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Perceptions of Luck and Investment Behavior

A quantitative study examining cognitive biases in financial decision making

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Abstract

The purpose of this thesis is to conduct research on the implication of luck, perceptions of luck and correction of misperceptions on investment behavior. Previous research suggests that luck plays a role in the behavior of individuals and their investment decision making, however perceptions of luck is a field of study lacking research. To investigate these relationships, we conducted an experiment consisting of two tasks: (1) a die roll game and (2) an investment game. The experiment was distributed to a general population sample in the U.S.

We analyze the actual and reported outcomes from the die roll game, and group individuals into different categories according to their perceived and actual luck. To estimate the correlation between different luck measures and investment behavior, we utilize ordinary least squares and logistic regression models. We find that individuals who were unlucky in the first game invest 20% more on average, while individuals who are optimistic regarding their own luck in the first game invest 11% less on average. Individuals who were pessimistic regarding their own luck but receive information confirming that they were luckier than they thought, invest 19% less on average. The results illustrate that perceptions of luck matter in investment decisions. In particular, our findings suggest that investors are subject to Gambler's Fallacy - meaning that people think lucky events are more likely to occur after unlucky events - and that our applied information treatment can help pessimistic individuals avoid this fallacy.

Keywords – Behavioral Finance, Perceptions of Luck, Risk Preferences, Gambler's Fallacy

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1 Introduction

There is no shortage of interest in and attempts to understand the determinants of success. While personal traits including passion, perseverance and intellectual curiosity do significantly explain differences in success (Kaufman, 2018), high-achieving persons often attribute part of their success to luck – that is, exogenous events outside their own control. In recent years, a number of studies and books – including those by risk analyst Nassim Taleb, investment strategist Michael Mauboussin, and economist Robert Frank – have suggested that luck and opportunity play a greater role in life trajectories than we ever realized (Kaufman, 2018). Traits and talent undoubtedly matter, but the data suggests that we miss out on an important piece of the picture when we disregard the role of luck and chance.

There are several examples of how seemingly minor random events alter life trajectories in major ways. For example, the number of CEOs born in June and July is much smaller than the number of CEOs born in other months (Qianqian et al., 2012), and females with masculine sounding names are more successful in legal careers (Coffey and McLaughlin, 2009). The importance of random events can be further magnified when accounting for the positive feedback process known as the Matthew Effect (Frank, 2016). The effect refers to a pattern in which those who begin with advantage accumulate more advantage over time, while those who begin with disadvantage become more disadvantaged over time (Dannefer, 1987; O'Rand, 1996). Consequently, this leads to an ever-widening gap between the advantaged and disadvantaged, although the initial advantage may be small and caused by luck. Even tiny variations often ramify into enormous differences in financial outcomes due to increased confidence and risk-taking, enhanced perceptions and opportunities, positive feedback loops, or self-fulfilling prophecies (Frank, 2016). The overall idea of luck breeding luck is that initial fortunate events can create advantageous conditions that increase the likelihood of further positive outcomes. In the short run, however, individuals may have a different perspective on luck. After sudden experiences of luck, people tend to avoid risk as they believe they have already received their fair share of luck. For example, investors may attribute significant gains in their assets to luck, and sell stocks that have gained value as they believe that the stocks will experience a downturn in the future (Shefrin and Statman, 1994; Odean, 1998).

Moreover, people may differ in what they infer from the same objective outcome. If people take decisions based on whether they were lucky or not in the past, the *perception* of their own luck could also affect these decisions. Consider two people that experience the same series of fortunate and unfortunate events. As both experienced the same events, they are equally lucky. However, they differ in what they are more attentive to. The first individual attributes his achievements solely to his own abilities, and downplays the role of external factors including luck. His attribution to skills fuels his confidence, and as a result he takes calculated risk and actively seeks out new opportunities. On the other hand, the second individual, despite experiencing the same series of fortunate and unfortunate events, consider herself lucky and attributes her success to favorable circumstances and external factors. Because she believes her success is driven by chance rather than being earned, she exhibits a more cautious approach, avoids taking risk and does not pursue new opportunities. The diverging perceptions of luck between the two ultimately lead to diverging life trajectories. While the first's belief in his own abilities drives him to to seek and seize opportunities, leading to a string of favorable outcomes that reinforces his favorable life trajectory, the latter's emphasis on luck prevents her to fully capitalize on potentially beneficial circumstances and ultimately limits her overall progress.

Why do some people feel lucky – is it because they are overly optimistic about the frequency of lucky events, or because they neglect unlucky events? Is it possible to influence how lucky people feel and thus affect their life decisions? While realized luck has been shown to affect decisions, perceptions of luck is a field of study lacking research. In an attempt to shed light on this issue, we carry out an experiment studying the implication of luck, perceived luck and correction of (mis)perceptions on investment behavior. The experiment comprises two main tasks. The first task aims to create differences in actual luck and investigate individuals' perception of their own luck. This task will allow us to identify individuals as lucky or unlucky (based on actual luck), and optimist or pessimist (based on perceived luck). We can also identify the source of overoptimism: Is it from people overstating the frequency of lucky events, or because they understate the frequency of unlucky events? The second task aims to map out the individuals' risk preference using the classic investment game developed by Gneezy and Potters (1997). By combining the two tasks, we can explore the correlation between actual or perceived luck and the willingness to take risk, controlled for other personal characteristics such as gender and overconfidence. To our knowledge, this experimental study is the first to estimate the impact of perceived luck on investment behavior. Our findings can therefore serve as a starting point for further research on perception of luck and behavioral finance.

The thesis is structured as follows: In chapter 2 we provide relevant literature on the topics of behavioral finance and attributions to luck. In chapter 3 we present the experimental design, before we present our hypotheses in chapter 4. In chapter 5 we present the methodology our analysis builds upon. The results from our analysis are reported in chapter 6, followed by a discussion of the findings in chapter 7. We finally summarize the results in chapter 8.

2 Literature Review

This chapter gives an overview of relevant literature to provide a better understanding of the relationship between this study and previous research. As aforementioned, our study is the first to investigate the effect of perceived luck on investment behavior. Accordingly, there is a lack of relevant literature on the relationship of interest. However, there exists extensive literature on the determinants for risk preferences as well as attributions to realized luck. In the following we will present literature on the link between actual luck and investment behavior, and give an overview of the existing literature on perceived luck. Lastly, we will present personal traits that are known to correlate with risk preferences.

2.1 Actual Luck

In recent years, research in economics and psychology has shown that luck is an important determinant for success. While talent and effort are indeed highly important qualities (Frank, 2016), the literature emphasizes the significant influence of luck on outcomes. Mauboussin (2012) elaborates on the *Paradox of Skill*: As skill improves, performance becomes more consistent and therefore luck becomes more important. For example, in competitive environments, organizations tend to follow the same strategies and become increasingly similar. Thus, luck becomes a key determinant for success. Frank (2016) argues that luck and chance have become even more important in recent decades due to technological advancement. In sectors where technology enables providers to capture entire markets, the quality difference between best and second best is often barely perceptible, but the corresponding difference in rewards can be enormous. In fields from manufacturing to academia, new methods of production and communication have amplified the effect of chance events and magnified the gaps between winners and losers. Moreover, Mauboussin (2012) elaborates on how the Paradox of Skill also applies to financial markets. If stock prices reflect all available information, implying that the market is efficient, it becomes challenging for investors to outperform the market based solely on skill. Consequently, luck becomes an important determinant for predicting price movements.

When it comes to choice under risk, one important cognitive ability is to properly estimate the probability of an event. Standard economic theory assumes that people are Bayesian information processors who maximize their expected utility (Thaler, 1992). Yet, we observe that individuals are often wrong when estimating probabilities. A possible explanation is *The Law of Small Numbers*, which says that people believe that a small sample should resemble closely to the underlying population, i.e., they underestimate the variability in small samples (Tversky and Kahneman, 1971).

The consequences of the law of small numbers in probability judgement can manifest in two ways, dependent on whether the probability distribution is known or not (Rabin, 2002). When the probability distribution is known by individuals, such as for a coin flip or a roll of a die, the law of small numbers implies that people have a tendency to believe that a particular outcome (e.g. a head) is less likely to occur if it has already been realized. This cognitive bias is called the *Gamblers Fallacy*: After observing a particular signal, individuals expect the next signal to be of the opposite type (Tversky and Kahneman, 1971). This line of thinking is incorrect, as past events does not change the probability that certain events will occur in the future. In the cases of known probability distributions, people are aware of the initial distribution, but they fail to understand that the distribution remains constant. The phenomenon is also known as the 'Monte Carlo Fallacy' named after a casino in Las Vegas where the bias was observed in 1913. The roulette wheel's ball had fallen on black several times in a row, which lead people to believe that it would fall on red soon, neglecting the fact that the odds of black or red remains the same for each shot (Owen, 2011).

The bias of Gambler's Fallacy has been observed in financial decision making. Shefrin and Statman (1994) developed a model to observe how traders infer from past observations. The researchers found that investors are either true Bayesian or make one of two common errors. They are either subject to base rate neglect where they underweight prior information and place more emphasis on recent events, or they commit the Gambler's Fallacy where they expect recent events to reverse. This is related to the disposition effect in finance which concerns the tendency of investors to sell (buy) stocks that have gained (lost) value. The reasoning behind this is that investors who have experienced repeatedly increased value in the past, are likely to believe that they will experience a downturn in the future (Shefrin and Statman, 1994; Odean, 1998).

In situations where the probability distribution is unknown, individuals are subject to overinference, a cognitive bias where individuals tend to make conclusions or judgements that go beyond available evidence (Rabin, 2002). After observing signals of one type, they expect the next signal to be of the same type. The literature provides empirical evidence indicating that investors are subject to this bias. Guillermo and Verbeek (2006) studied investors' overinference of managers' talent and found a relationship between the performance of a fund and the historical performance of a manager. Their research reveals that investors make decisions based on short-term performance streaks of managers. Thus, the longer the winning (losing) streak, the more likely they were to invest (divest) in a particular fund. Guillermo and Verbeek (2006) argues that the bias of overinference can be a driver for momentum investing, a phenomenon frequently observed due to investors' overreaction in the stock market.

2.2 Perceived Luck

Given the evidence that luck plays a role in the behavior of individuals and their investment decision-making, it follows that the perception of luck might also be an important factor. As previously pointed out, our study is the first to examine the effect of perceived luck on investment behavior. Accordingly, there is a lack of relevant literature. However, there exists literature on how perceptions of luck can influence decision making in general.

To begin with, human decision making in general is not rational and can be influenced by biases that impact individuals' choices and judgement. Two prominent biases in the literature are *Optimism Bias* and *Cognitive Dissonance*. Optimism Bias is defined as the difference between an individual's expectation and the outcome it follows. If expectations are better (worse) than reality, the bias is optimistic (pessimistic). It is found that humans have a tendency to overestimate the likelihood of positive events and underestimate the likelihood of negative events. For example, students tend to overestimate positive events in terms of numerous job offers and high salaries after graduating. On the other hand, people tend to underestimate negative events such as the time and costs required for a project (Sharot, 2011). Cognitive Dissonance, on the other hand, is the mental discomfort that results from holding two conflicting beliefs, values or attitudes (Cherry, 2022). To reduce this discomfort, individuals aim to align their decisions and beliefs with their desired self-image. An example of cognitive dissonance could be a smoker that is aware of the harmful health consequences of the habit, but refuses to quit. To reduce the discomfort, the smoker rationalize the action by referring to high stress levels (Cherry, 2022).

The literature further highlights that perceived luck can influence human decision making. Jiang et al. (2009) examine the effects of feeling lucky on consumer behavior in several experiments. The participants were exposed to a supraliminal priming technique to influence their perception of feeling lucky or unlucky. Afterwards, they were asked to indicate their likelihood of winning a lottery. The results found that participants who felt lucky also believed that they had a greater chance of winning the lottery.

Additionally, Smith (1998) elaborates on psychological factors related to perceived luckiness. As expected, self-perceptions of luck appear largely related to individuals experiencing numerous lucky events in the past. However, this memory can be unreliable, and people might selectively recall unlucky or lucky events. Thus, when looking back at past experiences, individuals tend to focus on either positive or negative events. Smith (1998) also suggests that there exists a relationship between perceived luckiness and expectations for the future. He argues that individuals with a strong belief of being lucky (unlucky) in the past, will continue to feel lucky (unlucky) in the future.

Overconfidence is a central topic in the context of perceived luck. It refers to a common tendency to overestimate one's ability to predict and control future outcomes. This bias can cause individuals to be overly optimistic about their abilities and to take on more risk than is warranted, which can ultimately lead to poor decision-making. Overconfidence can manifest in several ways, and one of them, commonly observed in the field of finance, is the *Better-Than-Average* (BTA) effect (Skala, 2008). The BTA-effect is a cognitive bias that describes the tendency for individuals to overestimate their own abilities and qualities relative to others, even when this is statistically impossible (Young-Hoon et al., 2017). The BTA-effect can be applied to analyze different aspects of people's optimism towards the future, by letting participants compare their chances of a potential fortune or misfortune to those of an average person.

Another aspect of overconfidence is a phenomenon called *Illusion of Control*. This concerns the tendency of individuals to believe that they can influence chance driven events based on their past experiences or skills. An example of this could be individuals insisting on rolling a die personally, as they believe they can influence the result. The existence of

Illusion of Control has been proven repeatedly in experimental research (Skala, 2008).

2.3 Personal Characteristics

In addition to luck and perceived luck, investment behavior is likely to be affected by a number of personal characteristics. The most obvious being an individual's general risk preference. With regards to risk preferences, investors can be categorized into three groups; risk averse, risk neutral and risk lover, based on their attitude towards risk and expected value. The term risk averse describes an investor who reject investment portfolios that are fair games or worse. They avoid risk and prioritizes the perseveration of capital over the possibility of earning higher-than average expected returns. Most investors tend to exhibit risk-averse behavior. On the contrary, risk neutral investors are indifferent to risk, and focus solely on potential gains from investment. Risk loving investors, however, are willing to engage in fair games and gambles and willing to take on additional risk for a relatively small increase in expected return (Bodie et al., 2021).

Moreover, there are various discussions in the literature with regards to how other personal characteristics affects investment behavior. Grinblatt and Keloharju (2009) analyzed the role of overconfidence on the trends and behavior of investors in capital markets. Their research concluded that investors with greater self-confidence are the ones most involved in the market. Additionally, Odean (2008) examined how overconfidence among traders affects the financial market and found an increase in trading volume to be the most robust effect. Johnson et al. (2006) find significant gender differences with regards to overconfidence in the sense that men have higher self-perceptions than women. In addition, Charness and Gneezy (2011) found that women are, on average, more risk averse than men in financial decision making. The literature also outlines differentiated levels of risk tolerance in demographic and socioeconomic factors such as age, occupation, income and education (Grable, 2000). However, the causality and direction of effect varies in the literature and thus remains unclear.

3 Data

In this chapter, we present the data used to investigate the effect of actual, perceived and correction of misperceived luck on investment behavior. We explain how the data was collected, the experimental design, and the variables in the data set. Lastly, we report descriptive statistics on the data collected from the experiment.

3.1 Data Collection

In order to identify the effect of perceived luck on investment behavior, we conducted an experiment where responses from N=799 individuals were collected. The survey was distributed to U.S. respondents via the platform Prolific. The respondents were incentivized to participate in the survey by a show up fee of $1. In addition, participants could earn a bonus dependent on the outcomes of two games included in the survey. We did not collect any information that could identify an individual participant. The entire survey can be found in Appendix 1.

3.2 Experimental Design

The objective of our experiment is to conduct research on the implication of luck, perceived luck and correction of potential misperceptions on investment behavior. For this purpose, the participants participated in two tasks: (1) a die roll game and (2) an investment game. In addition, we asked questions to collect standard socioeconomic variables and information about general life satisfaction, willingness to take risk and indicators of overconfidence.

Background Information

The first part of the survey consists of questions regarding demographic background and personal characteristics. The purpose of this section is primarily to ensure that our data is collected from a diverse sample. Furthermore, we aim to study the relationship between these background variables and the amount invested in the second game. This particularly concerns factors that the literature highlights as important for investment behavior, such as gender, risk appetite and overconfidence.

Die Roll Game

The survey then proceeds to the first game, the die roll game. In this game, participants are asked to roll an electronic die several times. Each time a die results in a six, the participants receive a monetary award of \$0.1. The number of dice rolls are randomly set to 36 or 48, but the number is not known to the participants in advance. After the last die roll, the participants are asked to state how many times they rolled the die and how many times they got a six.

The die roll game is included in the survey to investigate the individuals' perception of their own luck. On average, participants that roll the die 36 and 48 times should get a six 6, respectively 8 times. However, their *actual* luck might differ from these numbers. This enables us to classify people into lucky and unlucky individuals. We are also interested in individuals' *perceived* luck. The participants can be classified into optimistic and pessimistic individuals based on their guesses on the number of rolls and sixes. Optimistic individuals would report a higher number of sixes than they rolled, and/or a lower number of total rolls than rolled. The opposite counts for pessimistic individuals, that would report a lower number of sixes than they rolled, and/or a higher number of total rolls than rolled.

Investment Game

In the final part of the survey, the respondents participated in an investment game based on the design of Gneezy and Potters (1997). For this task, the individuals are offered \$0.5 and asked how much of it they would like to invest in a risky option. The money not invested is guaranteed for the participant to keep. The money invested will with 50% chance result in a return, and with 50% chance be lost and deducted from the participants' payment. Thus, the probability for the investment being successful (unsuccessful) is p = 0.5. If the investment is successful, the invested amount increases by a factor k = 3. As

$$
\begin{aligned}
p * k &> E(V)_{\text{Not investing}} \\
0.5 * 3 &> 0.5,
\end{aligned}
$$

it follows that the expected value of investing is higher than the expected value of not investing. As a result, both risk neutral and risk seeking participants will choose to invest the entire amount of $0.5.

By combining the results from the two games we are interested in understanding how luck and perception of luck is associated with investment behavior. For example, whether individuals that are, or perceive themselves to be, lucky tend to take more risk.

Information Treatment

In addition to being randomized into groups of 36 or 48 dice rolls, the participants were also randomized into a 'treatment' and a 'control' group. After completing the die roll game, the participants in the control group proceeded to the investment game without receiving information about their success in the first game. The participants in the treatment group received correct information about how many times they rolled the dice and how many times they rolled a six before proceeding to the next game. The rationale for this treatment is to investigate whether correcting individuals' misperceptions of luck affects the investment behavior in the investment game.

3.3 Descriptive Statistics

In this subsection we present descriptive statistics to characterize our sample in terms of background characteristics, the distribution of realized luck and perceptions of it.

3.3.1 The Sample

The sample consists of data from 799 respondents. Table 3.1 shows summary statistics of the demographics for the full sample.

Table 3.1: Demographic Statistics

Variable	Category	Frequency	%
Age Group	18-30	196	25%
	31-40	298	37%
	41-50	136	17%
	51-60	107	13%
	61-70	41	5%
	70+	17	2%
Gender	Male	509	65%
	Female	273	34%
	Other	11	1%
	Prefer not to say	2	0.25%
Education	Primary School	3	0.4%
	High School	294	37%
	Bachelor's Degree	347	44%
	Master's Degree	122	15%
	Doctoral Degree	29	4%
Employment	Private Sector	372	47%
	Public Sector	166	21%
	Entrepreneur	107	13.5%
	Unemployed	150	19%
Living Area	Very Rural	63	8%
	Somewhat Rural	180	23%
	Somewhat Urban	396	50%
	Very Urban	156	20%

Examining table 3.1 we observe that the majority of the sample are males, and that more than half of the respondents are under the age of 50. We also note that most individuals obtain higher education, work in the private sector, and live in urban or very urban areas.

With respect to income, table 3.2 shows a large spread in maximum and minimum salary, while both the mean and median income is around $50,000. Overall, the data sample seem to represent a varied collection of individuals.

Table 3.2: Salary Statistics

Median	Mean	Max	Min
$48,000	$53,478	$225,000	$0

Table 3.3: Self Assessed Risk and Overconfidence

Index	0	1	2	3	4	5	6	7	8	9	10
Risk	5%	9%	14%	14%	10%	12%	12%	13%	7%	1%	1%
Overconfidence	0.5%	0.2%	1%	3%	8%	17%	25%	24%	18%	3%	0.6%

Table 3.3 shows characteristics of the sample besides demographics. We were particularly interested to get a better understanding of an individual's risk attitude and degree of (over)confidence. We therefore asked respondents to assess how willing they were to take risk in general (as a proxy for risk attitude), and to evaluate their relative ability in terms of driving skills, math and IQ. The average score of the three latter serves as a proxy for overconfidence.

Regarding self-assessed risk levels, we see that most are somewhat willing to take risk. Further, we observe that relatively more people are strongly averse to risk than risk loving, which is consistent with the academic literature. In terms of overconfidence, the majority score above average on the overconfidence index, implying that they on average consider their IQ-level, driving and math skills to be above average. In fact, only 13% of the sample think they are below average on these metrics.

3.3.2 Luck Measures

In the following, we present the different types of luck we want to investigate. We describe how the measures are calculated and how they are distributed in our sample.

Actual Luck

Actual luck is a measure of how many sixes a participant gets relative to the number of dice rolls:

$$\text{Actual Luck} = \frac{\text{Number of Sixes}}{\text{Number of Dice Rolls}}$$

In the die roll experiment, the outcome of rolling a die is given by a discrete random variable with a uniform distribution, with equal probability $\frac{1}{6}$ for each of the values $\{1, 2, 3, 4, 5, 6\}$. Hence, the expected value for number of sixes relative to the number of rolls equals 0.167.

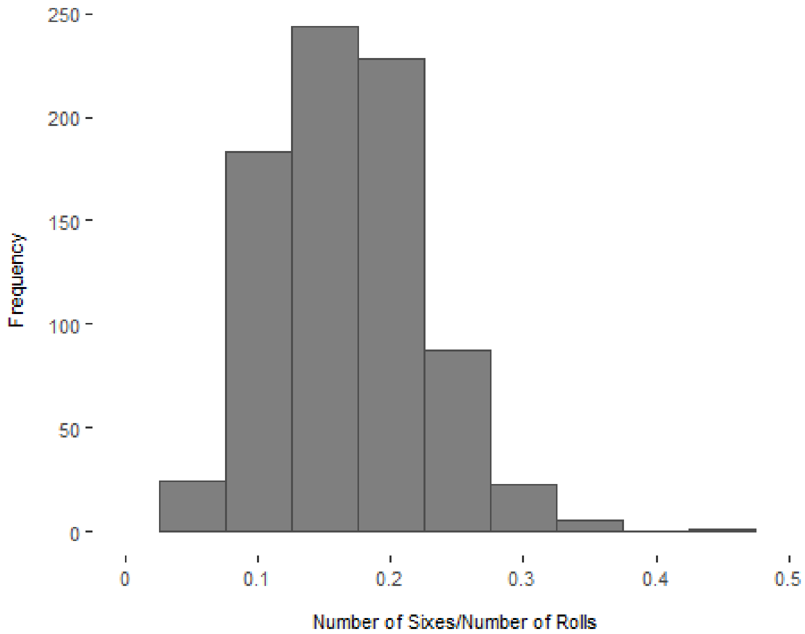

Figure 3.1: Distribution of Actual Luck

Figure 3.1 shows that actual luck, indeed, is centered around the expected value 0.167. However, the figure also reveals that some participants were lucky and got more sixes than expected, and some were unlucky and got fewer sixes than expected. To investigate the effect of actual luck on investment behavior, we divided the sample into three categories: *Lucky*, *Neutral* and *Unlucky*. The categorization is based on how the actual luck measure compares to its expected value, as illustrated in table 3.4.

Table 3.4: Categorization of Actual Luck

	Criteria	N
Lucky	$\frac{6}{\text{Rolls}} > \frac{1}{6}$	344
Neutral	$\frac{6}{\text{Rolls}} = \frac{1}{6}$	119
Unlucky	$\frac{6}{\text{Rolls}} < \frac{1}{6}$	332

Perceived Luck - Sixes

In the die roll experiment, the number of dice rolls is randomly set to 36 or 48. On average, participants should get 6 or 8 sixes, respectively. After completing the task, the participants were asked to state how many times they think they rolled a six. The stated number of sixes compared to the actual number of sixes can be used as a measure for perceived luck, as it reflects people's recollection of lucky events. Figure 3.6 illustrates how the statements of perceived number of sixes compares to the actual number of sixes for the two groups.

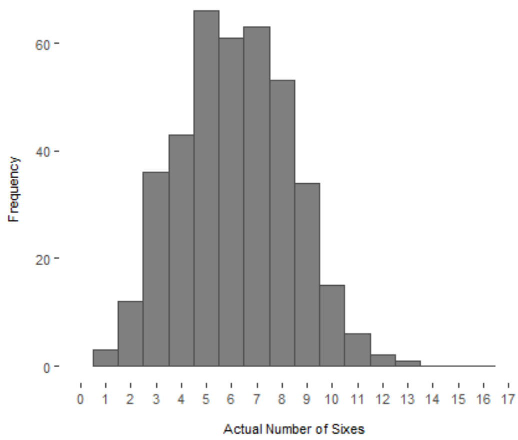

Figure 3.2: Actual Sixes Group 36

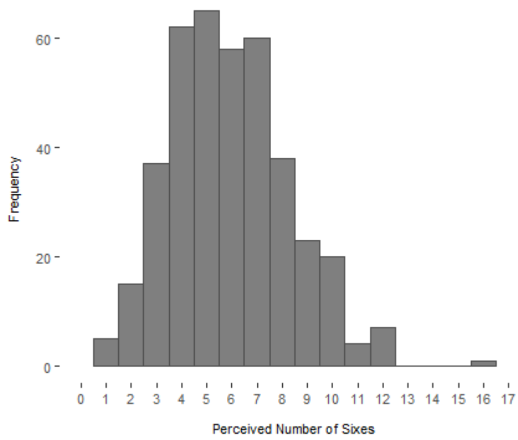

Figure 3.3: Perceived Sixes Group 36

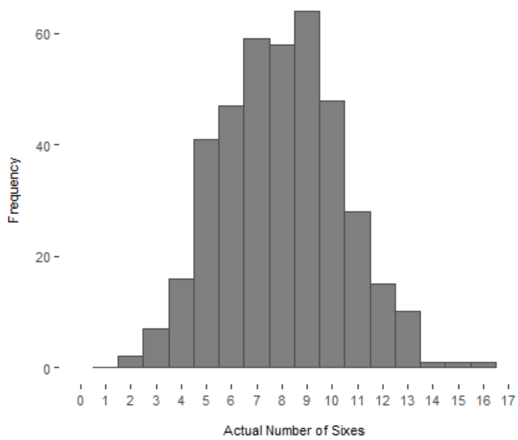

Figure 3.4: Actual Sixes Group 48

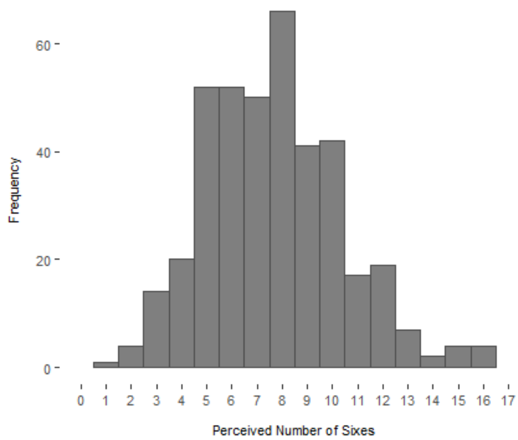

Figure 3.5: Perceived Sixes Group 48

Figure 3.6: Actual Number of Sixes vs Perceived Number of Sixes

From the distributions we see that the participants provide fairly accurate estimates of the number of sixes they have rolled. This may indicate that many have counted the number of sixes in the die roll game.

In order to estimate the effect of perceived number of sixes on the investment amount, we made an index for perceived luck with regards to number of sixes. The index is a measure of the individuals' perceived luck regarding number of sixes adjusted in proportion to the actual number of sixes.

$$\text{Perceived Number of Sixes Index} = \frac{\text{Perceived Number of Sixes - Actual Number of Sixes}}{\text{Actual Number of Sixes}}$$

Participants who state the correct number of sixes will score 0 on the index, and the lower the number, the more pessimistic the individual is regarding number of sixes. To illustrate, $Participant_1$, who got 11 sixes but stated that he got 7, obtains a score of -0.364:

$$\text{Perceived Number of Sixes Index}_1 = \frac{7 - 11}{11} = -0.364$$

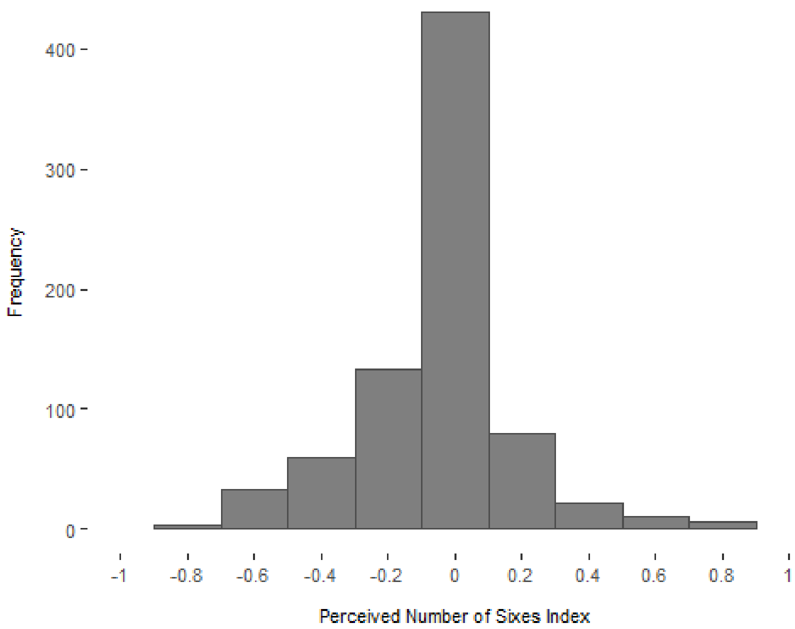

Figure 3.7: Distribution of Perceived Number of Sixes Index

Figure 3.7 shows the distribution of perceived number of sixes index. Again, we see that the participants report fairly accurate estimates of how many sixes they have rolled, as the distribution is centered around 0.

To estimate the effect of perceived luck with regards to number of sixes, we split the sample into three categories *Optimist*, *Realist* and *Pessimist*. The categorization is based on how the participants score on the perceived number of sixes index. Because our sample provided fairly accurate estimates of number of sixes, we used the same categorization criteria as for actual luck, as illustrated in table 3.5.

Table 3.5: Categorization of Perceived Number of Sixes

	Criteria	N
Optimist	$\text{Index}_{\text{Perceived Sixes}} > 0$	143
Realist	$\text{Index}_{\text{Perceived Sixes}} = 0$	419
Pessimist	$\text{Index}_{\text{Perceived Sixes}} < 0$	233

Perceived Luck - Rolls

The participants were also asked to state how many times they rolled the dice. The stated number of rolls compared to the actual number of rolls can be used as a measure for perceived luck, as it reflects people's recollection of unlucky events.

Figure 3.8 and 3.9 shows the stated number of rolls for group 36 and group 48. From the distributions we see that participants' estimates of the number of times they have rolled the die are quite far from the actual number of rolls, especially when compared to the correct statements on number of sixes, reported above. The distribution for both groups is left-skewed, indicating that most participants underestimate the number of times they have rolled the die. Hence, they tend to neglect unlucky events (i.e. rolls that did not result in a six).

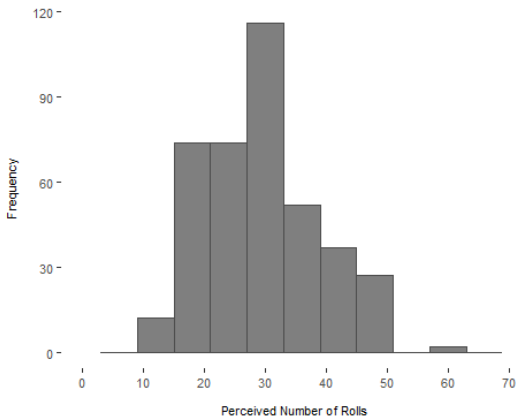

Figure 3.8: Perceived Number of Rolls Group 36

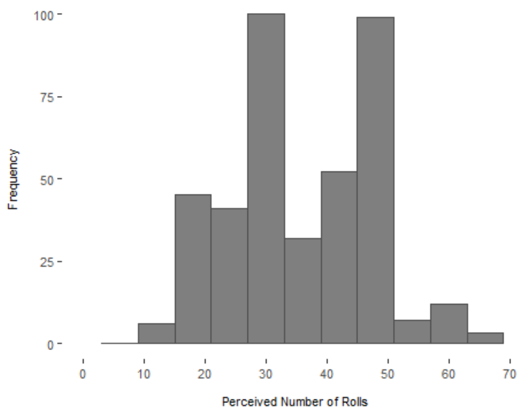

Figure 3.9: Perceived Number of Rolls Group 48

In order to estimate the effect of perceived number of rolls on the investment amount, we made an index for perceived luck with regards to number of rolls. The index is a measure of the individuals' perceived luck regarding the number of rolls adjusted in proportion to the actual number of rolls:

$$\text{Perceived Number of Rolls Index} = \frac{\text{Actual Number of Rolls - Perceived Number of Rolls}}{\text{Actual Number of Rolls}}$$

Participants who state the correct number of rolls will score 0 on the index, and the higher the number, to the larger extent the participant underestimate the number of dice rolls. To illustrate, $Participant_1$, who rolled the die 48 times but stated that he rolled the die 20 times, obtains a score of 0.583:

$$\text{Perceived Number of Rolls Index}_1 = \frac{48 - 20}{48} = 0.583$$

Figure 3.10 shows the distribution of the perceived number of rolls index.

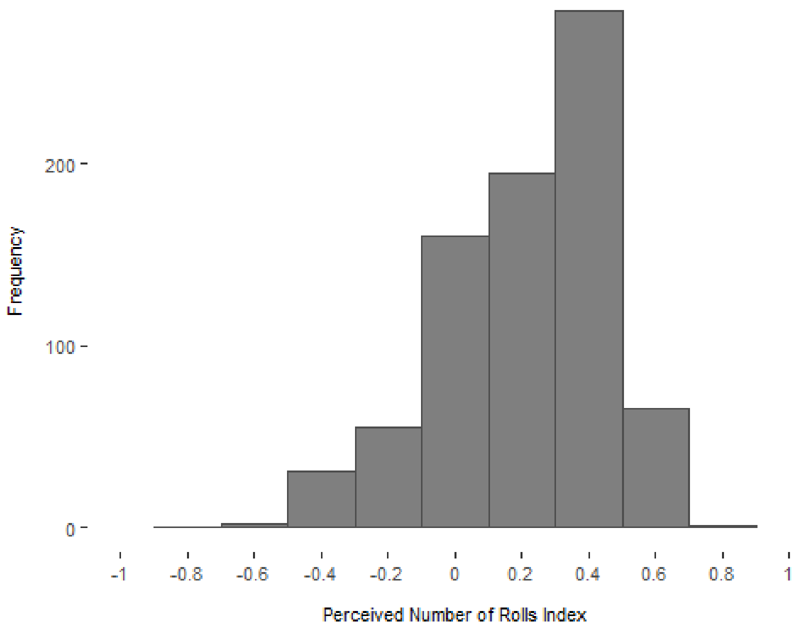

Figure 3.10: Distribution of Perceived Number of Rolls Index

The right-skewed distribution indicates that most participants are overconfident in the sense that they underestimate the number of unlucky events and therefore the number of rolls.

To estimate the effect of perceived luck with regards to number of rolls, we split the sample into the three categories *Optimist*, *Realist* and *Pessimist*. The categorization is based on how the participants score on the perceived number of rolls index. As most participants underestimate the number of rolls and thus score above 0 on the index, we expanded the criteria for being realistic to include 0-0.2. The categorization is illustrated in table 3.6.

Table 3.6: Categorization of Perceived Number of Rolls

	Criteria	N
Optimist	$\text{Index}_{\text{Perceived Rolls}} > 0.2$	386
Realist	$0 \leq \text{Index}_{\text{Perceived Rolls}} \leq 0.2$	215
Pessimist	$\text{Index}_{\text{Perceived Rolls}} < 0$	194

Perceived Luck - Total

To estimate the effect of perceived luck on investment behavior, we also made an index that takes both perceived number of sixes and perceived number of rolls into account. The index measures an individuals' perceived luck relative to their actual luck by putting perceived number of sixes and perceived number of rolls in proportion to the actual number of sixes and actual number of rolls:

$$\text{Perceived Luck Index} = \text{Perceived Luck - Actual Luck}$$

$$\text{Perceived Luck Index} = \frac{\text{Perceived Number of Sixes}}{\text{Perceived Number of Rolls}} - \frac{\text{Actual Number of Sixes}}{\text{Actual Number of Rolls}}$$

The index goes from [-1,1]. The higher the measure, the greater the degree to which the individual overestimates their own luck. Once again, we use Participant_1 to illustrate. We know that Participant_1 is pessimistic regarding number of sixes and optimistic regarding the number of dice rolls. In total, Participant_1 is optimistic because he underestimates the number of rolls to a greater extent than he overestimates the number of sixes. Participant_1 obtains a score of 0.121 on the perceived luck index:

$$\text{Perceived Luck Index}_1 = \frac{7}{20} - \frac{11}{48} = 0.121$$

Figure 3.11 shows the distribution of the perceived luck index.

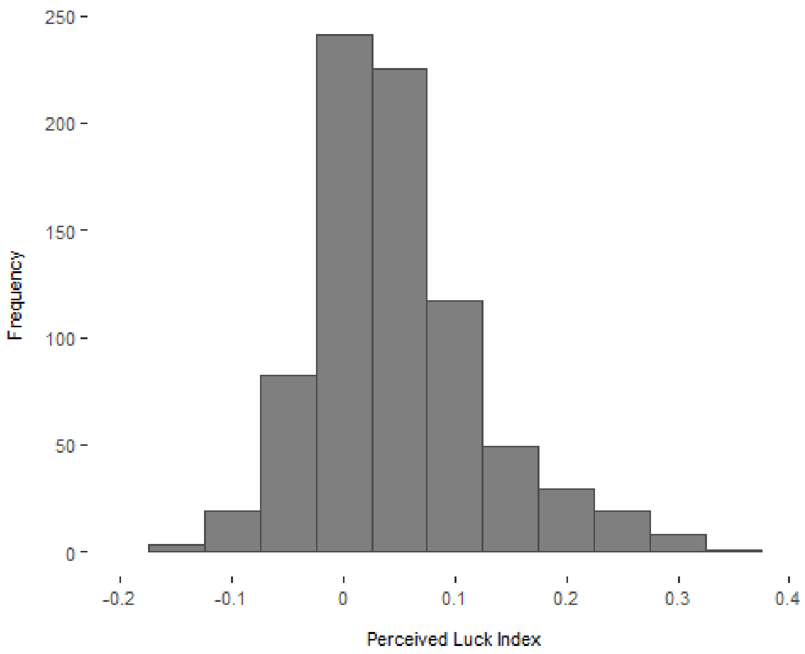

Figure 3.11: Distribution of Perceived Luck Index

The distribution is right-skewed, indicating that most participants are overconfident regarding their actual luck.

To estimate the effect of perceived luck with regards to both number of sixes and number of rolls, we split the sample into the three categories: *Optimist*, *Realist* and *Pessimist* based on how the participants score on the perceived luck index. Again, we observe that most participants score above 0 on the index. To account for this, and achieve a somewhat equal number of participants in the three categories, we expanded the criteria for being realistic to include 0-0.075. The categorization is illustrated in table 3.7

Table 3.7: Categorization of Perceived Luck

	Criteria	N
Optimist	$\text{Index}_{\text{Total}} > 0.075$	225
Realist	$0 \leq \text{Index}_{\text{Total}} \leq 0.075$	342
Pessimist	$\text{Index}_{\text{Total}} < 0$	228

4 Hypotheses

Based upon the literature review and the aim of our study, the following chapter will present our hypotheses. First, we present hypotheses regarding the effect of actual and perceived luck on investment behavior. Second, we present a hypothesis that addresses how possible misperceptions can be corrected by a treatment.

4.1 Hypothesis 1

The first hypothesis is concerned by the effect of actual luck on investment behavior. If people act rationally, their investment decision should not be influenced by whether they have had luck in the past or not. This forms the basis of our null hypothesis:

Hypothesis 1.0 Realized luck does not cause investors to take more or less risk

However, if realized luck does affect the investment decision, this can manifest in two different dimensions. Since the probability distribution in the investment game, and thus the expected value, is known, we expect to observe the Gambler's Fallacy rather than overinference. If investors are subject to the Gambler's Fallacy, they will invest based on the belief that having luck (unluck) in the past will increase the chance of being unlucky (lucky) in the investment:

Hypothesis 1.1 Realized luck (unluck) causes investors to take less (more) risk

On the other hand, if investors are subject to overinference, they would invest based on the belief that having luck (unluck) in the past will give them continued luck (unluck) in the investment game:

Hypothesis 1.2 Realized luck (unluck) causes investors to take more (less) risk

4.2 Hypothesis 2

The motivation for our thesis is to investigate whether not only realized luck, but also perceptions of luck, can have an impact on investment behavior. Once again, if people act rationally, the investment decision should not be influenced by their perception of luck.

This forms the basis of our null hypothesis:

Hypothesis 2.0 Perceived luck does not cause investors to take more or less risk

Then again, if individuals are subject to Gambler's Fallacy, they will invest based on the belief that their perceived luck (unluck) will give them unluck (luck) in the investment game:

Hypothesis 2.1 Optimistic (pessimistic) investors take less (more) risk

In addition, if individuals are subject to overinference, they will invest based on the belief that their perceived luck (unluck) will give them luck (unluck) in the investment game:

Hypothesis 2.2 Optimistic (pessimistic) investors take more (less) risk

4.3 Hypothesis 3

If we find that perceptions of luck do impact investment behavior, and that perceptions can be altered, this implies that people can be nudged towards making rational investment decisions. To test whether a treatment can correct possible misperceptions of luck, the null hypothesis and related alternative-hypotheses are:

Hypothesis 3.0 Correcting misperceptions of luck does not cause investors to take more or less risk
Hypothesis 3.1 Correcting misperceptions of luck causes optimistic (non-optimistic) investors to take more (less) risk
Hypothesis 3.2 Correcting miscperceptions of luck causes optimistic (non-optimistic) investors to take less (more) risk

5 Methodology

In this chapter, we present the estimation methods used to investigate the effect of luck, perceived luck and correction of potential misperceptions on investment behavior.

5.1 OLS as an Estimator

The OLS estimator estimates the relationship between two variables by minimizing the sum of squared residuals in a sample (Wooldridge, 2013). The simple linear regression model is defined as follows:

$$\mathrm{y} = \beta_0 + \beta_1 \mathrm{x}_1 + u \tag{5.1}$$

If more variables are added the model changes to a multiple linear regression model. A multiple linear regression model with k variables is defined as follows:

$$\mathrm{y} = \beta_0 + \beta_1 \mathrm{x}_1 + \beta_2 \mathrm{x}_2 + ... + \beta_k \mathrm{x}_k + u \tag{5.2}$$

Wooldridge (2013) presents five assumptions that are important for the causal interpretation and efficiency for OLS estimators. Next, we will present the assumptions and elaborate on whether they are fulfilled in our setting.

Linear in Parameters

The first assumption states that the population model must be linear in the parameters only. This implies that the dependent variable y is related to the independent variable x and the error term u. Without further need for discussion, this assumption is fulfilled.

Random Sampling

The random sampling assumption implies that individuals need to be randomly selected from the population, in order to make inference about the parameters. As our sample consists of survey responses from a general population sample in the US, we consider this assumption to be fulfilled.

No Perfect Collineraity

No perfect collinearity implies that none of the independent variables in the sample can be constant and that there can be no exact linear relationship among them. When investigating the relationship between our independent variables we find none with these characteristics. The assumption is fulfilled.

Zero Conditional Mean

The zero conditional mean assumption implies that the error term u has an expected value of zero given any value of the explanatory variables. When this assumption is violated, x is endogenous, and this prevents the casual interpretation of the OLS estimates. The assumption can be violated by omitted variable bias, reverse causality or measurement errors.

Omitted Variable Bias

For our models, we have used control variables that we consider to be important determinants of investment behavior. Hence, we remove as much as possible of the potential source for omitted variable bias when it comes to the analysis of the potentially endogenous variable perceived luck. Notice, however, that both actual luck and treatment assignment are exogenous by design.

Reverse Causality

The OLS models aim to estimate how perceived and actual luck affects investment behavior. It makes no sense for investment behavior to affect actual or perceived luck, as it was realized before the investment decision. Hence, we do not consider our models to have the problem of reverse causality.

Measurement Errors

A potential source of measurement error could be bias in the survey responses. Looking through the data we noticed certain extreme values for perceived sixes and rolls, implying that participants have not paid attention in the dice roll game. Consequently, four respondents have been removed from the dataset [1]. Aside from this, there are no concerns regarding measurement errors.

[1] All analyses performed on the original dataset with extreme variables included can be found in Appendix 2

Homoscedasticity

Homoscedasticity implies that the error term u has the same variance given any value of the explanatory variable. Violation of this assumption can affect the size of the standard errors and consequently the efficiency and precisions of our estimates. However, this assumption is not important for causal interpretation. As our thesis aims to assess the causal relationship between luck and investment behavior and do not concern prediction, we do not consider the need for further discussion of this assumption.

Under the first four assumptions the OLS estimates are unbiased estimators of the population parameter. Moreover, if the fifth assumption is satisfied, the OLS estimates have the smallest variance, hence they are more precise.

5.2 Logistic Regression

Further, we aim to estimate logistic regression models where the dependent variable for investment amount is a binary variable. The variable will fall into one of two categories:

$$Y = 1 \tag{5.3}$$

Implies that a participant have invested the total investment amount.

$$Y = 0 \tag{5.4}$$

Implies that a participant have not invested the total investment amount.

The logistical function gives the following model:

$$p(X) = \frac{e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_p X_p}}{1 + e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_p X_p}} \tag{5.5}$$

Instead of modeling the response for Y directly, logistic regression models the probablity that Y belongs to one of the categories. Thus, we aim to estimate the probability of investing everything for different categories of perceived and actual luck. Linear regression would not be appropriate method for this scenario as the model would allow for prediction of probabilities outside of the interval (0,1). In contrast, the logistic function will always produce an S-shaped curve, and accordingly always obtain a sensible prediction regardless of the value of X (James et al., 2013).

From equation 5.5 we find that:

$$\frac{p(X)}{1 - p(X)} = e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p} \tag{5.6}$$

The quantity calculated in equation 5.6 is called the odds and can take any value between 0 and ∞. Values close to 0 indicate a very low probability of investing the total investment amount (James et al., 2013).

5.3 The Models

OLS estimation is used to discover the relationship between luck and investment behavior. In addition, we utilize logistic regression models to estimate the probability of investing everything for various subgroups of perceived and actual luck. This section presents all of the models that will be used in the analysis.

Investment amount serves as the dependent variable for all the models. For the logistic regression models investment amount is a binary variable taking the value 1 if a participant have invested the total investment amount. For the OLS regressions investment amount is a numeric variable and includes a range of values between \$0 and \$0.5.

Model 1

The models used to test hypothesis 1 are presented in equation 5.7 and 5.8. The independent variables are dummy variables for three different levels of luck; "Lucky", "Neutral" and "Unlucky". Neutral serves as the base value for participants realizing the expected sixes to rolls ratio of 1/6. The dummy variable Lucky (Unlucky) take the value 1 (0) if the participant is getting more (less) sixes than the expected ratio.

$$\text{Investment Amount} = \beta_0 + \beta_1 \text{Lucky} + \beta_2 \text{Unlucky} + u \tag{5.7}$$

$$p(X) = \frac{e^{\beta_0 + \beta_1 \text{Lucky} + \beta_2 \text{Unlucky}}}{1 + e^{\beta_0 + \beta_1 \text{Lucky} + \beta_2 \text{Unlucky}}} \tag{5.8}$$

Model 2

To test hypothesis 2, we have used six different regressions. All the regressions include dummy variables for three different levels of perceived luck; "Optimist", "Realist" and "Pessimist". Again, realist serves as the base value for participants who state their perceived luck accurately according to their realized luck. The dummy variable Optimist (Pessimist) take the value 1 if the individual reports his perceived luck to be higher than realized, and zero otherwise. The interpretation of the dummy variable with regards to perceived luck is different for each equation. Equation 5.9-5.10, 5.11-5.12, and 5.13-5.14 concerns perceived luck regarding number of sixes, rolls and the two combined, respectively.

$$\text{Investment Amount} = \beta_0 + \beta_1 \text{Optimist}_{Sixes} + \beta_2 \text{Pessimist}_{Sixes} + u \tag{5.9}$$

$$p(X) = \frac{e^{\beta_0 + \beta_1 \text{Optimist}_{Sixes} + \beta_2 \text{Pessimist}_{Sixes}}}{1 + e^{\beta_0 + \beta_1 \text{Optimist}_{Sixes} + \beta_2 \text{Pessimist}_{Sixes}}} \tag{5.10}$$

$$\text{Investment Amount} = \beta_0 + \beta_1 \text{Optimist}_{Rolls} + \beta_2 \text{Pessimist}_{Rolls} + u \tag{5.11}$$

$$p(X) = \frac{e^{\beta_0 + \beta_1 \text{Optimist}_{Rolls} + \beta_2 \text{Pessimist}_{Rolls}}}{1 + e^{\beta_0 + \beta_1 \text{Optimist}_{Rolls} + \beta_2 \text{Pessimist}_{Rolls}}} \tag{5.12}$$

$$\text{Investment Amount} = \beta_0 + \beta_1 \text{Optimist}_{Total} + \beta_2 \text{Pessimist}_{Total} + u \tag{5.13}$$

$$p(X) = \frac{e^{\beta_0 + \beta_1 \text{Optimist}_{Total} + \beta_2 \text{Pessimist}_{Total}}}{1 + e^{\beta_0 + \beta_1 \text{Optimist}_{Total} + \beta_2 \text{Pessimist}_{Total}}} \tag{5.14}$$

Model 3

To test hypothesis 3, a dummy variable for treatment is used as the independent variable, taking the value 1 if an individual has received treatment and 0 otherwise. To inspect the treatment effect, we performed three regressions with different subsets of the data based on the individuals' perceived luck. Equation 5.15-5.16 is applied on the entire sample. Equation 5.17-5.18 and 5.19-5.20 are used on subsets with optimists and non-optimists, respectively.

$$\text{Investment Amount} = \beta_0 + \beta_1 \text{Treatment} + u \tag{5.15}$$

$$p(X) = \frac{e^{\beta_0 + \beta_1 \text{Treatment}}}{1 + e^{\beta_0 + \beta_1 \text{Treatment}}} \tag{5.16}$$

$$\text{Investment Amount}_{Optimist} = \beta_0 + \beta_1 \text{Treatment} + u \tag{5.17}$$

$$p(X)_{Optimist} = \frac{e^{\beta_0+\beta_1 \text{Treatment}}}{1+e^{\beta_0+\beta_1 \text{Treatment}}} \tag{5.18}$$

$$\text{Investment Amount}_{Non-optimist} = \beta_0 + \beta_1 \text{Treatment} + u \tag{5.19}$$

$$p(X)_{Non-optimist} = \frac{e^{\beta_0+\beta_1 \text{Treatment}}}{1+e^{\beta_0+\beta_1 \text{Treatment}}} \tag{5.20}$$

Control Variables

To isolate the effect of luck on investment amount and increase the precision of our estimates, all the above-mentioned regressions are run with control variables.

To control for demographic factors, we included dummy variables for age groups, levels of education, living area, gender and employment. In addition, we have a continuous variable for salary. To control for personal traits and individual characteristics , we included the variables “happiness” and “risk” which are based on self-assessments by respondents on a scale of 0-10. The variable “overconfidence” is based on the average of individuals’ responses on driving skills, IQ-level, and math skills, also on scale of 0-10. Lastly, we have controlled for the earnings participants won in the dice game.

The rationale behind the choice of control variables is the expectation that demographic factors and individual characteristics explain some of the variation in investment behavior. Another motivation is to reduce the potential sources of omitted variable bias.

6 Analysis

In this chapter, we aim to estimate the effect of luck, perceived luck and correction of potential misperceptions on investment behavior. We divide the chapter into four main sections with the purpose of testing the presented hypotheses. Firstly, we give an overview of participants' investment behavior and how it correlates with some important background variables. Secondly, we investigate the effect of actual luck on investment behavior. We then proceed with investigating the effect of perceived luck with regards to sixes, rolls and both of them combined on investment amount. In the last subsection, we investigate whether the treatment has an effect on the amount invested.

For the analysis, we utilize our models specified in subsection 5.3. In all regression tables, the two first regressions are linear models using the OLS-method, and the two latter are logistic regression models where the dependent variable investment amount is a binary variable that take the value 1 if an individual invests everything, and 0 otherwise. Regression (1) reports the results from the OLS-model without control variables, and regression (2) reports results when controlling for all variables. Regression (3) and (4) report results from the logistic model without and with control variables, respectively.

6.1 Investment Amount and Background Variables

Before proceeding to the main analysis, we give a brief overview of investment behavior and how it correlates with some important background variables. Moreover, we run regressions of these background variables on the indexes for perceived luck.

From figure 6.1, we notice a large variation in the investment behavior of individuals, however the majority have invested either zero, half or the total $0.5.

To isolate the effect of luck on investment amount, all of the following regressions are run with control variables. From the literature review, we found that gender, risk behavior and overconfidence can affect investment behavior. Therefore, we aim to investigate if we find a similar effect with these variables in our sample, and have run regressions for gender, risk and overconfidence on investment amount. Additionally, we estimate the correlation between these variables and perceived luck. The regression results are presented in table

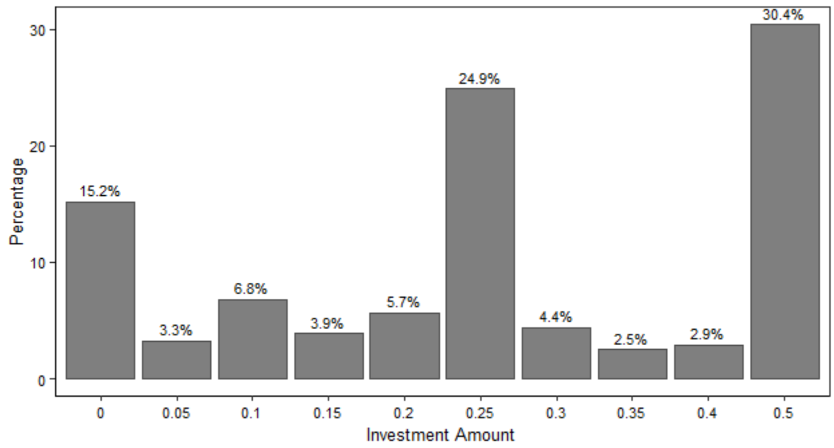

Figure 6.1: Distribution of Investment Amount

6.1.

Table 6.1: Background Variables on Investment Amount and Perceived Luck

	Investment Amount				Perceived Luck		
	(1)	(2)	(3)	(4)	(5)[1]	(6)[2]	(7)[3]
Male	0.044***			0.028*	0.029	-0.019	0.001
	(0.013)			(0.014)	(0.025)	(0.020)	(0.006)
Risk		0.012***		0.009***	-0.001	0.007	0.002
		(0.003)		(0.003)	(0.005)	(0.004)	(0.001)
Overconfidence			0.014**	0.008	-0.008	-0.009	-0.005*
			(0.004)	(0.004)	(0.008)	(0.006)	(0.002)
Constant	0.245***	0.223***	0.184***	0.159***	0.028	0.240***	0.070***
	(0.011)	(0.013)	(0.028)	(0.028)	(0.052)	(0.041)	(0.013)
Adjusted R^2	0.013	0.025	0.012	0.035	-0.001	0.003	0.0.004
Observations	782	795	795	782	782	782	782

Note: *p<0.1; **p<0.05; ***p<0.01
[1] Perceived luck with regards to rolls

[2] Perceived luck with regards to sixes

[3] Perceived luck with regards to both sixes and rolls

For regression model (1), the intercept value of 0.245 represents the average investment amount for female individuals. The coefficient for male is 0.044, implying that male participants have invested an additional \$0.044 (18%) on average compared to female participants. In regression (2), the coefficient for risk is 0.012, meaning that a one unit increase on the scale for self-assessed risk of 1-10 is associated with an increase in investment amount of \$0.12. In regression (3), the coefficient for overconfidence is 0.014 which means that an one unit increase on the overconfidence scale of 0-10 is associated with an increase in investment amount of \$0.012. All of the coefficients are statistically significant. However, when all three variables are combined in regression (4) the coefficient for overconfidence is no longer significant. Moreover, regression (4) shows that the coefficient for gender diminishes, but remains significant when controlling for other factors.

Further, we wanted to investigate how the measures for perceived luck with regards to sixes (5), rolls (6) and both sixes and rolls (7) correlates with gender, risk and overconfidence. For regression model (7), the coefficient for overconfidence is -0.005, which means that an one unit increase on the overconfidence scale of 0-10 is associated with a decrease of 0.005 in the perceived luck total index. The effect is statistically significant at the 10% level, but is relatively minor. The remaining models do not show significant results, and there are no clear patterns for gender, self assessed risk and overconfidence on perceived luck. Hence, perception of luck is not driven by these factors and must originate from other sources. In the next section we will proceed to the main part of the analysis, where we aim to estimate the effect of luck, perceived luck and correction of potential misperceptions on investment behavior.

6.2 Actual Luck

To estimate the causal effect of actual luck on investment behavior, we performed regressions of the categories of actual luck on investment amount. The regression results are reported in table 6.2.

For regression model (1), the intercept value of 0.24 represents the average investment amount for the neutral category, \$0.24. The coefficient for the lucky category is 0.037, which means that participants categorized as lucky invested an additional \$0.037 (15%) on average compared to those in the neutral category. The coefficient is statistically significant at the 10%-level, however it is not statistically significant when control variables are included in model (2). The coefficient for the unlucky category is 0.042, meaning that participants who were categorized as unlucky invested an additional \$0.042 (18%)

Table 6.2: Actual Luck on Investment Amount

	Investment Amount			
	(1)	(2)	(3)	(4)
Lucky	0.037*	0.032	0.191	0.165
	(0.019)	(0.021)	(0.246)	(0.278)
Unlucky	0.042*	0.047**	0.217	0.251
	(0.019)	(0.021)	(0.247)	(0.274)
Constant	0.240***	0.136***	-1.151***	-1.603***
	(0.016)	(0.046)	(0.215)	(0.605)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.007	-0.003		
Observations	795	795	795	795

Note: *p<0.1; **p<0.05; ***p<0.01

on average compared to those in the neutral category. This coefficient is statistically significant at the 10%-level. The effect is stronger and more significant when including control variables: Unlucky participants invest $0.047 (20%) more than neutral participants. The effect is statistically significant at the 5%-level. Thus, we find that actual luck has a statistically significant effect on investment amount for unlucky individuals, but the effect cannot be similarly observed or considered symmetric for lucky individuals.

For the logistic regression models, the intercept represents the estimated log odds of the reference group (when all predictor variables are equal to zero). Model (3) and (4) have a negative intercept, implying that the probability of investing everything is lower for "Neutral" participants compared to the two other groups. From model (3), we see that if an individual is categorized as "Lucky", compared to "Neutral", the estimated change in log odds of investing everything is 0.191. This means that the probability of investing everything is expected to increase by a factor $\exp(0.1909) = 1.21$ times (21%) for an individual who is categorized as "Lucky" compared to "Neutral" individual, ceteris paribus. For individuals categorized as "Unlucky", the odds for investing everything increases by 0.217. The probability for investing everything increases by a factor $\exp(0.217) = 1.24$ times (24%) when an individual is categorized as "Unlucky" compared to "Neutral". However, none of the results are statistically significant.

6.3 Perceived Luck

Conditional on the actual luck, the participants may be over- or underconfident with respect to *experienced* luck, manifested in the stated proportion of sixes being larger or smaller than it actually was. In this section, we aim to estimate the correlation between perceived luck and investment behavior. We divide the section into three subsections based on the different types of perceived luck: Perceived luck regarding number of sixes, perceived luck regarding number of rolls, and perceived luck for the sixes to rolls ratio.

6.3.1 Perceived Luck - Sixes

To estimate the correlation between perceived luck regarding number of sixes on investment behavior, we again performed both linear and logistic regressions. The results are reported in table 6.3.

Table 6.3: Perceived Number of Sixes Index on Investment Amount

	Investment Amount			
	(1)	(2)	(3)	(4)
Optimist	0.027	0.024	0.130	0.123
	(0.017)	(0.017)	(0.213)	(0.218)
Pessimist	0.000	-0.000	0.004	0.004
	(0.015)	(0.015)	(0.184)	(0.190)
Constant	0.269***	0.176***	-1.001***	-1.382**
	(0.008)	(0.038)	(0.110)	(0.509)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.007	-0.003		
Observations	795	795	795	795

Note: *p<0.1; **p<0.05; ***p<0.01

From the first regression the intercept value tells us that the average investment for the realist category, that is, those who stated the correct number of sixes, is \$0.269. The coefficient for the optimist category is 0.027, meaning that participants categorized as optimists invested an additional \$0.027 (10%) on average compared to the realistic participants. The result is not statistically significant. Being pessimistic regarding the number of sixes does not seem to have an impact on the amount invested. From regression (2) we see that the effect does not change much when including control variables, and it is not statistically significant.

For the logistic regression models the intercept values are negative, meaning that individuals categorized as "Realist" regarding number of sixes are less inclined to invest everything compared to the "Lucky" or "Unlucky" individuals. Being categorized as "Lucky" increases the odds of investing everything by 0.130, implying that the probability for investing everything is expected to increase by a factor $e^{0.130} = 1.13$ times (13%) compared to individuals categorized as "Realist", ceteris paribus. Being categorized as "Unlucky" seems to have a rather small effect on the probability of investing everything. None of the results are statistically significant.

6.3.2 Perceived Luck - Rolls

After completing the dice roll task, the participants were also asked to state how many times they think they rolled the dice. The extent to which participants under- or overestimate the number of rolls can also be used as a measure of perceived luck.

To estimate the correlation between perceived luck regarding number of dice rolls and investment behavior, we performed the same regressions as for perceived luck sixes. The results are reported in table 6.4.

Table 6.4: Perceived Number of Rolls Index on Investment Amount

	Investment Amount			
	(1)	(2)	(3)	(4)
Optimist	-0.033**	-0.032**	-0.162	-0.165
	(0.015)	(0.020)	(0.189)	(0.193)
Pessimist	-0.023	-0.020	-0.114	0.004
	(0.018)	(0.018)	(0.220)	(0.190
Constant	0.295***	0.206***	-0.870***	-1.223*
	(0.149)	(0.039)	(0.110)	(0.521)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.007	-0.003		
Observations	795	795	795	795

Note: *p<0.1; **p<0.05; ***p<0.01

The intercept value from regression (1) tells us that the average amount invested for the realist category is \$0.295. The coefficient for the optimist category is -0.033, implying that participants categorized as optimists invested \$0.033 (11%) less on average compared to the realistic participants. The result is statistically significant at a 5%-level. When including control variables, optimists invest \$0.032 (11%) less compared to the realists, the effect being statistically significant at a 5%-level. Being pessimistic regarding the number of rolls does not seem to have an impact on the amount invested, thus the effect cannot be considered symmetric.

For the logistic models the intercept values are negative, meaning that individuals categorized as “Realist” regarding number of rolls are less likely to invest everything compared to individuals categorized as "Optimists" or "Pessimistic". Being categorized as optimistic or pessimistic reduces the odds of investing everything by 0.162 and 0.114, respectively. This implies that the probability of investing everything is expected to decrease by $e^{0.162} = 1.18$ times (18%) when categorized as "Optimist" and by $e^{0.114} = 1.12$ times (12%) when categorized as "Pessimist", ceteris paribus. The effect for pessimists changes when control variables are included. However, none of the results are statistically significant.

6.3.3 Perceived Luck - Total

Further we wanted to investigate how the total measure of perceived luck, taking perceptions of both sixes on rolls into account, correlates with investment behavior. We performed the same regressions on the index for perceived luck total. The results are reported in table 6.5.

Table 6.5: Perceived Luck Index on Investment Amount

	Investment Amount			
	(1)	(2)	(3)	(4)
Optimist	-0.020	-0.021	-0.101	-0.108
	(0.015)	(0.016)	(0.193)	(0.198)
Pessimist	-0.014	-0.013	-0.069	-0.070
	(0.015)	(0.016)	(0.191)	(0.199)
Constant	0.283***	0.190***	-0.928***	-1.307*
	(0.001)	(0.038)	(0.120)	(0.506)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.007	-0.003		
Observations	795	795	795	795

Note: *p<0.1; **p<0.05; ***p<0.01

From regression (1), the intercept value tells us that the average amount invested for the realist category is \$0.283. The coefficient for optimists is -0.02, meaning that participants categorized as optimists with regards to total perceived luck on average invested \$0.02 (7%) less compared to the realistic participants. The coefficient for the pessimist category is -0.014, meaning that participants categorized as pessimists invested \$0.014(5%) less on average compared to the realists. However, none of the coefficients are statistically significant, nor when including all control variables in model (2).

From regression model (3) we have a negative intercept value, implying that individuals categorized as "Realist" are less likely to invest everything compared to individuals categorized as "Optimist" or "Pessimist". Being categorized as optimistic or pessimistic reduces the odds of investing everything by 0.101 and 0.069, respectively. This implies that the probability of investing everything is expected to decrease by $e^{0.101} = 1.10$ times (10%) when categorized as "Optimist" and by $e^{0.069} = 1.07$ times (7%) when categorized as "Pessimist", ceteris paribus. The coefficient does not change much when controlling for all variables in regression (4), however none of the results from the logistic models are statistically significant.

To inspect the external validity of the results for perceived luck on investment amount, we performed six regressions with different subsets of the data. The models are presented in table 6.6. Regression (1) and (2) are used on subsets with individuals over and under the age of 40, respectively. Regression (3) and (4) are used on subsets with male and female, respectively. Finally, regression (5) and (6) are used on subsets with individuals obtaining higher education or only high school, respectively.

Table 6.6: Perceived Luck Index on Investment Amount for Sub-samples

	Investment Amount					
	(1)[1]	(2)[2]	(3)[3]	(4)[4]	(5)[5]	(6)[6]
Optimist	-0.044*	0.027	-0.024	-0.018	-0.01	-0.028
	(0.019)	(0.026)	(0.020)	(0.025)	(0.022)	(0.026)
Pessimist	-0.031	0.010	-0.012	-0.028	-0.025	0.006
	(0.020)	(0.024)	(0.020)	(0.024)	(0.022)	(0.025)
Constant	0.289***	0.273***	0.299***	0.258***	0.287***	0.266***
	(0.012)	(0.016)	(0.012)	(0.016)	(0.014)	(0.017)
Adjusted R^2	0.007	-0.003	-0.001	-0.002	-0.002	-0.001
Observations	494	301	509	297	376	297

Note: *p<0.1; **p<0.05; ***p<0.01

[1] Regression (1): Age $<$ 40

[2] Regression (2): Age $>$ 40

[3] Regression (3): Male

[4] Regression (4): Female

[5] Regression (5): Higher Education

[6] Regression (6): No Higher Education

Examining table 6.6 we see a wide range of variation in the results. In regression (1) it is noticeable that the coefficient for the optimist category is -0.44 and significant at the 10 % level. The interpretation is that optimistic individuals under the age of 40 invest \$0.44 (15%) less on average compared to realistic individuals. On the contrary, the remaining models do not show significant results and there is no clear pattern in the subsets for individuals investing more or less depending on their perceived luck.

6.4 Information Treatment

We have found that unlucky individuals invest more on average, while individuals with a tendency to ignore unlucky events invests less on average. This pattern suggests that informing pessimistic people that the number of unlucky events was in fact lower than they thought will decrease their willingness to invest. Some of these pessimists are likely to have invested because they felt unlucky, but they were more lucky than they thought. To estimate the effect of treatment on investment behavior, we again utilized both linear and logistic regression models. In the linear regression model, treatment is a binary variable that takes the value 1 if an individual receives information treatment, and 0 otherwise. In the logistic regression model investment amount serves as a binary dependent variable, allowing us to investigate how receiving treatment affects the probability of investing everything. The results are reported in table 6.7.

Table 6.7: Information Treatment on Investment Amount for Total Sample

	Investment Amount			
	(1)	(2)	(3)	(4)
Treatment	-0.022*	-0.031**	-0.112	-0.154
	(0.013)	(0.013)	(0.159)	(0.163)
Constant	0.285***	0.218***	-0.920***	-1.281*
	(0.002)	(0.039)	(0.111)	(0.506)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.003	0.035		
Observations	795	795	795	795

Note: *p<0.1; **p<0.05; ***p<0.01

Examining table 6.7, we see that the treatment implied a decrease in investment amount. Average investment amount decreases by $0.022 (8%) in model (1) without control variables, and by $0.031 (11%) in model (2) with control variables, the latter effect being significant at the 5%-level. The logistic regression models implies that individuals receiving treatment are less likely to invest the entire amount. Being treated decreases the odds of investing everything by 0.112 or 0.154 when including control variables. This implies that the probability of investing everything is expected to decrease by $e^{0.112} = 1.12$ times (12%) or $e^{0.154} = 1.17$ times (17%) for individuals in the treatment group compared to the control group, ceteris paribus. However, the effects from the logistic regression models are not statistically significant.

Hence, receiving correct information on the number of sixes and rolls – and thereby one's actual luck – reduced the inclination to invest in a risky asset. A natural next step is to ask whether this treatment effect is driven by people that were overly optimistic or by people who were more on the pessimistic end of the spectrum. To do this, we split the sample into two groups based on their degree of optimism. The categorization is based on the index for total perceived luck, as illustrated in table 6.8:

Table 6.8: Categorization of Perceived Luck for Treatment Group

	Criteria	N
Optimist	$\text{Index}_{\text{Perceived Luck Total}} > 0$	545
Non-Optimist	$\text{Index}_{\text{Perceived Luck Total}} \leq 0$	250

We then ran the same regression of treatment on investment amount on the two sub-samples. The results are reported in table 6.9.

Table 6.9: Information Treatment on Investment Amount for Sub-samples

	Non-Optimist		Optimist	
	(3)	(4)	(5)	(6)
Treatment	-0.048**	-0.057**	-0.010	-0.018
	(0.022)	(0.023)	(0.016)	(0.016)
Constant	0.294***	0.152***	0.281***	0.232***
	(0.023)	(0.070)	(0.016)	(0.027)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.014	0.059	-0.001	0.027
Observations	250	250	545	545

Note: *p<0.1; **p<0.05; ***p<0.01

Examining table 6.9, we see that the treatment effect is driven by non-optimistic individuals. From regression (3) we see that non-optimistic individuals who received treatment invest $0.048 (16%) less on average compared to non-optimistic individuals in the control group. The effect is significant at the 5%-level. The treatment effect is even stronger in the model where control variables are included, as seen from regression (4). Non-optimistic individuals invest \$0.057 (19%) less on average when receiving treatment, the effect being significant at the 5%-level. For the ones categorized as optimists, the treatment does not seem to affect the amount invested.

7 Discussion

The previous chapter investigated the effect of luck, perceived luck and correction of misperceptions on investment behavior. In the following chapter we discuss the main findings and limitations of our results. Finally, we include a subsection regarding implications for further research.

7.1 Findings

For actual luck, we find that individuals that experienced a substantial number of unlucky events in the die roll game invested more in the investment game. Thus, we find partial evidence in support of hypothesis 1.1: Unlucky individuals are more prone to subsequently invest in risky assets. It is worth noting that the results are controlled for earnings, thus unlucky individuals are more inclined to invest regardless of how much they earned in the dice game. For perceived luck, we see the strongest correlation when it comes to the perception of negative events. Individuals who tend to forget unlucky events, and hence are categorized as optimists with regards to number of rolls, are less inclined to invest. Thus, optimism in terms of neglecting negative events affects investment behavior and we find partial evidence in hypothesis 2.1: Optimistic investors take less risk. From the literature the findings could be explained by Gambler's Fallacy. Individuals that experience unlucky outcomes in the die roll game expect lucky outcomes in the investment game, and thus become more inclined to invest. Individuals that perceive themselves as lucky in the die roll game expect unlucky outcomes in the investment game and become more reluctant to invest.

It is noteworthy that all the significant findings suggest that individuals are subject to Gambler's Fallacy. This is in line with Rabin (2002)'s model on what situations one would expect Gambler's Fallacy versus overinference, as the probability distribution is known in our experiment. Despite the participants being aware of the probability distribution for the investment game, they fail to understand that the probability remains constant regardless of their outcome in the dice roll game. Thus, our findings point to the importance of luck and perceptions of luck in explaining investment behavior. In our setting it led to Gambler's Fallacy, which suggest that overinference could materialize in another setting where the probability distribution is unknown.

Although we observe significant results and evidence in our hypothesis for perceived luck, it is important to clarify that the results are based on perceived luck with regards to number of rolls. The results for number of sixes as well as perceived luck in total are not significant. With regards to this, we observe that there is a large difference in individuals' perceptions of number of sixes compared to rolls. From the distributions presented earlier it is apparent that participants provide fairly accurate estimates of the number of sixes, but inaccurate estimates of the number of rolls. Consequently, our findings suggest that the number of rolls serves as a better measure for perceived luck as this is where most participants have misperceptions of their actual luck. The misperceptions with regards to rolls can be explained by biases presented in the literature review. Participants may be subject to optimism bias as they are overconfident in the sense that they underestimate the number of unlucky events and therefore the number of rolls. Further, individuals' decision making in the dice game may be influenced by cognitive dissonance. Participants have a desire to feel lucky in the dice game due to the monetary award, however they may face a conflict as they are asked to report the number of negative events (rolls) in the experiment. Individuals may resolve this discomfort and realize their desire to feel lucky by underestimating the number of rolls.

With regards to the information treatment, we find that individuals in the treatment group invest 11% less on average than the control group. Receiving information about one's actual luck reduces the inclination to invest in a risky asset, thus we can reject the null hypothesis that correcting misperceptions does not affect investment behavior. The treatment effect is clearly driven by non-optimistic participants who invest 19% less. Thus, we find partial evidence in the support of hypothesis 3.1: Correcting misperceptions of luck causes non-optimistic investors to take less risk. In line with the observed Gambler's Fallacy, we would expect the non-optimistic participants in general to take more risk. However, the treatment effect seems to make some non-optimistic individuals realize that they indeed were luckier than they thought, and therefore become less likely to invest. They no longer rely on the feeling of being unlucky as a rationale for taking risk in the investment game, but rather make an informed decision. Thus, as intended, the information treatment helps non-optimistic individuals avoid the Gambler's Fallacy. This suggests that correcting misperceptions could be an approach for altering people into making certain investment decisions.

Consistent with the literature review we confirm a gender difference in investment behavior and find that male individuals on average have invested 18% more than female individuals. As gender has consistently been shown to influence investment behavior, it is interesting to compare the results with the effects for perceived luck and actual luck on investment amount. For actual luck we find that unlucky participants invest an additional 20%, while for perceived luck we find that optimists invested 11% less. Moving on to the treatment effect we find that the treatment reduce the investment amount for individuals by 11% overall and by 19% for non-optimistic individuals. All the aforementioned regressions are controlled for gender. From our results, it is therefore evident that luck and perceptions of luck can have a similar or even greater effect than gender on investment decisions. Thus, our findings suggest that luck and perceptions of luck is another aspect of importance for individuals' investment choices.

Obtaining the maximum yield of $1.5 in our investment game is rather unlikely to have significant implications for the participants' personal finance. However, if the investment behavior in our experiment represents the participants' attitude towards risk in other investment decisions, the implications will be of greater magnitude. Our findings suggest that individuals who are optimistic regarding their experienced luck are more reluctant to invest in risky assets, even when the expected value of investing is positive. If this is a recurring behavior in investment decisions with positive expected value, it will inevitably have repercussions on their personal finances in the long run, and ultimately lead to a wealth gap between optimists and pessimists.

7.2 Limitations

7.2.1 Internal Validity

The internal validity of the study regards whether the established causal relationship is net of all other confounding factors (Gertler et al., 2016), and thus, can be trusted. A high internal validity implies that perceived luck is not affected by any confounding factors. In the experiment, perceived luck was measured based on the participants' rolls and sixes. As previously discussed, our findings show inaccurate estimates for the total number of rolls, but accurate estimates for total number of sixes. This suggests that people tend to neglect unlucky events compared to lucky events, however the low number of sixes is less cognitively challenging to count compared to the number of dice rolls. In addition, participants receive a monetary award of $0.1 each time a die result in a six. This could incentivize participants to be more attentive towards the number of lucky events. For these reasons, one could argue that the measure for perceived luck is affected by the experimental design. Ideally, we would conduct more experiments to identify this potential bias, which we will elaborate on in section 7.3.

7.2.2 External Validity

The external validity of a study is essential to be able to draw conclusions about the population based on the sample (Gertler et al, 2016). External validity is obtained when the evaluation sample is representative for the population. The analysis is based on survey responses from a general population sample in the U.S. where a varied collection of individuals are represented. Furthermore, the estimated effect for overconfidence and gender on investment amount in our sample are consistent with the findings in the literature review. This could indicate that our dataset is representative and valid for estimating other effects. However, we notice that the majority of the participants in the study are male and under the age of 50. The regressions presented in table 6.6 reveal a wide range of variation in the effect of perceived luck on investment amount for different subgroups, which indicates that the findings may differ in other populations. The effect of perceived luck is most significant for younger participants. This indicates that if our sample consisted of a larger proportion of old individuals, or results might be weakened.

Furthermore, one could argue that the investment amount of $0.5 is too small to demonstrate a causal effect. However, we know from literature that risk preferences in small investments are representative for larger investments. Benartzi and Thaler (2011) argue that individuals who exhibit a certain investment behavior for small amounts are more likely to employ similar strategies when making larger investment decisions. Moreover, Figure 3.1 illustrates significant variation in the amount invested in the experiment. If the investment amount was in fact too low to demonstrate risk preferences, we would expect individuals to exhibit more similar investment patterns.

7.3 Implications for Further Research

Results from this study indicate that individuals are subject to Gambler's Fallacy based on their actual and perceived luck, and that correction of misperceptions helps non-optimistic individuals to avoid the Gambler's Fallacy. However, the estimated effects are not symmetric. For actual luck we find effects for unlucky individuals, but not for individuals that were lucky. For perceived luck, we find effects for optimistic individuals, but not for pessimists. These findings suggests the need for further investigation. Further research should aim to check for the robustness of the effects, by conducting similar studies which can identify potential drivers of the effects and determine if the effects are observed for the same categories. Moreover, the treatment effect can not be considered symmetric as it is not seen for optimistic individuals. Understanding why the treatment effect is not observed for optimistic individuals is an interesting question for further research. Mitigating biases, Gambler's Fallacy included, is always a good thing because it helps individuals make more rational choices. Thus, it would be interesting to carry out additional experiments aiming to find a treatment that applies to optimists as well.

The limitations regarding internal validity are related to participants being more attentive towards number of sixes compared to number of rolls. For further research, it would be ideal to increase the ratio between lucky events and total events. One possible approach to make the number of lucky events more equal to the number of total events is to conduct an experiment where participants receive a monetary award for each roll that does not result in a six. To illustrate, consider the group that rolls the die 48 times. When rolls that do not result in a six are considered lucky events, the expected number of lucky events will increase from 8 to 40. This adjustment would make the statements of perceived number and rolls more cognitively challenging to an equal extent. Furthermore, it would be beneficial to control for the monetary incentive by including a reward for participants who provide a reasonably accurate estimate of the total number of dice rolls.

8 Conclusion

While realized luck has been shown to affect decision making, perceptions of luck is a field of study lacking research. Given the evidence supporting the view that luck plays a role in the behavior of individuals and their financial decisions, it follows that perception of luck might also be an important factor.

The purpose of this study was to conduct research on the implication of actual and perceived luck on investment behavior. In addition, we aimed to investigate whether correcting individuals' misperceptions of luck could influence their financial decision making for the better.

In order to test the hypotheses, we conducted an experiment consisting of two tasks: (1) a dice roll game and (2) and investment game. The survey was distributed to a general population sample in the U.S. via the platform Prolific, and we collected responses from 799 individuals. To investigate the correlation between the different luck measures and investment behavior, we employed both ordinary least square and logistic regressions.

We find evidence that both actual and perceived luck affect investment behavior. Specifically, we observe that unlucky participants tend to invest more and optimists invest less. These two findings are in line with Gambler's Fallacy. Individuals that experience unlucky outcomes in the die roll game expect lucky outcomes in the investment game, while individuals who perceive themselves as lucky in the die roll game expect unlucky outcomes in the investment game. Moreover, we find that correcting misperceptions of luck causes non-optimistic investors to invest less. Thus, as intended the information treatment helps non-optimistic individuals avoid the Gambler's Fallacy.

In summary, our overall findings show that perceptions of luck matter in investment decisions. From previous research it has been established that actual luck impacts investment behavior. Our thesis contributes to this research by suggesting that perceived luck is a matter of importance as well, perhaps to the same extent as established determinants for risk preferences such as gender. Thus, investors are not rational and subject to cognitive biases. In order to alter people towards better decision making, it is important to mitigate these biases. Our information treatment helps individuals avoid the Gambler's Fallacy, suggesting that correcting misperceptions of luck could be an effective approach to address biases in financial decision making.

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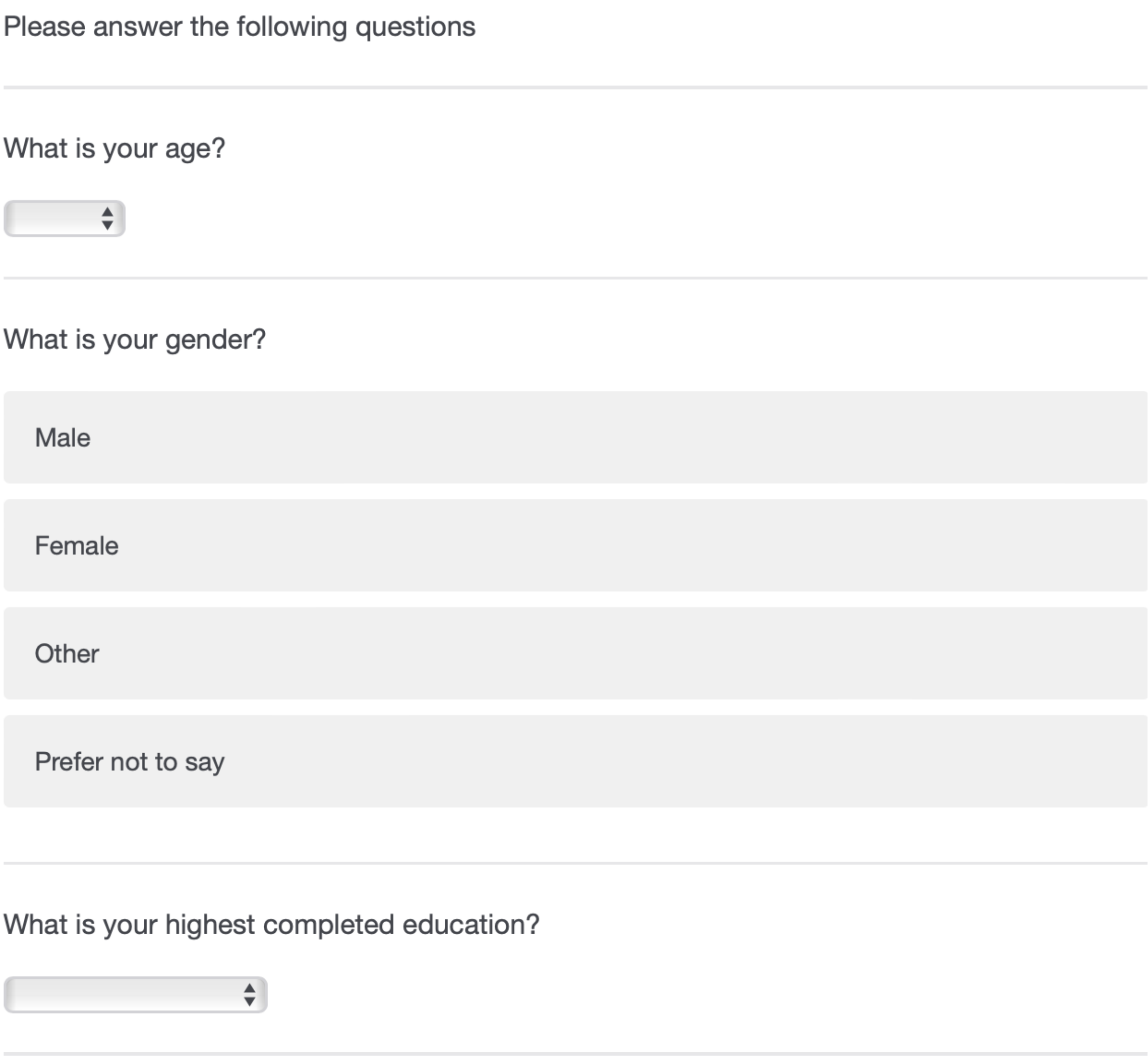
Appendix

A1 Survey

A1.1 Background Variables


Please answer the following questions

What is your age?

What is your gender?

Male

Female

Other

Prefer not to say

What is your highest completed education?

Figure A1.1: Background Questions

What is your primary employment status?

- Unemployed
- Employed in private sector
- Employed in public sector
- Entrepreneur (self-employed)

What is your annual salary in USD (before tax)?

Do you live in an urban or in a rural area?

- Very urban (big city)
- Somewhat urban
- Somewhat rural
- Very rural (small village)

Figure A1.2: Background Questions Continued

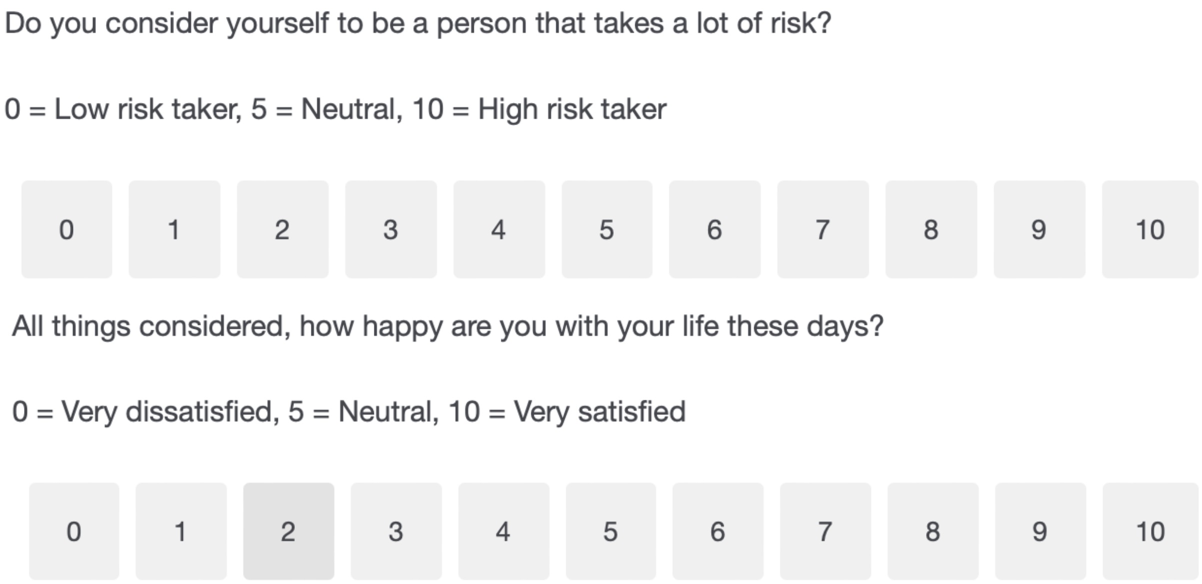


Figure A1.3: Risk Appetite and Happiness

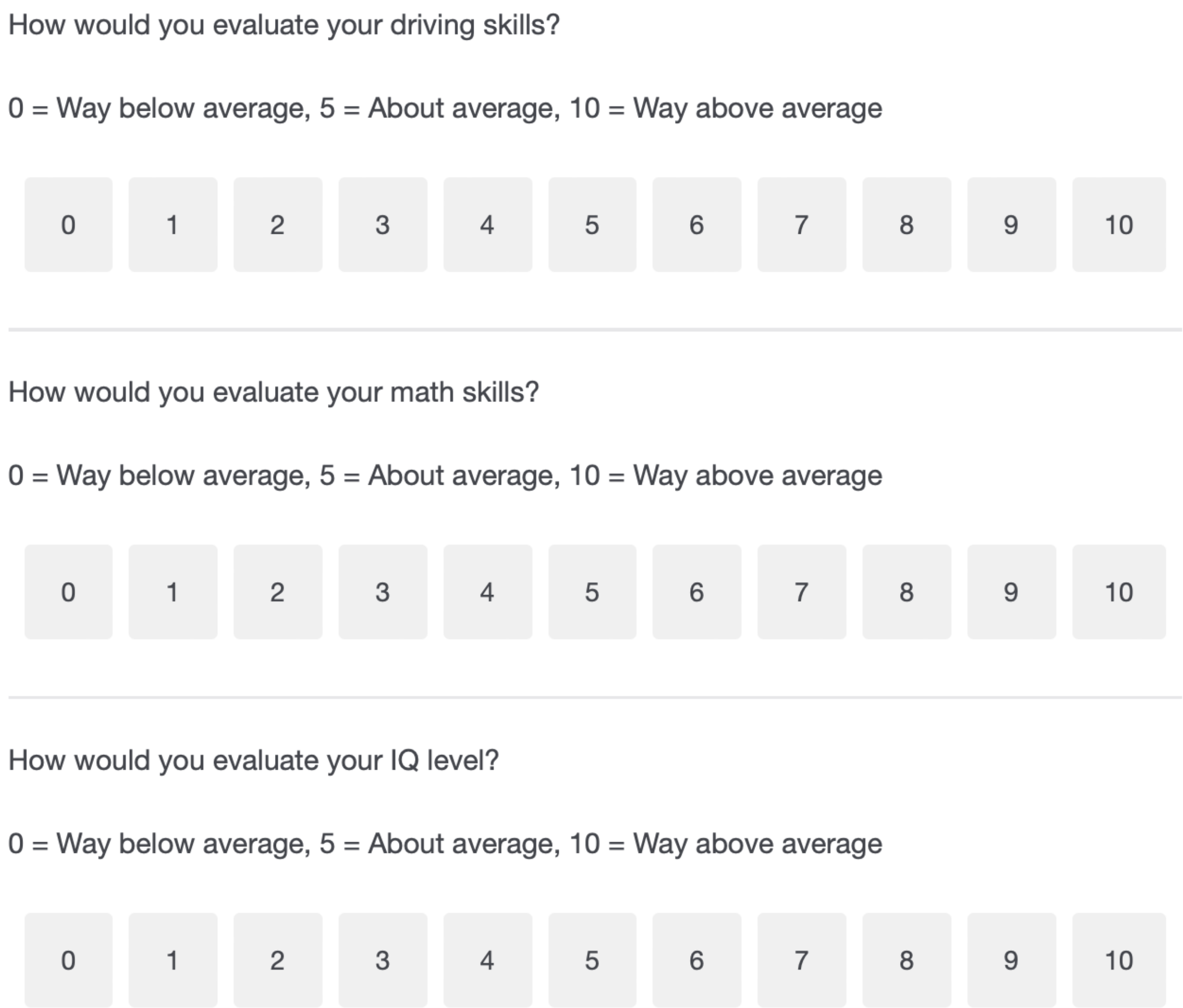


Figure A1.4: Overconfidence Measures

A1.2 Die Roll Game

On the next screen, you will perform an electronic dice roll. Click on the arrow to roll the dice, and the result will be presented on the screen. The dice is fair, meaning that the outcome is completely random with equal probability to result in a 1, 2, 3, 4, 5 or 6.

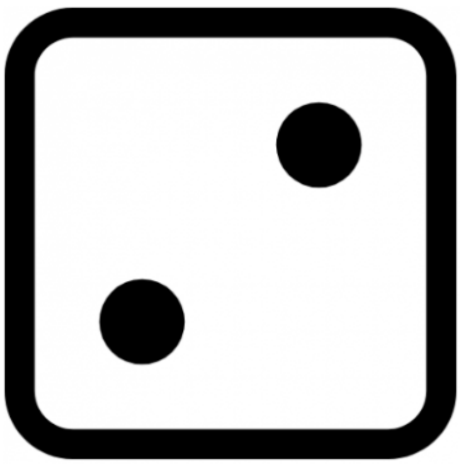
In this dice game you will earn an additional bonus. You gain 0.1 USD for each time you die a 6. Continue to roll the die until you are told otherwise.

Figure A1.5: Die Roll Game Instructions

Roll the die by clicking on the arrow.

Figure A1.6: Die Roll

Your result is:



Roll the die again by clicking on the arrow.

Figure A1.7: Die Roll Result

You have now finished the dice rolling game.

How many times do you think you rolled the dice?

How many times do you think you rolled a 6?

Figure A1.8: Perceived Luck Statements

Thank you for completing the first game. You will now proceed to the investment game.

For your information: You rolled the dice 36 times and you got the outcome six 13 times

Figure A1.9: Information for the Control and Treatment Group

A1.3 Investment Game

Instructions: Investment Game

You have now reached the second game and final part of this survey. In addition to your participation fee, and any amount earned in the dice game, we now provide you with 0.5 USD. With this money, you will get the chance to decide how much to invest in a risky asset. The money not invested is guaranteed and yours to keep. The money that you choose to invest will with 50% chance result in a return, meaning that the investment is successful, and that the invested amount increases by a factor 3. With 50% chance the investment is unsuccessful, meaning that the invested amount is lost and deducted from your payment. Whether the investment is successful or unsuccessful is decided by an electronic coin flip that is decided on the next screen.

(head=dollar=successful; tail=blank=unsuccessful)

How much of 0.5 USD do you want to invest in the risky asset?

0	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5

Please flip the coin to determine whether the investment is successful or not, by clicking on the arrow.

Result: Head

Congratulations! Your investment of USD 0.5 was successful, meaning that an amount of USD 1.5 will be included in your bonus payment.

A2 Regressions with Original Dataset

Table A2.1: Background Variables on Investment Amount and Perceived Luck

	Investment Amount				Perceived Luck		
	(1)	(2)	(3)	(4)	(5)[1]	(6)[2]	(7)[3]
Male	0.044**			0.028*	0.026	-0.017	-0.001
	(0.013)			(0.014)	(0.025)	(0.020)	(0.008)
Risk		0.012***		0.010***	-0.00	0.006	0.001
		(0.003)		(0.003)	(0.005)	(0.004)	(0.002)
Overconfidence			0.014**	0.009	-0.007	-0.008	-0.002
			(0.004)	(0.004)	(0.008)	(0.007)	(0.003)
Constant	0.245***	0.222***	-0.182***	0.158***	0.021	0.242***	0.065***
	(0.011)	(0.013)	(0.028)	(0.028)	(0.052)	(0.042)	(0.017)
Adjusted R^2	0.012	0.026	0.012	0.036	-0.002	0.001	-0.003
Observations	799	799	799	799	799	799	799

Note: *p<0.1; **p<0.05; ***p<0.01

[1] Perceived luck with regards to rolls

[2] Perceived luck with regards to sixes

[3] Perceived luck with regards to both sixes and rolls

Table A2.2: Actual Luck on Investment Amount

	Investment Amount			
	(1)	(2)	(3)	(4)
Lucky	0.037	0.030	0.192	0.164
	(0.019)	(0.021)	(0.245)	(0.278)
Unlucky	0.042*	0.048*	0.221	0.256
	(0.019)	(0.021)	(0.246)	(0.272)
Constant	0.239***	0.150**	-1.155***	-1.631**
	(0.016)	(0.046)	(0.214)	(0.604)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.007	-0.003		
Observations	799	799	799	799

Note: *p<0.1; **p<0.05; ***p<0.01

Table A2.3: Perceived Number of Sixes Index on Investment Amount

	Investment Amount			
	(1)	(2)	(3)	(4)
Optimist	0.027	0.025	0.132	0.125
	(0.017)	(0.017)	(0.214)	(0.219)
Pessimist	0.000	-0.000	0.003	0.001
	(0.015)	(0.014)	(0.184)	(0.190)
Constant	0.269***	0.193***	-1.003***	-1.406**
	(0.009)	(0.039)	(0.110)	(0.509)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.007	-0.003		
Observations	799	799	799	799

Note: *p<0.1; **p<0.05; ***p<0.01

Table A2.4: Perceived Number of Rolls Index on Investment Amount

	Investment Amount			
	(1)	(2)	(3)	(4)
Optimist	-0.033**	-0.033**	-0.165	-0.168
	(0.015)	(0.015)	(0.189)	(0.193)
Pessimist	-0.023	-0.021	-0.114	-0.110
	(0.018)	(0.018)	(0.220)	(0.228)
Constant	0.295***	0.225***	-0.871***	-1.242*
	(0.012)	(0.040)	(0.149)	(0.520)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.003	0.030		
Observations	799	799	799	799

Note: *p<0.1; **p<0.05; ***p<0.01

Table A2.5: Perceived Luck Index on Investment Amount

	Investment Amount			
	(1)	(2)	(3)	(4)
Optimist	-0.021	-0.022	-0.108	-0.114
	(0.009)	(0.015)	(0.192)	(0.197)
Pessimist	-0.013	-0.014	-0.069	-0.070
	(0.015)	(0.016)	(0.192)	(0.199)
Constant	0.283***	0.208***	-0.928***	-1.327**
	(0.001)	(0.039)	(0.120)	(0.506)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.007	-0.003		
Observations	799	799	799	799

Note: *p<0.1; **p<0.05; ***p<0.01

Table A2.6: Perceived Luck Index on Investment Amount for Sub-samples

	Investment Amount					
	(1)[1]	(2)[2]	(3)[3]	(4)[4]	(5)[5]	(6)[6]
Optimist	-0.045*	0.025	-0.026	-0.017	-0.013	-0.026
	(0.019)	(0.026)	(0.019)	(0.025)	(0.022)	(0.025)
Pessimist	-0.031	0.010	-0.012	-0.028	-0.025	0.006
	(0.020)	(0.024)	(0.020)	(0.024)	(0.022)	(0.025)
Constant	0.289***	0.273***	0.299***	0.266***	0.287***	0.266***
	(0.012)	(0.016)	(0.012)	(0.016)	(0.014)	(0.017)
Adjusted R^2	0.008	-0.004	-0.000	-0.002	-0.002	-0.001
Observations	799	799	799	799	799	799

Note: *p<0.1; **p<0.05; ***p<0.01

[1]: Age $<$ 40

[2] : Age $>$ 40

[3] : Male

[4] : Female

[5] : Higher Education

[6] : No Higher Education

Table A2.7: Information Treatment on Investment Amount for Total Sample

	Investment Amount			
	(1)	(2)	(3)	(4)
Treatment	-0.022*	-0.030**	-0.110	-0.151
	(0.013)	(0.013)	(0.159)	(0.162)
Constant	0.284***	0.213***	-0.924***	-1.310**
	(0.009)	(0.039)	(0.111)	(0.504)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.002	0.035		
Observations	799	799	799	799

Note: *p<0.1; **p<0.05; ***p<0.01

Table A2.8: Information Treatment on Investment Amount for Sub-samples

	Non-Optimist		Optimist	
	(3)	(4)	(5)	(6)
Treatment	-0.048**	-0.057**	-0.009	-0.017
	(0.022)	(0.023)	(0.023)	(0.016)
Constant	0.294***	0.152**	0.280***	0.226***
	(0.016)	(0.070)	(0.011)	(0.048)
Control Variables	No	Yes	No	Yes
Adjusted R^2	0.014	0.059	-0.001	0.028
Observations	250	250	549	549

Note: *p<0.1; **p<0.05; ***p<0.01