffet to “*Be fearful when others are greedy and greedy when others are fearful*”. Finally, by taking

⁸ Intuition rule 2: Go bullish when the market was gaining or dropping considerably (more than 1%).

⁹ Intuition rule 3: Go bullish when the market was gaining considerably or losing considerably (more than 1% and less more -1%, respectively).

¹⁰ Intuition rule 4: Go bullish if the market was losing considerably (more than -1%) or starting to revert (gaining more than 1%)

¹¹ Bull-Bear Spread is calculated by subtracting the AAIIBEAR Index to the AAIIBULL Index.

¹² Intuition rule Bull-Bear Spread: Go with the sentiment; bullish if investors expectations are more bullish and vice-versa.

the VIX Index as the sentiment indicator, three rules¹³ were tested. The first was to go bearish if the VIX weekly variation (from one IC to another) was positive. The second was to go bearish if the VIX was higher than the average of the last 5 days. Finally, the last rule is a “range rule” that is, if the value is above 50% of the last 5 days range, one would go bearish and if it is below one would go bullish. The rule that gave the best results was the third one. By applying it, 47% of the times the market sentiment was right and the NSP decisions were only 45% of the time according to the market sentiment. However, the best strategy would be to invest according to the market sentiment and would yield a cumulative return of 2.82%. Additionally, if one followed a contrarian investment strategy and invest with the opposite signal from the one given by rule 1, one would predict the best decision correctly in 68% of the time. A graph for the cumulative return of the three best rules can be found in appendix 7.

After this study, it can be concluded that, for the period studied, the best proxy for subsequent return is the S&P 500, if following the best rule mentioned, at least on a weekly basis, and consequently, is also the one that would give the highest return (2.93%). On the other hand, the Bull-Bear Spread proved not to be a good proxy and a good return would be obtain not to invest according with sentiment but against it (2.85%). This is in accordance with the literature as Brown and Cliff (2005) find that sentiment is positively correlated with market returns, but they find no evidence of profitable short-run trading strategies based on sentiment. The statistics mentioned regarding the sentiment indicators can be found below.

Table 2. Comparative statistics for the three sentiment indicators chosen

	SPX Index	Bull-Bear Spread	VIX Index
Best rule	Rule 4	Only 1	Rule 3
% of times sentiment indicator was right	84%	42%	47%
% of times NSP decision was according with sentiment	45%	55%	45%
Cumulative return following market sentiment	3.18%	2.27%	2.82%
Cumulative return against market sentiment	2.18%	3.09%	2.54%

¹³ Intuition for the VIX rules: all the three rules follow the intuition behind the VIX that is if it is increasing (either measured in terms of average, variation or range), investors are more bearish.

Although the results are confirmed by the literature, it is important to test them in a longer period to infer about the validity of the conclusions obtained. Hence, it was performed a backtest from when there was data available (March 2012¹⁴) until October 2016. The backtest was done using the exact same rules used before for studying just the NSP investing period. Firstly, by using the market as a sentiment indicator, the best rule was rule 2, predicting the best decision in 54% of the time. Secondly, by using the Bull-Bear Spread as sentiment indicator, it predicts correctly the best decision in 57% of the time, being the best result achieved and contrasting with what happened when testing just the NSP period. Finally, by using the VIX, the best rule is rule 1, which predicts correctly the best decision in 52% of the time. A summary with the statistics of this backtest can be found in appendix 8.

Regarding VIX, statistical tests by Connors (2002) prove that it is able to tell when market top or bottom is in place, meaning that the biggest drops in SPX happen when VIX is low, but when it comes to predicting short-term moves, the signal is weaker and a low VIX rather means buying put options than selling stocks and buying bonds (Chadwick, 2006).

Overall, the results are consistent with literature as Brown and Cliff (2004) found that there is correlation between sentiment indicators and market returns but does not directly reveal the causal relation between sentiment and the market. However, very little evidence suggests that sentiment explains subsequent market returns and so the authors conclude that strategies trying to time the market in the short term based on sentiment indicators are not profitable. This is exactly the case here and so the conclusion is that it is very difficult for the NSP students and investors as a whole to use sentiment indicators in order to profitably time the market and decide their overweight/underweight in equities and bonds. Additionally, SPY US Equity and BOND US Equity have a higher correlation of 0.9 and the average differences in the performances of both the 60/40 and the 55/45 allocation strategies is close to 0 p.p. so it is difficult to predict whether to go bullish or bearish in each IC.

¹⁴ BOND US Equity Index was only created in March 2012.

6. Conclusion

This Work Project presents a new approach to the Behavioural Finance field as it not only focuses on the theoretical part but also tries to apply Behavioural Finance findings into a specific portfolio (NSP) as well as present recommendations. This area is a growing paradigm in Finance which joins standard finance with other social sciences namely psychology to try to answer some of the flaws of the classical finance theories. Behavioural Finance argues that these flaws in financial markets are due to behavioural biases and heuristics. This paper tries to explain 10 of the most well known ones and finds somehow evidence of them within the NSP fund.

It is very important to understand how to avoid incurring in these biases. Firstly, it is very important that investors understand the biases and recognize them. Investors should also be completely aware of their investment criteria and more important, quantify these criteria. Keeping a diversified portfolio is crucial, as it would decrease the risk even if they incur in some of the presented biases. Furthermore, investment objectives should be established in terms of risk and return and investors should be aware of important constraints as the liquidity and the time horizon.

Regarding sentiment, although investors trade much based on it, it is very difficult to predict, and this paper found no evidence that the investor sentiment impacts asset prices in the short-term. As it was found in this paper, the influence of the biases presented can be very costly in terms of performance, mainly in the context of a student managed fund with inexperienced investors. Consequently, and to conclude, the main message of Behavioural Finance is that humans are irrational and they translate that in their investments so the best way to make the right decision is to be aware of the findings of Behavioural Finance and then try to choose the right combination of risk and return.

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