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Behavioural Finance and Prospect Theory

A survey of financial outcomes

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Abstract:
Behavioural finance is crucial for ensuring the soundness and stability of financial markets, as it concerns all actors from individual investors to regulatory institutions. This study quantifies the effect of three biases related to Prospect Theory, a model famously introduced by Kanheman and Tverksy (1979) which explains human behaviour under risk. The biases in question are loss aversion, the representativeness heuristic and the disposition effect. There were two main findings: buying stocks that have performed well in the past correlates positively with portfolio returns and satisfaction, but this strategy is ineffective for achieving particularly high profits. Secondly, never selling investments at a loss leads to a worse perceived portfolio performance compared to all other investors.

Acknowledgements

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The econometrics course taught by Luca Margaritella has also been absolutely invaluable for understanding and constructing the econometric models in this thesis. The Intermediate Microeconomic Analysis course taught by Davide Pietrobon has also been particularly useful as it contributed to my deeper understanding of microeconomic principles and economic agent behaviour. Finally, I am deeply grateful for my exchange semester at Erasmus School of Economics, which has greatly expanded by knowledge and passion of financial markets.

This paper is in the memory of Amos Tversky and Daniel Kahneman who have inspired my passion for behavioural economics. Their research has motivated me deeply when writing this thesis.

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1 Introduction

In neoclassical economic theory, it is usually assumed that humans are rational and act to maximise their utility (Kahneman, 2011). Behavioural economics research started around the 1970s and by the 1990s it gained significant traction (Truc, 2022). It is an interdisciplinary research area which combines economic theory with principles from psychology. The pioneers of behavioural economics are often considered to be Daniel Kahneman and Amos Tversky, who researched human behaviour in the context of economic decision-making. In 1979 they introduced prospect theory, which is a model of several aspects of mental accounting and the way losses and gains are perceived. In conjunction with this theory, they introduced the idea of heuristics (i.e. mental shortcuts that allow us to think and make decisions faster), which can lead to cognitive biases (which are pitfalls in information processing that lead to irrational thinking and/or behaviour). The concepts brought forth by prospect theory served as the starting point for theories on different biases such as the endowment effect, framing effect and loss aversion. These were the initial theories of behavioural finance, after which theories related to market inefficiency followed. The idea is that since the stakeholders involved in financial markets are not fully rational, they can over- or underreact to news, leading to stock prices that may not accurately reflect the intrinsic value of the stock. This is also related to phenomena such as price reversals and the updated “behavioural capital asset pricing model”, which includes behavioural factors in the prediction of returns of stocks based on riskiness.

Similarly to behavioural economics, behavioural finance is concerned with decision-making, but in the context of financial investments. Behavioural finance explores the role of irrational behaviour in investment decisions, potentially providing insights into how to optimise financial outcomes. This paradigm shift has several implications; due to the irrational behaviour of investors markets are not assumed to be strongly efficient unlike in traditional finance, and thus stocks may be under- or overvalued. This paradigm shift brought about a more accurate and realistic view of how financial markets work. Behavioural finance research concerns investors as well as asset managers and other financial advisors and institutions. It aids all stakeholders in understanding the stock market and the behaviour of the parties involved to ensure sound financial market functionality, as behavioural theories have been used to explain phenomena such as stock market crashes and bubbles, thus playing a key role in financial market regulations. Prospect theory also served as an important theory in explaining concepts like the disposition effect (which is the tendency to hold onto losing investments and quickly sell profitable investments) and the equity premium puzzle (which is the tendency for stocks to attain much higher returns than safer assets; Benartzi and Thaler, 1995) among other phenomena.

This paper focuses on three biases related to prospect theory: loss aversion, representativeness heuristic, and the disposition effect. Loss aversion refers to the higher psychological impact that losses have on economic agents compared to corresponding gains (Kahneman & Tversky, 1991). As such, loss-averse investors will act to minimise losses. The representativeness heuristic refers to the tendency to assume that one characteristic is representative of a certain trait. In the context of equity investments, this could mean that people tend to assume that past performance is representative of future success. It is about the belief that one "can see patterns in a truly random process" (Luo, 2013, p.153). Lastly, the disposition effect is the tendency for investors to "sell winners too early and ride losers too long" (Sheffrin & Statman, 1985, p. 777), meaning that investors often hold onto losing investments in the hope that they will recover and sell profitable investments to lock in gains. These biases are all related to the prospect theory model, and all seem to occur frequently amongst investors and have been investigated extensively in the literature, but there is still more to be explored.

Using a survey method, evidence for these biases and associated investment behaviour will be linked to portfolio performance. The survey was conducted independently, and all questions were constructed for the purpose of this paper. The survey included several questions measuring portfolio performance, as well as several questions for each of the biases. Two robust econometric linear regression models will be constructed, with the biases as independent variables, similar to the method used by Renu Isidore and Christie (2019). Firstly regressing portfolio performance against the biases, then against the actual investment behaviour related to these biases. This method of statistical analysis is the most appropriate for quantifying the chosen behavioural biases and for answering the research question (it has also been commonly used in previous academic research). This research proposal specifically aims to answer the question: "What role do cognitive biases and their associated investment behaviour play in equity investment financial outcomes?" The hypothesis is that these biases will negatively impact portfolio performance, which is generally the consensus from academic literature. The aim of this research is, above all, to attempt to quantify behavioural biases and their effect on self-reported portfolio performance, by also linking the evidence for the three biases with associated investment behaviour.

This research will add to the body of literature by quantifying the representativeness heuristic, potentially challenging the consensus on how the disposition effect impacts portfolio performance, and settling the debate of whether loss-averse investors achieve better financial outcomes. Thus, this paper will contribute to the understanding of human behaviour and cognitive biases and their impacts on portfolio performance in several ways that add to the literature on the topic. There is still much that needs to be researched and this paper is a small contribution to the body of academic literature. This research has implications on a micro and a macro scale. Understanding investment behaviour can, above all, help asset managers and investors on a personal level to achieve better returns and minimise unnecessary risk. Additionally, it can also help policymakers to ensure the soundness, stability, and efficiency of financial markets through regulations and nudges for investment decisions. For example, the trading platform eToro often uses a warning stating that past performance is not an indicator of future success to mitigate the effects of representativeness among its investors. Considering this, behavioural finance research is important for the broader economy as well, not just for individual investors. Although investment advice and suggestions for policies to mitigate behavioural biases in financial markets will not be discussed in depth, this is a necessary area for future research.

This paper is structured in five main parts besides the bibliography and appendices. The following section will present a literature review of behavioural finance research, focusing on the three aforementioned biases and their impact on portfolio performance. Next, the data and methods will be reviewed. After that, there will be an analysis section presenting the analysis and results, and discussing the findings in relation to literature. Finally, there will be a conclusion section to summarise the paper and discuss potential future research areas.

2 Theory

Truc (2022) provides a historical review of behavioural finance as a field. Around the 1970s, economic theory became increasingly dominated by psychological principles, which led to the idea that economic agents cannot always be fully rational. Kahneman and Tversky introduced the concept of heuristics (i.e. mental shortcuts that can lead to irrational behaviour) and cognitive biases. There have been countless biases found throughout the years, initially developed within the field of behavioural economics. However, it became clear that they affect equity investors significantly, as most of them relate to economic decision-making and how we process information regarding such decisions. Thus, in the 1990s, behavioural finance research began gaining momentum, which specifically focuses on the behaviour of investors. A significant part of the behavioural finance paradigm shift can be explained by prospect theory (Baker & Nofsinger, 2010), notably introduced by Kahneman and Tversky in 1979. This theory, which is a model that explains decision-making in risky and uncertain situations, essentially pioneered behavioural economics research.

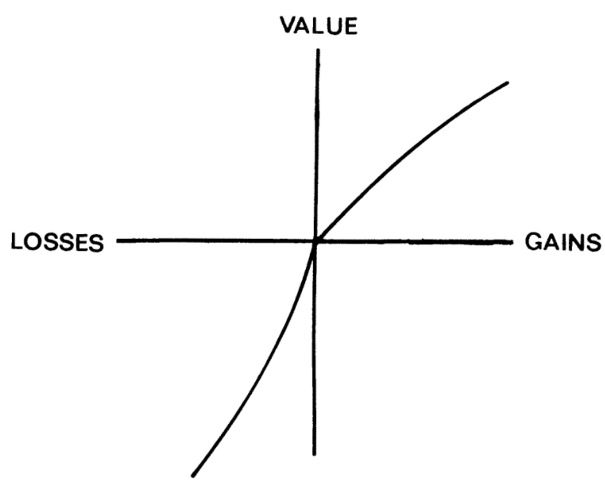

Figure 1: Prospect Theory (Source: Kahneman and Tversky, 1979)

This theory has three key features. Firstly, it implies that "losses loom larger than corresponding gains" (Kahneman and Tversky, 1991, p. 1039). Losses and gains are also regarded as relative to an initial reference point, and there is diminishing marginal sensitivity to both losses and gains, meaning that utility functions are non-linear. Many psychological phenomena, heuristics, and biases can be linked to the principles of prospect theory.

This theory can be seen as a more realistic version of its predecessor, the expected utility theory. Baddeley (2017) explains that Kahneman and Tversky did not agree with some of the fundamental assumptions of expected utility theory, which is how prospect theory surged. Expected utility theory assumes that economic agents are utility maximisers and use all available information to determine their most preferred choices, which we do not deviate from, as choices are assumed to be consistent. However, the Allais and Ellsberg paradoxes showed that preferences are sometimes inconsistent, and this (along with other effects Kahneman and Tversky noted in their own research) served as inspiration for the updated theory. The difference between the two theories mostly relies on how choices are ranked. Instead of using all available information to make a choice, economic agents instead weigh choices against a reference point. The author explains that "our decisions are driven by changes relative to our reference points, and not by all the information we have available to us." (p. 62). These differences imply several behaviour patterns. First is the framing bias, which means that preferences may change depending on whether the outcomes are presented as losses or gains. Secondly, the possibility effect is the tendency to overweigh low probabilities (or underestimate high, but not certain, probabilities). Lastly, there is the idea that economic agents will tend to be risk-averse when it comes to gains, but risk-seeking when it comes to losses.

A clear bias implied by prospect theory is loss aversion. The consensus from the literature is that loss aversion can lead to worse financial outcomes, i.e. return on investment or portfolio performance (Renu Isidore and Christie, 2019). This is mostly because loss-averse individuals might make worse investment decisions for the sake of minimising losses. Benartzi and Thaler (1995) attribute the equity premium puzzle (which they define as the tendency for stocks to largely outperform bonds) specifically to myopic loss aversion. Myopia simply refers to the tendency of investors to review their portfolios often. Theoretically, the equity premium should not happen as large corporations should grow at a pace close to the risk-free rate, but historical returns data shows that they have grown around seven times more. Academic literature has explored several explanations, but this study argues that myopic loss aversion explains this phenomenon. They argue that an investor will not be willing to accept the risks of equity investments if the investor is loss-averse and often checks her portfolio. This is because frequent revision of one's portfolio makes the investor aware of the volatility of stocks, and therefore they may perceive it as a less desirable investment than bonds, when in reality, in the long run, stocks outperform bonds. In essence, a sensitivity to losses and observing the highly volatile nature of the equity market may provide unnecessary stress to investors. Benartzi and Thaler take a quantitative approach to arrive at this conclusion. Although there is no standardised way of measuring loss aversion such as the Global Preference Survey (i.e. Falk et al., 2018), methods usually include surveys or some kind of questionnaire to determine the extent of loss aversion in the sample (Kahneman and Tversky, 1979; Lee and Veld-Merkoulova, 2016; Thaler, Tversky, Kahneman and Schwartz, 1997). Kahneman and Tversky (1979) use an experimental method to quantify loss aversion using gambling questions.

Benartzi and Thaler (1995) also discuss the concept of mental accounting, i.e. the tendency to mentally categorise investments in terms of utility (Thaler, 1985). They propose that losses and gains are coded differently (not simply as a vector of overall profits) since utility functions are different on the losses and gains domains. Barberis and Huang (2001) explore mental accounting and loss aversion in the context of equity investments and conclude that portfolios of investors affected by such principles are excessively volatile, but surprisingly, have a high mean return. That being said, this finding only holds when investors are loss-averse for individual stocks they own, not over the whole portfolio. It is also noteworthy that this research does not include stock market data. It is rather a hypothetical quantitative approach which uses gambling questions as the basis for this argument. Nevertheless, this conclusion goes against that of Renu Isidore and Christie (2019). Thus, a key component of this research analysis is to settle the debate of how these concepts affect financial outcomes, not just the extent to which they affect investors.

Also related to the concept of loss aversion is the disposition effect, which is the tendency to hold onto losing investments too long and to quickly sell profitable stocks (Shefrin and Statman, 1985). This arithmetic also leads to suboptimal portfolio performance as often it is wiser to hold onto investments that follow an upward trend and sell losing investments to minimise further losses. Research on the disposition effect has been mostly focused on the extent to which it appears in stock market transactions (Kaustia, 2010; Birru, 2015; Goo et al., 2010), but the literature is lacking in explaining how it affects financial outcomes. Interestingly, Kaustia (2010) argues that the disposition effect cannot be explained by prospect theory, but this is in disagreement with Li and Yang (2013), who sustain that the literature has generally attributed prospect theory as a possible explanation for the disposition effect.

The representativeness heuristic has also been closely linked to loss aversion (Renu Isidore and Christie, 2019). In behavioural economics, this heuristic relates to how individuals assess the likelihood of an event based on whether it is "(i) similar in essential properties to its parent population; and (ii) reflects the salient features of the process by which it is generated" (Kahneman and Tversky, 1972, p. 431). In other words, an event will be regarded as more likely if it is representative of pre-conceived ideas of the event in question. This was first studied using the "Linda problem" where the sample was asked to evaluate the probability that Linda is a) a feminist, b) a bank teller, or c) a bank teller and a feminist based on a description representative of feminist attributes (Tversky and Kahneman, 1983). Most evaluated option c as more likely than option b although in theory, the probability of c should be less than (or equal) to the probability of b. In the context of financial investments this heuristic can manifest as the belief that if a stock has performed well in the past, it will continue to do so. Previous positive performance is representative of future positive performance which leads to a higher perceived profitability potential. The fact that an investment has performed well previously does not always mean that it will continue to do so as when it comes to equity investments as there are many exogenous factors affecting stock prices such as market conditions. Investors often choose stocks that have performed well in the past, which can, unsurprisingly, lead to worse portfolio performance. Regret aversion also has a high correlation with both loss aversion and representativeness according to Renu Isidore and Christie (2019). According to Bilek, Nedoma and Jirasek (2018), the representativeness heuristic in behavioural finance has been investigated using experimental methods, sometimes using stock market data. The survey method has been used by Arend et al. (2016 cited in Bilek, Nedoma and Jirasek, 2018), but this investigates the representativeness heuristic in a managerial context, not for investments specifically.

Finally, an important concept in prospect theory is that of reference points. This is the initial benchmark against which losses and gains are perceived and calculated. Knetsch (1989) introduces the related endowment effect to explain that people value their initial reference point more than subsequent gains. This is also a detrimental way of assessing financial outcomes which can lead to impaired profitability depending on the initial reference point (Sell Macedo et al., 2007).

In terms of research methods, behavioural finance started as a highly qualitative field where it was not unusual to explain how biases might affect investors. However, once these theories started surging, it became common to attempt to quantify these biases (either to find evidence for them or to show how they affect investor behaviour or portfolio performance). One study that quantifies biases is Renu Isidore and Christie (2019), which used a similar method as this paper. Using responses to a survey, they created an econometric model where they regressed behavioural biases against financial outcomes, and found that most biases (except anchoring, overconfidence and optimism) correlated negatively with portfolio performance. A similar method will be used, but only loss aversion, representativeness heuristic and disposition effect will be included in the model proposed. The disposition effect has not been included in Renu Isidore and Christie (2019), but the other two have.

To sum up, the literature above presents the theory behind investor thought processes and how they can be affected by several biases, all arising from the basic principles of prospect theory (and mental accounting). Studies have been done on the extent to which certain biases such as herding behaviour (Chang, Cheng, and Khorana, 2000) affect investors. However, there is very little empirical research on the extent to which (and how) prospect theory-related biases affect investment decisions and related financial outcomes. The research mostly focuses on finding evidence for these biases, for which there seems to be significant evidence. There has also been research done on how these biases can be mitigated, but this is beyond the scope of the following research. This paper aims to fill the literature gap regarding the relationship between three prospect theory biases (loss aversion, the disposition effect, and representativeness heuristic) and the portfolio performance of equity investors. It also aims to settle the debate introduced by Barberis and Huang (2001) arguing that loss aversion can lead to higher portfolio mean returns.

3 Data & Methods

3.1 Data

The data was collected randomly from participants on the survey platform Prolific. The platform affirms that it "deliver[s] high-quality human-powered datasets" (Prolific, n.d.). On this platform, once the necessary funds are uploaded to the project and all the details are specified (eg sample characteristics, what is needed from the participants to carry out the survey, the payment sum for completing the survey, etc.), one can launch the survey anytime. Data collection is quick and very simple. One can approve or remove submissions (I had to remove a couple as will be explained below).

The only criteria that restricted the sample were location and investment experience. Only individuals based in the United States have been used for this analysis. Additionally, only participants who answered yes to the following question had access to the survey: "Have you ever made investments (either personal or through your employment) in the common stock or shares of a company?". This comes from the prescreening questions automatically given by Prolific within the category of finance, and more specifically investments. This was the most pertinent choice for prescreening the sample as the survey is only relevant to individuals who have invested in the equity market. Due to budgeting constraints, a representative sample of the United States population could not be guaranteed by Prolific, although the descriptive statistics seem realistic for the adult population, with a relatively good gender ratio and age distribution.

	Observations	**Mean**	**Standard Deviation**	**Minimum/Maximum**
Age	99	38.84	11.66	20/76

Gender	**Percentage**
Female	47.47
Male	52.53

Employment Status	**Percentage**
Full-time employment	73.74
Part-time employment	7.07
Student	6.06
Retired	6.06
Self-employed	7.07

Table 1: Sample Descriptive Statistics

3.2 Research Design

The research method for this paper was conducting an online survey. A survey is the most simple and appropriate way of quantifying these biases. This is a method that is commonly used in academic literature, and it is the most pertinent way of collecting data which is suitable and useful for answering the research question. The funds for this survey (£218) have been granted by the Economics Department at Lunds University School of Economics and Management. Based on the length of the study and the hourly rate pay suggested by Prolific, the study was able to gather 103 respondents. The participants earned £1.50 for completing the 10-minute survey.

Before the study was launched, a pre-registration was made. This is a research plan which briefly explains how data will be collected and analysed. This is thought to improve the scientific credibility and robustness of the results (APA, 2024). There has been one pre-registration made before data collection and one made after the pilot study. As the first version is vague in its estimated sampling methods, the second version can be found in Appendix I.

Survey Sections
Demographics (3 questions)
Investment experience/knowledge/style (4 questions)
Loss aversion (6 questions)
Attention check question
Representativeness & Disposition (6 questions)
Investment behaviour (3 questions)
Portfolio performance (3 questions)

Table 2: Survey Overview

The survey was created on Google Forms. The process of linking the pre-existing Google Form to Prolific is very simple. There is a section in the project details where one can choose whether to run the study in Prolific or whether to provide an external link to the survey. The questionnaire was divided into seven sections with a total of 26 questions (for all questions see Appendix II).

First, there were three demographic questions which included age, gender, and employment status. The intention was to keep the number of questions to a minimum, and since the following section covers investment experience and knowledge in greater detail, employment status could give us more information about the sample than general education levels. The second section covered investment experience/knowledge, where respondents were first asked whether or not they have ever invested in the stock market. This has been done to double-check the reliability of the prescreening offered by Prolific, which turned out to not be fully accurate as four participants have never invested in the stock market, so their responses had to be deleted. Next, participants were asked how long they have been investing, to rate their level of investment knowledge and general risk tolerance. The question on general risk tolerance has been taken from the Global Preference Survey (2018), and it is supposed to measure general risk aversion, which is important for the following section which includes gambling questions.

The next section was the "loss aversion" section, where 5 hypothetical gambles were presented, after which a self-reported loss aversion question had to be answered. This way of structuring the questionnaire was inspired by the GPS (i.e. Global Preference Survey), although the GPS investigates risk aversion instead of loss aversion. The same question format was taken and applied to the concept of loss aversion. The only difference was that the prospects in the gamble questions were changed to include losses as well as gains, which would make measuring loss aversion possible. The GPS only frames the gambles in terms of gains, which is more appropriate for measuring risk aversion.

The gamble questions in this study included a certain option, and a 50/50 gamble, which is what the GPS did as well. The GPS had 5 rounds of conditional questions, however, since the study was carried out on Google Forms, there was no option for programming conditional questions. Thus, the survey included 5 rounds of gambling questions based on the following logic.

Safe Option	Gamble Option
\$100 (1.0)	\$200 (0.5), \$0 (0.5)
\$100 (1.0)	\$400 (0.5), -\$100 (0.5)
\$0 (1.0)	\$150 (0.5), -\$100 (0.5)
-\$100 (1.0)	\$100 (0.5), -\$200 (0.5)
-\$100 (1.0)	-\$150 (0.5), \$0 (0.5)

Table 3: Gamble Questions (probabilities in brackets)

Firstly, the "safe" option was programmed which could be of three types: positive, zero, or negative. Two questions with positive safe options, one with a safe option of zero, and two with the safe option being a loss were chosen. This was to ensure that there are a wide range of scenarios presented in order to get a more holistic view of loss-averse behaviour and participant preferences. The sums were chosen such that the certain option is either +\$100, \$0 or -\$100 for simplicity.

Next, the gamble prospects were constructed. As per the format of the GPS, two prospects were presented, each with a 50% probability. For a certain prospect of zero, the only combination of gambles that would make sense is a positive and a negative value. If for such a gamble, the outcomes are zero or a positive sum, the participants will always prefer this gamble over the safe option, and vice versa for gambles with a negative outcome or nothing. Following the same logic, for a certain prospect of +\$100, two combinations make sense for the gamble: a larger positive sum or zero, or an even higher positive sum but with a chance of incurring a small loss. Vice versa in the case of a negative certain prospect. Thus, we arrive at five total possible formats for the gamble questions (which can be seen in Table 3).

The gambles were programmed such that the expected value of the gamble options is higher than the safe option (except for the first question, where the expected values are the same). The first question had the same expected value for both the safe option and the gamble option. This was done purposefully. Since this question does not include any losses, it rather measures risk aversion, not loss aversion. As such, this question (combined with the question on self-reported risk aversion from the previous section) can be used to control for risk preferences in the regression model. As for all the other four questions, the expected value of the gamble was always higher than the safe option. This is because one way that loss aversion can be defined is loss-minimising behaviour. Since all the other gambling options presented the risk of losing more than by picking the safe option, loss-averse participants may have wanted to steer away from the gambles to minimise potential losses. Prospect theory would predict that participants would place excessive emphasis on the probability of losing the gamble, and the principles of loss aversion would make it such that participants would want to minimise potential losses when faced with these gambles. As such, to compensate for this, a higher expected value was placed on the gambles to offset the potential aversion to the gamble option due to higher potential losses. Despite this logic, the higher expected value may not be immediately evident to all participants, but some may have calculated the expected value or simply noticed this fact.

That being said, the expected value is simply not enough to determine what the most rational choice for each gamble question is. This is because utility functions are different in the gains and losses domain. As such, the utility was calculated for each of the options, and it seems like in some cases (the second and third question), the safe option results in higher utility, despite the higher expected value of the gamble option. Appendix III shows all utility calculations for the gamble questions.

The loss aversion section also included a self-reported loss aversion question which was: "Generally, how do you feel about selling an investment at a loss (e.g. to prevent further losses or to reallocate funds to a potentially more profitable investment)?", which seems to be the most appropriate way of framing such a question. It was formulated in general terms, but still in the context of equity investments. This format was inspired by the GPS. The phrasing of the self-reported risk aversion question was changed to measure loss aversion in the context of equity investments instead.

The next section was solely dedicated to the attention check question where participants had to choose the number 4 on a 5-point scale. The attention check question was important for testing whether the participants paid attention to the gamble questions. The repetitive format and varying sums presented may have been tiring for the respondents, so to ensure that the participants were paying attention, this question was added in straight after the gamble questions. Such attention-check questions have been recommended by Haaland, Roth and Wohlfart (2023).

The next section included 6 questions, three for the representativeness heuristic and three for the disposition effect. The questions for the disposition effect were taken from Goo et al. (2010) and rephrased to ensure enhanced clarity. The representativeness questions were composed internally with the help of OpenAI (2024), as no surveys or questions were found in the existing literature that could measure this heuristic in an investment context. The complete set of questions can be found in Appendix II.

The following section included three questions on actual investment behaviour, one for each bias. As an example, the loss aversion question was: "I often sell investments that have experienced a significant loss, even if I believe they may recover in the future (e.g. to prevent further losses or to reallocate funds to a potentially more profitable investment)." where participants had to rate this on a 5-point scale. Ideally, real investment behaviour measures (such as transaction data) would have been preferred, but this was not realistic for the purpose of this paper, and given the short time span. This is a potential limitation of the study.

The final section measured portfolio performance with three questions. Participants had to rate financial outcomes in terms of satisfaction, profits and relative to other investors. The questions were chosen such that participants would not have to check their portfolios to give exact figures on portfolio performance, as there would have been incentives to lie by not revising the portfolio, or by slightly embellishing the reported data. This way, participants just had to give their subjective assessment of their portfolio performance. While this may not be the most reliable measure, the idea was to keep the survey simple and avoid any possibility that participants would be incentivised to lie or overthink their answers.

As mentioned, a pilot study was launched before the official study to ensure clarity of the questions. 7 answers have been collected for the pilot study. Some of the participants included LU students, and other investors found through snowball sampling. Some questions had to be edited as a result of the pilot study. These included the scale format of one question (negative sentiment was previously on the right but was moved to the left of the scale) and the phrasing of another question.

After the final version of the study was run and data was collected, the inappropriate observations had to be eliminated. Initially, the sample included 103 respondents, but 4 answers were excluded. The survey included the question “Have you ever invested in the stock market?” to ensure the prescreening was fully accurate, but 4 respondents answered “no” to this question. Ergo, their responses have been eliminated from the subsequent analysis. No respondents failed the attention check question, meaning that the eliminated respondents have solely been removed due to lack of investment experience. There were also two missing answers for the age question.

The next step was to clean up the data and modify the variables. First, variables for each of the biases were constructed. The construction of the loss aversion variable was the most sophisticated as it involved the most data transformations. First, the most loss-averse answers to the gamble questions were determined. This was done by calculating utility, which can be seen in Appendix III. This essentially created a dummy variable out of the answers. The self-reported loss aversion question was transformed into a 0-1 scale and was combined with the gamble questions to create the loss aversion bias variable. The gamble questions were given a weight of 0.473, and the rest was given to the self-reported dimension (weights taken from the GPS, 2018). As such, the loss aversion variable was created, and measured on a 0-1 scale. Similarly, for the other biases, an index was constructed with equal weights given to each of the three questions included. The other two bias variables are also measured on a scale of 0-1. The bias questions were simply modified such that the scale is also 0-1. Another index was created for the questions measuring portfolio performance or financial outcomes.

The reliability of this data should be relatively high. Knowing that the data was constructed and measured internally for this study means that the data has been thoroughly scrutinised before the data analysis took part. The survey was highly standardised and included various "quality check" questions, such as the attention check question and the question of whether the participant has ever invested in stocks. To further test the reliability of the data, Cronbach's alpha has been used when constructing the variables. The alpha value for the "portfolio performance" index (created out of 3 questions) is 0.87, which shows good internal consistency for this variable and the questions used to measure it. Similarly, the two dimensions (gambling questions and self-reported loss aversion) of the loss aversion variable highly correlate with the overall loss aversion variable.

As mentioned, Prolific could not guarantee a representative sample. However, the demographic data looks reasonable. There is almost an even split between sexes, with slightly more males than females. The median age is 38.9 as of July 1, 2022, which is very close to the mean from this sample (Census.gov, 2024). Some potential differences between the average citizen and those enlisted on Prolific may exist such as differences in average education levels. However, this should not significantly impact the results as stock market investors (enlisted on Prolific or not), likely have higher education levels than the average citizen in any case. The differences in education between investors who are not on Prolific and those who are are not expected to be significant. Another noteworthy potential difference between the Prolific sample and the general population may be differences in motivation to answer the questions honestly and carefully due to monetary incentives.

A homogenous sample was chosen instead of a comparative approach as this is a more accurate way of measuring how these biases manifest in the chosen sample and how they affect portfolio performance. Comparing two samples would have shifted the focus towards other factors, such as cultural differences and their effects on cognitive biases in investment decisions, which is not what the aim of this research is.

In terms of the validity of the data, most of the questions have been taken from other studies. For some, the wording has been changed to ensure clarity for respondents. Such questions are expected to have high construct validity. Other questions had to be created internally due to a lack of survey literature on the representativeness heuristic specifically. While such questions may have lower construct validity, they are still very much related to the concept of representativeness heuristic in the context of equity investments. Unfortunately, there is no standardised way of measuring this, so the questions had to be constructed internally. The portfolio performance questions are also quite subjective, but this was done in order to avoid incentives to lie or to misreport actual portfolio returns. Potential concerns regarding the validity of the questions of this study will be considered in more depth in the discussion section. The questions will be discussed in more detail in the following section.

4 Empirical Analysis

4.1 Analysis

After the variables had been transformed appropriately for them to be used for the data analysis (on a scale of 0-1), first the data was inspected in various ways. Descriptive statistics of the variables of interest and a pairwise correlation matrix are presented below.

	Mean	**Std. Dev.**	**Min/Max**
Loss Aversion	0.436	0.173	0.105/0.895
Representativeness Heuristic	0.616	0.114	0.333/0.933
Disposition Effect	0.650	0.135	0.267/0.867
Loss Averse Behaviour	0.685	0.239	0.200/1.00
Representativeness Heuristic Behaviour	0.590	0.230	0.200/1.00
Disposition Effect Behaviour	0.580	0.202	0.200/1.00
Portfolio Performance	0.640	0.178	0.200/1.00

Table 4: Descriptive Statistics of the Main Variables

	LA	**RH**	**DE**	**LAB**	**RHB**	**DEB**
Loss Aversion	1.000					
Representativeness Heuristic	-0.085	1.000				
Disposition Effect	-0.107	0.049	1.000			
Loss Averse Behaviour	-0.357	-0.172	0.238	1.000		
Representativeness Heuristic Behaviour	-0.161	0.263	0.054	-0.119	1.000	
Disposition Effect Behaviour	0.211	0.093	0.276	-0.235	0.156	1.000
Portfolio Performance	0.300	-0.111	0.002	-0.107	0.174	0.057

Table 5: Pairwise Correlation

Before any additional data analysis will take place, it is crucial to discuss some of the assumptions of the model. Some of the key assumptions of any econometric model are the Gauss Markov assumptions. These assumptions are crucial to ensure that the ordinary least squares estimates in the linear regression model are the best linear unbiased estimates. In other words, the linear regression model that will be created will try to estimate the effect of the independent variables on the dependent, and these estimates must be linear and unbiased. To ensure that this is the case, the following assumptions must be satisfied. First of all, random sampling is necessary to fulfil these conditions. This has been achieved through the Prolific population although, naturally, the whole US population could not be reached for this paper. Even so, the sampling method is as unbiased as possible.

The next important assumption is that the independent variables are exogenous. This means that the error term in the linear regression model cannot be correlated with the explanatory variables at all. Mathematically, this assumption can be expressed as follows: $E(\varepsilon_i|x_i) = 0,\ i = 1, 2, 3$ for the three independent variables, being the biases in question. This assumption is reasonable because there is no bidirectional ambiguity in this relationship. These biases likely affect portfolio performance by influencing investment behaviour, but portfolio performance cannot induce cognitive biases. Moreover, the controls in the regression serve to account for potential confounding variables affecting this relationship, so it is not expected that there is any endogeneity in the model.

The next assumption is that of homoscedastic error terms. This means that the error terms have the same variance for all values of the independent variables. Mathematically, this assumption is written as follows: $E(\varepsilon_i|x_i) = \sigma^2,\ i = 1, 2, 3$. To ensure there is no heteroscedasticity, robust standard errors will be used for the model, as these will ensure that even if there is homoscedasticity, inference will be approximately correct as the number of observations is relatively large.

Moreover, since there are multiple explanatory variables, there must be no specification errors such as redundant variables, missing variables, multicollinearity or measurement errors. In the case of redundant variables, these can always be omitted from the model. In terms of measurement errors, there is not much that can be done to solve this, but it is not expected that this should be a problem in the following model. Clearly, there are a plethora of variables that affect portfolio performance from other biases to completely exogenous variables such as macroeconomic conditions. There will be variables omitted, but this is not the idea of the following regression. The aim is to determine to what extent these three biases affect portfolio performance. They are not expected to explain variation in portfolio performance to a large extent, as many other factors likely affect portfolio performance more. There should be no multicollinearity as the correlations between the independent variables are very low as per Table 5 (except the ones between the bias and its associated behaviour, which should be higher). That being said, it is curious that the correlation between the loss aversion variable and the variable for loss-averse behaviour is negative. Possible explanations for this will be explored in the discussion section below.

What follows now is to state the main LRMs. In both of the LRMs of interest, there will be three main control variables: age, gender, investment experience and knowledge, and risk aversion. Below is the formula for the two models that will help to answer the research question:

$$(1)\ Performance = \alpha + \beta_1 LA + \beta_2 DE + \beta_3 RH + \beta_4 age + \delta_5 gender + \beta_6 xp\_know + \beta_7 risk$$

$$(2)\ Performance = \alpha + \beta_1 LAB + \beta_2 DEB + \beta_3 RHB + \beta_4 age + \delta_5 gender + \beta_6 xp\_know + \beta_7 risk$$

Note: LA is the loss aversion variable comprised of the gamble questions and the self-reported loss aversion question; DE refers to the variable measuring the disposition effect; RH measures the representativeness heuristic; xp_know is a variable that measures the level of investment knowledge (self-reported) and experience (baseed on how many years the participant has been an investor for); LAB, DEB and RHB are the behavioral variables, measuring to what extent actual investment behaviour reflects evidence of the biases.

Before discussing the additional analyses to be conducted, the choice of the control variables must be justified. Knowledge and experience must be accounted for when investigating portfolio performance, and these are arguably the most important variables. Age has been accounted for due to the same logic, although it seems to play an infinitesimal and negligible role in explaining portfolio performance, as per the coefficient value. Risk aversion has been accounted for as it has been found to affect portfolio returns since it affects investment behaviour (Martins Fittipaldi Torga et al., 2023). Gender also plays a role in investment style and affects investment returns (Barber and Odean, 2001), and for the same reason, it was added as a control variable.

Besides running these LRMs, there will be additional analyses conducted. This was, above all, done to confirm the robustness of the initial results by changing the control variables. Controlling for different variables is justifiable and the alternative models are equally important to the analysis, as will be explained in deeper detail in the following section. Also, experimenting with different versions of the dependent variable is important to identify whether the results are driven by a specific measure of portfolio performance, thus providing more insight into the results and the relationship between the variables.

4.2 Results

First, the linear regression model with the biases as the explanatory variables was estimated. The results of the regression are somewhat surprising. Firstly, the adjusted R-squared value (which is of more use than the R-squared value as it accounts for the number of independent variables) tells us that 39.2% of the variance of the portfolio performance variable can be explained by the independent variables chosen. This was to be expected as there are many other biases and exogenous variables affecting portfolio performance. Even so, a significant part of the variance in portfolio performance can be explained by the chosen biases. That being said, if portfolio performance is regressed on just the bias variables without the controls, we find that only 8% of the variance is explained by the biases. This makes sense, as there likely are many other variables that affect portfolio performance to a larger extent. This simply means that the control variables explain more of the variance in portfolio performance than the biases do. This is not a problem, however, as the hypothesis is merely that the impact of the biases on portfolio performance is negative, and is not concerned with the extent to which these biases contribute to explaining the variance in portfolio performance. However, the alternative models will consider excluding some of the controls from the original models proposed as they may have too much explanatory power in the model.

Portfolio Performance	**Coefficient**	**Robust Std. Err.**	**t**	**P>|t|**	**95% C.I.**	
Loss Aversion	0.139	0.103	1.53	0.13	-0.047	0.363
Disposition Effect	-0.011	0.101	-0.11	0.91	-0.211	0.189
Representativeness Heuristic	0.177	0.136	1.30	0.20	-0.094	0.447
age	-0.002	0.001	-1.75	0.08	-0.005	0.000
gender	0.040	0.030	1.33	0.19	-0.020	0.100
xp_know	0.597	0.088	6.79	0.00	0.422	0.772
risk	-0.016	0.081	-0.20	0.84	-0.177	0.144
constant	0.207	0.127	1.63	0.11	-0.046	0.459

Number of observations = 95
F-statistic = 11.50
Prob>F = 0.000
R-squared = 0.437
Adjusted R-squared = 0.392
Root MSE = 0.136

Table 6: First Linear Regression Model

The only bias with a negative coefficient (-0.011) is the disposition effect. This coefficient means that if the disposition effect variable increases by 1 unit (going from the minimum score to the maximum score), portfolio performance worsens by 0.011 units. The other two biases have positive coefficients, suggesting that a higher degree of loss aversion and the representativeness heuristic have a positive relationship with portfolio returns. This being said, none of these coefficients are statistically significant as the p-values are too large. This could be due to several reasons. Perhaps some of the questions measuring the biases weaken the statistical significance of this relationship. This possibility will be explored further in this section, through the alternative models. The lack of statistical significance is likely not due to multicollinearity between the variables, as the three bias variables are only weakly correlated (see Table 5). The high p-values for the coefficients are not expected to be due to heteroscedastic error terms or endogenous variables. Robust standard errors ensure that heteroscedasticity does not affect the model, and the variables are expected to be exogenous, as explained in the previous section.

Below is the second linear regression model output table, this time with the behaviour associated with each bias as the independent variables.

Portfolio Performance	Coefficient	Robust Std. Err.	t	P>|t|	95% CI	
LA Behaviour	-0.019	0.060	-0.32	0.75	-0.139	0.101
DE Behaviour	0.073	0.067	1.08	0.28	-0.061	0.206
RH Behaviour	0.200	0.050	3.98	0.00	0.100	0.299
age	-0.003	0.001	-2.18	0.03	-0.006	0.000
gender	0.038	0.031	1.23	0.22	-0.023	0.100
xp_know	0.575	0.082	7.03	0.00	0.412	0.738
risk	0.102	0.082	1.25	0.22	-0.061	0.265
constant	0.200	0.095	2.10	0.04	0.011	0.390

Number of observations = 95
F-statistic = 13.81
Prob>F = 0.000
R-squared = 0.482
Adjusted R-squared = 0.433
Root MSE = 0.131

Table 7: Second Linear Regression Model

This regression yields the first statistically significant (at any level) coefficient thus far, being the coefficient for the representativeness heuristic behaviour. This coefficient tells us that the more someone exhibits investment behaviour associated with the representativeness heuristic, being that they mostly invest in stocks that have performed well in the past, the higher their self-reported portfolio performance is. As representativeness behaviour increases by one unit (going from the minimum score to the maximum score), portfolio performance increases by 0.2 units. The fact that 0 is outside the 95% confidence interval makes this finding more significant as well, as the coefficient is almost certainly positive. The coefficients for behaviour associated with loss aversion and the disposition effect are much smaller, but positive as well.

This is, once again, surprising as the hypothesis was that these biases should negatively impact portfolio performance. Similarly to the first regression, the adjusted R-squared value is relatively high considering the few explanatory variables included in the model and the complexity of the stock market. This regression was also run without the control variables, which states that around 3% of the variance in portfolio performance can be explained by the behaviour associated with these biases. This, again, is logical due to the countless factors affecting equity investment returns. The statistical insignificance is not expected to be due to heteroscedasticity or endogenous variables of the variables, as explained in the previous section.

Perhaps the lack of statistical significance can be attributed to a misspecification error. It could be that there are better ways to measure the biases and portfolio performance, perhaps some of the questions used are redundant and weaken the regression results. There were different versions of the LRM that were tried out. First, different controls were tested. In the end, the experience and knowledge control variable was excluded for the alternative models as it is significant in both of the LRMs above. In fact, the correlation between this control variable and the bias and behaviour questions is negative (except for the loss aversion bias variable). This means that with experience and knowledge, the extent to which investors are affected by the representativeness heuristic and the disposition effect decreases, which is logical. For some reason, however, the opposite is true for loss aversion; more evidence for loss aversion has been found in investors who claim to have better investment knowledge, specifically. Due to these relationships, it may be beneficial to exclude this control from the model, as controlling for experience and knowledge may actually remove some of the effects of the bias variables from the model. This possibility is worth investigating. This was also beneficial in ensuring that the model is not overfitted as there are quite a few control variables specified in the original LRM. The dependent variable was also changed to solely include one of the three dimensions of portfolio performance (and regressions were run with each of the three dimensions as the dependent variable). There was no attempt to construct a different performance index consisting of solely two variables, as this would not increase Cronbach's alpha of the index significantly, so only the individual dimensions were investigated. This was done to identify whether the relationship between the biases and portfolio performance is driven by any of the particular measures of portfolio performance, which would shed light on more specific relationships between how the biases relate to different aspects of portfolio performance. Lastly, some non-linear transformations of the bias variables have been used in the alternative regressions, as the relationship between the bias and portfolio performance could also be non-linear as will be explained in deeper detail below. To summarise, different combinations of the two LRMs were run by isolating different dimensions of the dependent variable, by removing the knowledge and experience control, and by experimenting with non-linear transformations of the explanatory variables.

There were a few noteworthy findings from these alternative models. Statistically significant results from the alternative regressions are presented below.

LRM 1 or 2	Changes Made to Original LRM	Findings
1	- Drop control xp_know	- β_1=0.235, $p<0.05$
1	- DV: comparison to all other investors - Drop control xp_know	- β_1=0.317, $p<0.05$
2	- Drop control xp_know	- β_3=0.216, $p<0.01$
2	- DV: self-reported portfolio satisfaction - Drop control xp_know	- β_3=0.273, $p<0.001$
2	- DV: comparison to all other investors - Drop control xp_know	- β_1=-0.148, $p<0.1$
2	- DV: self-reported portfolio returns - Drop control xp_know	- β_3=0.257, $p<0.01$

Table 8: Alternative LRMs and Findings

By dropping the experience and knowledge control, the first LRM yields a significant coefficient. By increasing loss aversion by one unit, portfolio performance improves by 0.235 units. It seems like this relationship is specifically driven by the dimension of portfolio performance where investors had to rate their portfolios compared to all other investors. The relationship between this dimension and loss aversion is even greater, with a coefficient of 0.317. There are several possible explanations for this finding. It could be that by being loss-averse, investors are under the impression that they perform above average. Loss-averse investors might invest in safer assets and therefore it is likely that they experience less severe losses in their portfolios. However, this does not necessarily mean that their portfolios have higher returns than less loss-averse investors. They might just be under the impression that the overall quality of their portfolio is better due to the fact that they incur smaller losses (which is perhaps more important to a loss-averse investor than high returns, given the prospect theory utility curves). Another plausible explanation for this relationship could be that the loss aversion variable has low validity. The gamble questions, to an extent, measure risk aversion as well. This might make it such that the relationships are not truly reflective of how loss aversion affects portfolio performance. This is a plausible explanation as the correlation between this variable and the loss-averse behaviour variable is negative. Thus, this variable likely measures risk aversion to a great extent too, due to the gamble questions. That being said, excluding the gamble questions and only using the self-reported loss aversion question in the regression yields a smaller (statistically significant) coefficient. Thus, the most plausible explanation is that the results are not fully accurate since the measures of portfolio performance are quite subjective. If a more objective measure of portfolio performance would have been used instead, such as specific figures on profits/losses, the results would have been different.

There were also a few interesting findings when altering the variables in the second LRM. Even without the experience and knowledge control variable, the representativeness behaviour variable yielded a similar coefficient as the original LRM. However, it seems that this is mostly driven by the satisfaction and the returns dimensions. This could, again, be due to several reasons. A plausible explanation is that the subjective measures of portfolio performance may not be truly reflective of actual returns. It could also be due to the fact that the respondents believe their portfolios are of better quality, and may be excessively pleased with smaller returns due to this reason. The relationship between self-reported returns and investing in stocks that have previously performed well is also positive, potentially indicating that stocks that previously performed well also tend to perform better currently. However, this relationship may not necessarily be linear. It would be expected that previous performance only correlates with returns up to a certain level. This sub-hypothesis has been tested by taking the square root of the representative heuristic behaviour variable, and it yielded statistically significant results as well. This transformed variable was run against all three individual portfolio performance measures as well as against the index variable specified in the original LRM, both including and excluding the experience and knowledge control. The results are similar; the coefficient is only not significant when the dependent variable is the comparison measure of portfolio performance. The only difference is that for the permutations of the LRM using the square root of the representativeness behaviour variable, the coefficients are generally higher. Excluding the experience and knowledge variable does not make much of a difference. Therefore, a square root of this variable is perhaps a better fit for this model.

Finally, in the second LRM by excluding the experience and knowledge control and using the comparison measure of portfolio performance as the dependent variable, we get a statistically significant coefficient of -0.148 for the loss-averse behaviour variable. This was hypothesised, as loss aversion is typically thought to correlate negatively with returns.

There are several implications of the findings of these alternative regression models. Overall, it seems like the questions chosen to measure portfolio performance may be a limitation of this study due to their subjective nature. The comparison question may not be an accurate estimation of actual portfolio performance, as the sample may be under the wrong impression that they perform better than the average investor, without necessarily knowing the average investor's returns. No questions were asked where respondents had to give exact figures on their portfolio returns to ensure that there was no incentive to lie or to not check their portfolios before answering and potentially reporting an inaccurate estimate. This being said a possible solution could be to provide profit ranges (in percentages) for self-reported returns. For example, participants could be asked to estimate their returns since the beginning of their investments, as well as solely in the last year from the following options: 0-5%, 5-10%, 10-25%, >25%; on both the losses and gains domain. This would have given a more accurate estimate of returns without having to ask for specific figures.

4.3 Discussion

The hypothesis was that evidence for these biases and their associated behaviour should negatively impact portfolio performance, and as it turns out, this is not necessarily the case. The initially proposed regressions did not yield statistically significant results, except for the fact that investment behaviour reflective of the representativeness heuristic correlates positively with portfolio performance. As explained above, the lack of statistical performance in the original model is likely due to inaccurate measurements of portfolio performance. This is the main limitation of this study, that there are potentially more effective and reliable ways of measuring the variables of interest. Another example of this is that if the gamble questions could have been programmed to be conditional, a more nuanced loss aversion variable could have been constructed (but this was not possible due to lack of more sophisticated survey tools, funding, and time constraints). The sample size could have also been larger, but due to budgeting constraints, this was also not possible.

The key findings that came from the alternative regressions were more interesting. By excluding the experience and knowledge control variable from the LRMs, some of the coefficients became significant. This was done as controlling for experience and knowledge is expected to weaken some of the effects of the biases on portfolio performance. As it turns out, excluding this control reveals that loss aversion correlates positively with portfolio performance, and specifically with perceived superiority to all other investors. This could likely be due to the limited losses a loss-averse person suffers due to a potentially more conservative investment style.

As for the second LRM, excluding the experience and knowledge control did not yield drastically different results. As it turns out, the positive relationship between portfolio performance and behaviour reflective of the representativeness heuristic is mostly driven by the self-reported portfolio satisfaction and returns dimension of portfolio performance. It is hypothesised that investing in stocks that have previously performed well does in fact yield higher returns, but up to a certain point. Ergo, a square root transformation of this variable was included in the model instead. This transformation was more statistically significant (its coefficient had a lower p-value) and a higher coefficient, and is thus a better fit for the model. Therefore, investing in stocks that have previously performed well may not necessarily be a detrimental investment strategy, but it may limit potential profitability beyond a certain point.

Another interesting finding is that in the second model, by excluding the experience and knowledge control and changing the dependent variable to the comparison measure of portfolio performance, the loss-averse behaviour coefficient became statistically significant and had a negative value. This was expected, as per the hypothesis. This finding goes against the positive coefficient that loss aversion has with the portfolio comparison variable. However, it is expected that the negative relationship is more accurate, as the loss aversion variable may actually measure risk aversion to a large extent, and therefore may not be fully valid.

Some of these findings are at variance with the literature, but others are in accordance with the consensus. For instance, Renu Isidore and Christie (2019), who used a very similar method to this paper, found that loss aversion and the representativeness heuristic negatively correlate with portfolio performance. This paper confirms the negative relationship between portfolio performance and loss aversion but found a positive relationship between the representativeness heuristic and financial outcomes.

The lack of statistical significance in the originally proposed regressions and other unexpected findings such as the negative correlation between loss aversion and loss averse behaviour is likely due to some misspecification error of the variables. Arguably the greatest limitation of this study is the subjective measure of portfolio performance. As suggested above, perhaps providing general ranges of portfolio returns in the last year and beyond would have been a better, more objective measure of portfolio performance. No specific figures woul dbe asked, so the participants would have likely not had to check their portfolios before answering, as they likely are aware of the general range of returns they achieved. As mentioned, the loss aversion bias variable likely measures risk aversion to a large extent, and therefore may not be fully valid. Lastly, it would have been ideal to have real measures of behaviour (such as trading data) instead of asking self-reported behavioural questions, but due to limited access to such data, this was not possible for the purpose of this study.

5 Conclusions

5.1 Research Aims & Objectives

This paper aimed to investigate how loss aversion, the disposition effect and the representativeness heuristic affect the financial outcomes of equity investments. The research question is: "What role do cognitive biases and their associated investment behaviour play in equity investment financial outcomes?". The hypothesis was that there would be a negative relationship between these biases and portfolio performance. The method for this study was an internally designed survey. Part of the results were in line with the hypothesis, but other findings went against the hypothesised relationships.

5.2 Chapter Summary

A survey method was used to answer the research question. 103 US-based participants took part in the survey through the survey platform Prolific. The survey included 26 questions that included demographics, investment experience and style questions, questions for measuring the three biases in question and for all of the biases' associated investment behaviour, and finally a section measuring self-reported portfolio performance. All questions were designed for the purpose of this study. Using the survey results, an ordinary least squares linear regression model was constructed to identify the relationship between the evidence for these biases and how they affect portfolio performance. Two LRMs were proposed originally: one regressing portfolio performance on the biases, and the other on the behaviour associated with each bias.

The only statistically significant finding from the originally proposed LRMs was that there is a positive relationship between behaviour reflective of the representativeness heuristic and portfolio performance. Different variations of the original LRMs were run to identify more concrete patterns between the variables and there were several noteworthy findings. All of these re-specifications excluded the experience and knowledge control, as it was thought that it would mitigate the effects of the biases on portfolio performance to a large extent. Firstly, the positive relationship between representativeness heuristic behaviour and portfolio performance is mostly driven by self-reported satisfaction and returns. The relationship was also hypothesised to be non-linear. In other words, investing in stocks that have performed well previously may result in positive portfolio performance, but only up to a certain extent. This sub-hypothesis was accepted as the coefficient was significant. This finding is at variance with previous literature but is plausible nonetheless. Another finding of the alternative models was regarding loss aversion and loss-averse behaviour. Evidence for loss aversion correlates positively with a higher perceived portfolio quality compared to all other investors, but the opposite is true for the relationship between loss-averse behaviour (i.e. never selling stocks at a loss) and the comparison variable. The relationship that is likely more accurate is the latter. This is due to concerns regarding the validity of the loss aversion behaviour, as it also measures risk aversion to an extent, which may mean there is a misspecification error in this variable. Moreover, the latter aligns with the consensus from the literature.

This research is not without its limitations, which likely play a significant part in the lack of statistical significance in the originally proposed models. A greater sample size would always offer additional reliability and robustness to the results. Moreover, it may be that the measures chosen for portfolio performance are problematic. Since these are relatively vague, self-reported measures of portfolio performance, they might not give the most accurate results. Initially, these measures were chosen in this way to ensure that incentives to misreport performance are minimised. If specific numbers had been asked, there is always a possibility that the participants would have never checked their portfolios and would have reported a problematic and inaccurate approximation. However, a possible solution could have been to provide several ranges of profit/losses where participants would likely know more or less what range their portfolio fits in. These ranges could be presented in percentages, which would give a more accurate and objective measure of portfolio performance. There may have also been a potential misspecification error in the loss aversion bias variable. However, there is no standardised way of measuring loss aversion, so more research is needed on what the most accurate way of quantifying loss aversion in surveys is. Lastly, actual measures of investment behaviour would have been better instead of questions on self-reported behaviour. However, due to a lack of data accessibility, this has been a challenge and remains a limitation of this study.

Overall, the hypothesis could not be proved in the way that was originally planned. However, the alternative models show that buying only stocks that previously performed well in the past may not be a detrimental investment strategy, but it may be a limit to achieving higher profit levels. Also, avoiding selling investments at a loss seems te be a detrimental strategy. Allocating these funds to a potentially profitable investment, or selling before the stock sinks into the bear market further, likely is a better strategy. Thus, investors should not be afraid of booking losses sometimes, as this could lead to better financial outcomes in the long run.

5.3 Practical Implications

This paper has several practical implications. It mostly serves as an addition to the body of literature in quantifying the role of behavioural biases on portfolio performance. Such research aids investors in understanding their psychology as well as that of other equity market agents. An understanding of cognitive biases in the context of equity investments can potentially contribute to more rational decision-making and better financial outcomes of investments. This is valuable knowledge for fund managers and investment bankers as well. Although their investment strategies are much more complex than the average investor, they are not immune to cognitive biases either. Finally, behavioural finance research is also necessary to ensure sound functionality of the financial markets. This kind of research could be useful for financial institutions, which could focus their policies on mitigating these biases, which could help with preventing the formation of bubbles and excessive volatility in the stock market. For example, some trading platforms (such as eToro) incorporate such strategies by providing warnings such as that past performance is not an indicator of future success. Behavioural finance policies can extend beyond such nudges and encompass even investment advice services and other financial market regulations which aim to stabilise the market.

5.4 Future Research

Future research could take several routes. Firstly, quantifying the effect of behavioural biases on portfolio performance and abnormal price shifts in stock prices is very important for creating a better understanding of the role of psychology in financial markets. This study can be replicated with better measures of portfolio performance and a larger sample size.

Another possible extension of this study would be to use panel data to see how these biases behave over time. One can incorporate data on the frequency of stock transactions and other data such as the frequency with which the portfolio is checked. It would be interesting to see how trading behaviour changes over time and what role behavioural biases and prospect theory play in this process.

Perhaps it would be interesting to explore behavioural finance from a psychological perspective other than cognitive. One could take a biological approach and combine brain imaging techniques in a trading game experiment, or perhaps even take a sociocultural approach and examine the role of culture and one's ingroup on financial decisions. The inspiration has been taken from OpenAI (2024) for some of these future research suggestions.

That being said, as a field, behavioural finance could benefit from more research on how to mitigate cognitive biases for investors. More research is needed to evaluate the efficacy of different policies implemented by financial institutions.

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7 Appendices

Appendix I - Preregistration

ASPREDICTED

Wharton CREDIBILITY LAB
UNIVERSITY of PENNSYLVANIA

Behavioural Finance and Prospect Theory - A survey of financial outcomes (#171956)

Created: 04/23/2024 04:38 AM (PT)
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1) Have any data been collected for this study already?
It's complicated. We have already collected some data but explain in Question 8 why readers may consider this a valid pre-registration nevertheless.

2) What's the main question being asked or hypothesis being tested in this study?
To what extent can prospect theory-related cognitive biases explain equity investment decisions and their associated financial outcomes? The study specifically focuses on loss aversion, the disposition effect, and representativeness bias. The hypothesis is that we will find significant evidence for these biases and that they will affect financial outcomes negatively.

3) Describe the key dependent variable(s) specifying how they will be measured.
Self-reported portfolio performance (and investor behaviour)

4) How many and which conditions will participants be assigned to?
No conditions, it is a survey.

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
Three LRM using OLS: 1) regress self-reported investor behaviour on the biases (three regressions for this category, one for each bias), 2) regress portfolio performance on the biases, 3) regress portfolio performance on investment behaviour. Control for age, gender, investment knowledge and experience. Test for GM assumptions and statistical significance. Also test for Cronbach's alpha for the indices constructed for the biases.

6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
Answers from those failing the attention check and who have never invested will be excluded.

7) How many observations will be collected or what will determine sample size? No need to justify decision, but be precise about exactly how the number will be determined.
According to Prolific, 103 answers will be collected using the funding allocated to this study given the recommended rate.

8) Anything else you would like to pre-register? (e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)
The collected data was part of the pilot study which will not be used for the final data analysis.

Version of AsPredicted Questions: 2.00

Available at https://aspredicted.org/m34zy.pdf
(Permanently archived at http://web.archive.org/web/*/https://aspredicted.org/m34zy.pdf)

Appendix II - Survey Questions

LU Research Survey

This survey will be used for a research project at Lund University about investor behaviour. An investor is a person who has bought stocks at some point. As a participant, you consent to this data being used for research. This survey is anonymous. Answer the questions truthfully to ensure accurate results of the data analysis. You have the right to withdraw your responses at any point.

* Indicates required question

Demographics

Please answer the following questions.

1. Age *

   ____

2. Gender *

   Mark only one oval.

   - Male
   - Female
   - Other: ____________________

3. Employment status *

   Mark only one oval.

   - Full-time employment
   - Part-time employment
   - Student
   - Unemployed
   - Retired
   - Self-employed
   - Other

Investment Experience

Please answer the following questions.

4. Have you ever invested in the stock market? *

   Mark only one oval.

   - Yes
   - No

5. How long have you been an investor for? *

   Mark only one oval.

   - <1 year
   - 1-3 years
   - 3-5 years
   - 5-10 years
   - 10+ years
   - Not actively investing

6. How would you rate your level of investment knowledge? *

   Mark only one oval.

	1	2	3	4	5	
Begi	◯	◯	◯	◯	◯	Expert

7. On a scale of 0-10, in general, how willing are you to take risks? *

   Mark only one oval.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

This part is very important for the research analysis. Please answer truthfully.

8. You can choose between two hypothetical investments:

   Mark only one oval.

   - Receive $100
   - 50/50 chance of winning $200 or nothing

9. You can choose between two hypothetical investments:

   Mark only one oval.

   - Receive $100
   - 50/50 chance of winning $400 or losing $100

10. You can choose between two hypothetical investments:

    Mark only one oval.

    - Receive nothing
    - 50/50 chance of winning $150 or losing $100

11. You can choose between two hypothetical investments:

    Mark only one oval.

    - Lose $100
    - 50/50 chance of winning $100 or losing -$200

12. You can choose between two hypothetical investments:

    Mark only one oval.

    - Lose $100
    - 50/50 chance of losing $150 or nothing

13. Generally, how do you feel about selling an investment at a loss (e.g. to prevent further losses or to reallocate funds to a potentially more profitable investment)?

    Mark only one oval.

	1	2	3	4	5	
Extr	◯	◯	◯	◯	◯	Extremely comfortable

Untitled Section

Please answer the following question.

14. To what extent do you agree with the following statement? This is an attention check question, please choose number 4.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly agree

Untitled Section

This part is very important for the research analysis. Please answer truthfully.

15. I will keep holding stocks even though they are losing and will never think about selling stocks until they balance the losses.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly agree

16. I usually sell profitable stocks to realise gains first when I am in want of money. I keep holding unprofitable stocks and wait for the price to go up.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly agree

17. In my experience, the gains from multiple share transactions sometimes do not outweigh a single loss.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly agree

18. When evaluating potential investment opportunities, how much weight do you typically give to past performance as an indicator of future success?

Mark only one oval.

	1	2	3	4	5	
Non	◯	◯	◯	◯	◯	A great deal

19. How likely are you to invest in a company or asset solely because it has performed well recently, without considering other factors?

Mark only one oval.

	1	2	3	4	5	
Very	◯	◯	◯	◯	◯	Very likely

20. When evaluating potential investment opportunities, how important is it for you to see patterns or similarities between the current opportunity and past successful investments you have made?

Mark only one oval.

	1	2	3	4	5	
Extr	◯	◯	◯	◯	◯	Not important at all

This part is very important for the research analysis. Please answer truthfully.

21. I often sell investments that have experienced a significant loss, even if I believe they may recover in the future (e.g. to prevent further losses or to reallocate funds to a potentially more profitable investment).

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly agree

22. I often sell investments that gained value relatively quickly after purchasing them and/or hold onto investments that lost value relatively quickly after purchasing them.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly agree

23. I only buy stocks that have performed well in the past.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly agree

Portfolio Performance

This part is very important for the research analysis. Please answer truthfully.

24. How satisfied are you with the overall performance of your investment portfolio? *

Mark only one oval.

	1	2	3	4	5	
Very	◯	◯	◯	◯	◯	Very satisfied

25. Compared to all other investors, you consider your portfolio performance to be: *

Mark only one oval.

	1	2	3	4	5	
Very	◯	◯	◯	◯	◯	Excellent

26. How would you rate your portfolio performance in the last year? *

Mark only one oval.

	1	2	3	4	5	
Extr	◯	◯	◯	◯	◯	Excellent (significant gains)

Thank you for participating!

If you wish to withdraw your answers from the survey or get access to the research results, please contact sa6222ma-s@student.lu.se

Appendix III - Gamble Utility Calculations

As per the prospect theory, the utility functions are different in the losses and gains domain. On the losses domain, the utility function can be said to be twice as steep (Tversky and Kahneman 1991; Kahneman, Knetsch, and Thaler 1990) as losses loom larger than gains. The utility functions also flatten out to decrease marginal sensitivity to losses and gains. As such, the formula for the utility function on the gains domain should be $U_G = \sqrt{x}$, while on the losses domain, it should be $U_L =- 2\sqrt{x}$

Question Number	Safe Option Utility	Gamble Option Utility
1	$\sqrt{100} = 10$	$0.5 \times \sqrt{200} + 0.5 \times \sqrt{0} = 7.07$
2	$\sqrt{100} = 10$	$0.5 \times \sqrt{400} - 0.5 \times 2 \times \sqrt{100} = 0$
3	0	$0.5 \times \sqrt{150} - 0.5 \times 2 \times \sqrt{100} =- 3.88$
4	$- 2 \times \sqrt{100} =- 20$	$0.5 \times \sqrt{100} - 0.5 \times 2 \times \sqrt{200} =- 9.14$
5	$- 2 \times \sqrt{100} =- 20$	$0 - 0.5 \times 2 \times \sqrt{150} =- 12.3$

Based on these calculations, the loss-averse response was determined, which is the option with the highest utility given the loss-averse utility functions described by prospect theory.