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The wisdom gap: Does knowledge of decision theory improve decision-making?

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Abstract

Scientific research has led to a growing understanding of human behavior and decision-making. This increasing knowledge of decision theory has spread throughout academia and the general population. The existing literature does not address the impact of such dissemination of knowledge on decision quality. This paper seeks to do so by investigating how knowledge of decision theory impacts decision-making regarding decision biases. An online randomized control trial was designed. 225 subjects completed six decision tasks in which sub-optimal behavior has been systematically documented in the literature. These tasks concerned the Sunk-cost fallacy, Present bias, Allais paradox, Ellsberg paradox, Positive/Negative framing bias, and Anchoring and adjustment bias. The effect of shallow levels of knowledge was studied by inducing conceptual awareness of the biases via a brief informal explanation. The effect of deeper levels of knowledge was studied by controlling for formal education in behavioral economics. Of the tasks analysed, surface knowledge had a significant effect only in the Ellsberg paradox task, while deeper knowledge had so in both the Ellsberg paradox and the Sunk-cost fallacy task. Overall, knowing decision theory does not appear to be sufficient to consistently reduce the frequency of decision biases.

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"*The saddest aspect of life right now is that science gathers knowledge faster than society gathers wisdom*" (Asimov, 1988, pg. 281)

1. Introduction

Wisdom is defined as the ability to use knowledge and experience to make good decisions and judgments (Cambridge, 1995). Such an attribute has been valued throughout mankind's history. Where it is absent, the prevalence of poor decision-making has negative consequences affecting several dimensions of society, ranging from international policy to personal life (Nickerson, 1998).

Several cognitive processes leading to errors in decision-making have been documented throughout recent decades, a great part of which fall into the category of biases. This extensive body of research shows that human decision-making tends to deviate from normative prescriptions in systematic manners (Kahneman, 2003; Payne, Bettman, & Johnson, 1993). Although not necessarily translated into bad decisions, such cognitive processes can often create an extensive departure from optimal decision-making (Arkes, 1991).

Decision biases impact individuals in their personal lives. Research shows that people making less biased decisions tend to have healthier social interactions, less risk of substance abuse, lower infancy delinquency rates, greater professional foresight, and superior problem-solving skills (Parker & Fischoff, 2005). The biases impact both laypeople and trained experts in several areas including education, business, medicine, and law (Morewedge & Kahneman, 2010; Payne, Bettman, & Johnson, 1993). The consequences of such sub-optimal decisions reach different levels of magnitude, including macroeconomic levels, as suggested by the documented systematic poor-decision making in policy professionals (Banuri, Dercon, & Gauri, 2019). The outcomes of such decisions can theoretically affect any sphere of society where human decision-making is decisive and unsupported.

To address these issues, a substantial amount of research has explored processes for the improvement of decision-making (Fischhoff, 1982; Soll, Milkman, & Payne, 2013). Although research regarding debiasing mechanisms has partly investigated the effect of providing bias-related information in training and warning contexts, minor attention appears to have been directed at the isolated relationship between the level of knowledge individuals have on cognitive biases and the possible effects of such knowledge in their decisions.

The relevance of understanding such effects is highlighted by the increasing spread of knowledge of decision theory. This spread of knowledge goes beyond academia reaching industry, government, and the overall public (Barberis, 2018). This is done through different media including but not limited to news articles, events, talks, popular books, and social networks. The popularization of the concept of biases and heuristics is a notable phenomenon of which consequences appear yet to be studied. It is important to understand the potential effects of both this surface-level knowledge, such as mere awareness of concepts, as it is to understand the effect of deeper levels of knowledge, such as having a formal education in behavioral science.

Speculation regarding the impact of deep knowledge of decision theory on decision-making varies from expert sources. When asked if the long-life study of cognitive biases helped him make better decisions, Nobel prize winner Professor Daniel Kahneman answered negatively (Parrish, 2019). Faced with the same question, accomplished behavioral economics Professor Daniel Ariely answered positively, speculating that studying decision-making helped in the making of better decisions (Parrish, 2018).

The interest in this question is not new, as it was formally stated in the *Blackwell handbook of judgment and decision making* (Koehler & Harvey, 2004). After mentioning the growing presence of behavioral decision theory in academic curricula, Larrick (2004) laid out the interest in understanding if courses on decision-making would mitigate decision biases. 17 years since, to the best of my knowledge, still no research has been conducted on this issue.

Hence, provided the importance of the topic and the apparent lack of research on it, the paper at hand aims at contributing to the further understanding of such a relevant inquiry. The importance of exploring the potential impact of the spread of knowledge of decision theory in people's behavior is relevant to understand regardless of its magnitude, given the possible repercussions of any significant change in human decision-making. This paper seeks to explore the effects of such knowledge in decision biases. It attempts to do so at different levels of depth of knowledge, ranging from mere conceptual awareness to higher levels of understanding of decision theory.

Overall an exploration of the possible gap between knowledge and its application is done within the context of decision theory, seeking to understand if wisdom ensues and better decisions are made. This study, therefore, seeks to address the following research question:

To what extent does knowledge of decision theory affect biased decision-making?

To explore this question, an experiment is designed. A sample of subjects is used where individuals go through an online survey. Subjects are randomly assigned to one of two groups. The sole difference between groups is a treatment where an explanation of a decision bias is provided previous to the decision task where such bias is often observed. To analyse the effect of deeper forms of knowledge, education in behavioral economics is controlled for.

This thesis will analyse six core decision tasks where decision biases have been consistently documented. A decision bias can be defined as a systematic pattern of deviation from norm or rationality in decision-making (Haselton, Nettle, & Murray, 2015). Although there are relevant and often justified disagreements in the literature as to what type of decision can be considered to be "biased" (Besharov, 2004) as well as if a biased decision is "poor" (Orasanu, Calderwood, & Zsambok, 1993), this thesis will consider the departure from normative theory as biased and will categorize such decisions as sub-optimal. This is done for the sake of consistent terminological analysis and is an inherent limitation to the conclusions that may be extrapolated from the paper at hand.

With the aim of conciseness and in an attempt of avoiding unwarranted complexity, a simple and flexible knowledge scale is used as a theoretical framework. The Depth of knowledge scale (DoK) (Webb, 2002) was developed to categorize different levels of understanding. Initially designed for students, it can establish the context in which individuals express the depth and extent of knowledge, ranging from a shallow to a deep state of conceptual comprehension. Given that formal education in a field is positively correlated with a deeper level of understanding, while mere awareness with a shallower level (Murphy & Alexander, 2002), these two states can be investigated in an experimental setting. The shallower state will be simulated by an experimental condition where awareness of a concept is induced. The deeper state is represented by formal education in behavioral economics. The relation of these levels of knowledge regarding decision theory concepts with performance in decision tasks will be studied in an immediate context.

The remainder of this thesis is organized as follows. Initially, relevant literature is reviewed leading to the development of the hypotheses. Secondly, the methods section describes the experimental design, as well as the statistical analysis used. Next, the results obtained are outlined. Finally, the discussion is presented, followed by the conclusion.

2. Literature review

In the following two sections the relevant literature is reviewed. Section 2.1. covers research related to shallower levels of knowledge, namely forms of awareness and its impact on decision-making. Section 2.2 outlines literature associated with greater degrees of depth of knowledge and its potential impact on decision-making.

2.1. Related literature on warning-based debiasing

Within the debiasing literature, three main strategies have surfaced: The use of incentives, the design of the decision environment, and the training of individuals (Morewedge et al., 2015). The latter is more closely related to the research question of this paper, where providing information related to decision theory is the focus.

The initial tries to avoid cognitive biases via informational training were often failures (Fischhoff, 1982; Kahneman, 2003). Different attempts have been made with both inconclusive results (Arkes, 1991; Milkman, Chugh, & Bazerman 2009; Phillips, Klein, & Sieck, 2004) and more recently, some promising ones (Clegg et al., 2014; Morewedge et al., 2015).

Effects of warning

The findings regarding the immediate effect of providing knowledge are not consistent. Conclusions vary depending on decision-making contexts. When studying the case of overconfidence, Fischhoff (1982) indicated that merely informing subjects about the pervasiveness of a bias and warranting caution made a negligible difference. In the case of the anchoring and adjustment bias, making individuals aware of the possible effect had little to no success (Chapman & Johnson, 2002; Jacowitz & Kahneman, 1995; Epley & Gilovich 2005). Ohlert & Weisenberger (2020) concluded that warning about the existence of the sunk cost fallacy did not affect people's course of action, yet a positive effect was found for taking courses in accounting (Fennema & Perkins, 2008).

Other studies making individuals aware of potential biases via warning manipulations have been found to be somewhat successful in the mitigation of some decision biases. Research has found that the hindsight bias can be eliminated via a warning (Hasher, Attig, & Alba, 1981; Reimers & Butler, 1992). Similarly, evidence has surfaced suggesting that the outcome bias (the tendency to evaluate a decision on the basis of its outcome rather than on what factors led to the decision) can be mitigated via warning (Clarkson, Emby, & Watt, 2002). Although with a relatively small magnitude of effect, cautioning for the existence of the positive/negative framing effect likewise appears to have a significant debiasing effect (Cheng & Wu, 2010; McNeil, Pauker, Sox, & Tversky, 1982). Jia, Furlong, Gao, Santos, & Levy (2020) found evidence suggesting that learning about the Ellsberg paradox reduces ambiguity aversion.

Post-decision inputs

Regarding manipulation post-decision, Barberis & Thaler (2003) indicate that once a bias is explained individuals frequently comprehend it, however, they often immediately proceed to violate it once again. On the other hand, there is evidence suggesting that people who become aware of using certain biases may correct their judgment (Block & Harper, 1991). Recently, Nielsen & Rehbeck (2020) found evidence suggesting that most individuals wish to follow the canonical axioms of normative theory once becoming aware of them, and will adapt their choices to be consistent with such axioms.

Some research thus suggests that if individuals consider a decision to be a mistake, they are more likely to correct it. Relatedly, the term "bias" tends to carry negative connotations (Pot, Kieusseyan, & Prainsack, 2021). Therefore, it is reasonable to speculate that when people are informed of a decision bias using such terminology, they will often associate the concept of a "biased decision" with an undesirable decision or decision error. If this is true, individuals might be more likely to adapt their behavior to the normative theory if they are aware of the possible decision bias.

Debiasing training

Consistent with the above, recent trials of informational training in an immediate setting and within a 2-month post-intervention period have been successful (Morewedge et al., 2015). Although initial investigation indicated that decision biases tended to endure mitigation through training, this more recent research indicates the opposite may occur. Although awareness of the presence of decision biases is not identical to a more extensive training intervention, there are notable similarities.

Despite the mixed evidence, the combination of previous findings may lead to reasonable speculation that a direct effect may occur through awareness of a bias. Therefore, this study hypothesizes as follows.

Hypothesis 1: *Informing people of the existence of a decision bias has an immediate debiasing effect.*

2.2. The effects of competence and domain knowledge on decision-making

Domain knowledge

In the realm of formal education and the direction of expertise, there is no clear translation of knowledge into decisions within different fields. Domain knowledge tends not to mitigate the propensity for decision biases (Reyna, Chick, Corbin, & Hsia, 2014). Expertise in a particular domain does not appear to increase the consistency nor accuracy of judgment in the presence of potential biases, regardless of familiarity with the topic. Philosophers educated in logic show similar preference reversals in the same moral dilemmas as scholars without instruction in logic (Schwitzgebel & Cushman, 2012). Physicians who were trained in the analysis of medical data and medical students with experience in statistical analysis were as susceptible to cognitive biases as their untrained patients (McNeil et al., 1982). There is evidence that economists fall prey to biases such as overconfidence as much as those without such education (Angner, 2006). Taking a course in economics appears not to reduce the propensity to commit the sunk-cost fallacy (Arkes & Blumer, 1985). On the other hand, Arkes (1991) also predicted that those with training in accounting would be less likely to commit the sunk-cost fallacy than those without such training. There is also evidence that training in cost-benefit analysis can mitigate this fallacy (Larrick, Morgan, & Nisbett, 1990). Likewise, there is data suggesting that those with more advanced financial knowledge tend to make better decisions in the financial context (Robb & Woodyard, 2011). However, concerning behavioral economics, no study appears to have been conducted on the possible differences in the decision-making performance due to having a formal education in the field. Despite there being evidence of the same sub-optimal decision-making regarding experts across different fields, these findings cannot be directly extrapolated to experts in decision-making.

Competence effects

The competence hypothesis states that individuals prefer to bet on their beliefs in situations where they feel knowledgeable, and prefer to bet on chance when they do not (Heath & Tversky, 1991). Evidence suggests that decisions can be influenced by the level of knowledge individuals believe to have, namely in risk preferences. It is possible that the decisions of those knowledgeable in decision theory may be affected by the belief in having such knowledge. Nevertheless, there appears to be no evidence indicating less biased decision-making due to levels of competence alone.

Learning through decision-making

Myagkov & Plott (1997) speculated that convergence of behavior to what is predicted by classical normative theory increases once levels of understanding by individuals increase. There is evidence suggesting that learning in certain contexts can lead people to converge to normative predictions, namely that of expected utility theory (EUT) (Birnbaum & Schmidt, (2015); Nicholls, Romm, & Zimper (2015); Nielsen & Rehbeck, (2020); Van de Kuilen & Wakker (2006)). A relevant distinction is made in the literature separating learning by thought, where individuals do not experience the consequences of their decisions, from learning by experience, where they do (Myagkov & Plott, 1997). Although in the pursuit of a behavioral economics degree students do not necessarily make choices, they study the decision-making scenarios and decision-making mechanisms. Myagkov & Plott (1997) explicitly pointed out that a better understanding of the context of decision-making would tend to bring decisions closer to what classical theory predicts. The assumption that those with education in decision theory have a greater understanding of the context of the decisions by them studied than those without such education is reasonable.

Debiasing training

Studies of debiasing through informational training also bear some resemblance to formal education, in that knowledge of decision biases is increased. They may therefore provide partial evidence in support of a hypothesis. If training lasting less than a day showed significant debiasing effects not only on decisions made in the same day but also within a 2-month time frame since the training intervention (Morewedge et al., 2015), one could speculate that university education in decision theory might also lead to debiasing effects, provided the similarities carry some of the observed effects.

It is sensible to expect that individuals educated in behavioral economics are more aware of the existence of decision biases than individuals who do not have such education. Thus, it is plausible that such individuals are more likely to be able to recognize potential decision errors and avoid them. Furthermore, since the first hypothesis of this thesis states that those who are aware of a decision bias are less likely to act in accordance with it, the speculation regarding the possession of formal education in decision theory follows coherently from the first hypothesis. Therefore, this study hypothesizes the following.

Hypothesis 2: *Individuals with formal education in behavioral economics are less prone to biased decision-making than individuals without it.*

3. Methods

This section covers the details of the experiment conducted to analyse the possible relationships between levels of knowledge about decision theory and performance on decision tasks. The experimental design is outlined in section 3.1. Information about the subjects is presented in section 3.2. The incentives used are in section 3.3. The decision tasks and variables utilized are described in section 3.4. An overview of the procedure is provided in section 3.5. The analysis methods are outlined in section 3.6.

3.1. Experimental design

The experiment consisted of an online randomized control trial using Qualtrics survey software. All subjects were randomly assigned to one of the two treatment groups. In the *control* group subjects completed six decision tasks. In the *treatment* group, a short text with an explanation of the bias associated with each decision task appeared on the page previous to the task. This explanation was scientifically accurate and presented in simple terminology, seeking to simulate the common format used to describe decision biases in the non-academic world. This was the only difference between each of the groups. A between-subjects design was used where the dependent variable studied varied per task. In the case of the Sunk-cost fallacy, Allais paradox, Ellsberg paradox, and Present bias decision tasks, the dependent variable was the choice or set of choices made by subjects that were either a violation of normative theory or not. In these 4 tasks, the dependent variable is binary. In the case of the anchoring and adjustment and positive/negative attribute framing tasks, the dependent variables are continuous and ordinal, respectively. After the decision tasks, subjects were asked to rate the extent to which they believed to be biased when making decisions, as well as to rate the average person. Then, questions related to demographic variables including gender, age, and level of education were posed. A specific question asked whether subjects had previously completed or were currently pursuing a degree in behavioral economics. Finally, a page for voluntary participation in a gift card lottery was displayed. Upon completion of the survey, subjects were thanked for their participation.

To ensure that there were no order effects, randomization was used in this study. The order of all decision tasks in the survey was random. If two questions were asked within each decision task, the order of occurrence of each question was also randomized.

3.2. Sample

The sample was composed of 237 subjects, 12 of which were eliminated due to the incompletion of the experiment. After cleaning the data, 225 observations remained. The data are fairly balanced in terms of gender, with 102 subjects of the female gender (45.3%) and 123 of the male gender (54.7%). The average age of subjects was 25.4, with a standard deviation of 3.9. The youngest subject was aged 18 and the oldest was aged 51. Regarding the highest level of education obtained at the time of the experiment, 113 (50.2%) subjects had a Bachelor degree, 93 (41.3%) had a Master's degree, 12 (5.3%) had a high school diploma, and 4 (1.8%) had either a Ph.D. or a Doctorate. 2 (0.9%) of the subjects had some high school education or less, and 1 subject preferred not to say. At the time of participation in the survey, 47.6% of subjects were living in the Netherlands.

Concerning formal education in the area of behavioral economics, 108 (48%) subjects were either currently pursuing or had previously completed a degree in the field. 114 (50.7%) had not completed, nor were currently pursuing such a degree. 3 (1.3%) of subjects preferred not to say. With respect to the 2 treatment groups, *Control* and *Treatment*, subjects were close to evenly distributed. Given the Qualtrics software randomization process, 116 (51.6%) subjects were assigned to *Control*, while 109 (48.4%) were assigned to *Treatment*. The descriptive statistics of the sample are in table 1. A-priori sample size calculations are in appendix C.

Table 1: Descriptive statistics

Variables	Observations	Mean	Frequency	SD	Min	Max
Male	225	-	54.7%	-	0	1
Age	221	25.4	-	3.9	18	51
Education Level	225					
- Some high school or less	2	-	0.9%	-	1	5
- High school diploma	12	-	5.3%	-	1	5
- Bachelor	113	-	50.2%	-	1	5
- Masters	93	-	41.3%	-	1	5
- Ph.D./Doctorate	4	-	1.8%	-	1	5
Dutch residency	225	-	47.6%	-	0	1
Education in behavioral economics	225	-	48%	-	0	1

Note: For binary and categorical variables frequencies are shown.

3.3. Incentives

Participation in the experiment had an average duration of 7.24 minutes. To increase the participation rate, a lottery incentive system was used. A €20 amazon gift card was randomly assigned to one of the subjects who chose to participate in the lottery. To this end, a text entry was provided at the end of the survey where subjects who wished to apply for the gift card could enter their email address for further contact in case of winning. All subjects were informed that these data would only be used to allocate the prize, after which it would be deleted.

3.4. Decision tasks and variables

Six decision tasks related to core concepts of the behavioral economics literature were posed. These tasks were selected given their relevance in behavioral science and because the concepts associated with these tasks are an integral part of the formal education curricula in behavioral economics degrees. When possible, simple decision tasks were selected, for uncomplicated choice design is recommended when testing subject's rationality (Cubitt, Starmer, & Sugden, 2001). Below is a description of each task and the relevant variables, separated by paragraph. After the decision tasks, a self-awareness question was posed to evaluate the degree to which individuals see themselves as making biased decisions when compared to others. The complete survey is in appendix A.

Allais paradox

This decision task stems from one of the oldest consistency tests, the Allais paradox (Allais, 1953). The questions are taken from Kahneman & Tversky (1979), who introduced a slightly simpler task than the one originally introduced by Maurice Allais. The version is that of the common ratio.

Subjects consider two choice problems, of which the order of appearance is randomized. They are asked to choose between prospects A1 and B1, where:

$$\begin{cases} \text{A1} = 100\% \text{ chance of winning €3,000} \\ \text{B1} = 80\% \text{ chance of winning €4,000} \end{cases}$$

Secondly, the subjects are asked to choose between prospects A2 and B2, where:

$$\begin{cases} \text{A2} = 20\% \text{ chance of winning €4,000} \\ \text{B2} = 25\% \text{ chance of winning €3,000} \end{cases}$$

There are therefore 4 possible combinations of answers (A1A2, A1B2, B1A2, B1B2). Two of these combinations reveal inconsistent choices that violate expected utility theory (A1B2 & B1A2). The substitution axiom of utility theory states that if B1 is preferred to A1, then any (probability) mixture (B1, p) must be preferred to the mixture (A1, p). Choices that violate this axiom can be considered as sub-optimal, following what may be referred to as the Allais paradox decision bias (Weber, 2008).

Since subjects can make sets of choices that either violate EUT or not, a binary variable is created for further analysis. The variable allviolation takes a value of "1" if the subject's answers violate EUT and "0" otherwise.

Sunk-cost fallacy

The sunk-cost fallacy was examined using a decision task introduced by Arkes & Blumer (1985). Subjects were presented with a hypothetical question where there are two possible answers. They were given the choice between going on one of two trips where different amounts of money had previously been spent to purchase the travel tickets and there was no possibility of a refund. Subjects were also informed of the predicted pleasure of each trip, with the cheapest option being the more enjoyable. If subjects chose the more expensive trip, the fallacy was considered to be displayed. If subjects chose the least expensive trip, it was not.

Given that subjects can either act as per the sunk-cost fallacy or not, the dependent variable is a binary one. The variable *skf* takes a value "1" if the subject's answer is following the sunk-cost fallacy and "0" otherwise.

Present bias

The present bias decision task used in this experiment was suggested by Frederick, Loewenstein, & O'donoghue (2002). Two choice problems were posed to subjects, where their order of appearance is randomized. Subjects were asked to choose between two different prospects at different points in time, A1 and B1, where:

$$\begin{cases} \text{A1} = \text{A payment of €100 today} \\ \text{B1} = \text{A payment of €120 in 1 month} \end{cases}$$

Secondly, the subjects were asked to choose between prospects A2 and B2, where:

$$\begin{cases} \text{A2} = \text{A payment of €100 in 12 months} \\ \text{B2} = \text{A payment of €120 in 13 months} \end{cases}$$

There are therefore 4 possible combinations of answers (A1A2; A1B2; B1A2; B1B2). One of these combinations reveals the existence of present bias (A1B2). The combination indicates that individuals give stronger weight to payoffs in the present time when considering trade-offs between two moments, acting as per what is considered the present bias (O'Donoghue & Rabin, 2015).

Since subjects can make sets of choices that are either considered to present biased or not, a binary variable is created for further analysis. The variable *presentbias* takes a value "1" if the subject's answer combination is A1B2 and "0" otherwise.

Ellsberg paradox

This decision task comes directly from the original paper by Daniel Ellsberg (1961). Subjects were presented with a hypothetical scenario where an urn contains 90 balls. Subjects were informed that every ball had one colour (red, black, or yellow) and that 30 balls are red. Of the remaining 60 balls, there was no information regarding numbers by colour. Subjects were then asked to suppose that a ball is drawn at random from the urn, and to bet on its colour. They were then presented with two choice problems, the order of which was random. In one choice problem, a decision was to be made between two different prospects, A1 and B1, where:

$$\begin{cases} A1 = \text{Win €100 if ball is red} \\ B1 = \text{Win €100 if ball is black} \end{cases}$$

Secondly, subjects were asked to choose between prospects A2 and B2, where:

$$\begin{cases} A2 = \text{Win €100 if ball is red or yellow} \\ B2 = \text{Win €100 if ball is black or yellow} \end{cases}$$

There are therefore 4 possible combinations of answers where the order is of no relevance (A1A2, A1B2, B1A2, B1B2). Two of these combinations (A1B2 & B1A2) reveal choices that violate normative theory, namely the sure thing principle (Savage, 1954), which would require the ordering of A1 to B1 to be preserved in A2 to B2. These combinations can be considered as sub-optimal decisions, stemming from the phenomena described as ambiguity aversion (Ellsberg, 1961). Since subjects can make sets of choices that either violate normative theory or not, a binary variable is created for further analysis. The variable *ellsbergviolation* takes a value “1” if the subject’s answers violate normative theory and “0”otherwise.

Positive/Negative framing

The framing bias occurs when an individual’s choices are influenced by different descriptions of identical problems, such as the highlights of positive or negative features involved in a decision (Kahneman & Tversky, 1979). A pleura of possible decision tasks involving framing bias has been studied (Kühberger, 1998). The example used in this experiment is similar to that used by Gamliel & Kreiner (2013). Subjects were presented with a hypothetical scenario in which they know a driving instructor whose learner drivers pass (fail) their driving test 85% (15%) of the time. Subjects were then asked to rate on a 7-point Likert scale how likely they would be to recommend the driving instructor to someone they know. The scale ranges from (1) “extremely unlikely” to (7) “extremely likely. Each subject was randomly presented with either the positive attribute version (85% pass) or the negative attribute version (15% fail). The variable *Negativeframing* takes a value “1” if the negative attribute version was presented and “0” otherwise.

Anchoring and adjustment

The anchoring effect takes place when people's numerical estimates are affected by the initial exposure to a number which is subsequently used as a reference point, regardless of how arbitrary this number may be (Tversky & Kahneman, 1974). The decision task used in this experiment is based on a question from Jacowitz & Kahneman (1995). First, subjects were asked if they believed the length of the Mississippi river to be greater or less than 3200km (115km). Then, subjects were asked to estimate the length of the Mississippi River. The initial question had two versions: high anchor (3200km) or low anchor (115km). Jacowitz & Kahneman (1995) derived these anchors from a calibration group where the question of the uncertain length of the river was posed with no anchors. The 15th and 85th percentiles of estimates from this group were used as low and high anchors, respectively. The same anchors were used in this experiment, with each subject being shown one of the two versions in a randomized fashion. The variable *Lowanchor* takes a value "1" if the low anchor version was presented and "0" otherwise.

Bias blindspot

Research has shown that people tend to believe themselves to be less biased than others when making decisions (West, Meserve, & Stanovich, 2012). University students tend to perceive themselves as less biased than their peers, airline passengers tend to perceive themselves as less biased than other customers, and United States citizens tend to perceive themselves as less biased than the average USA citizen (Pronin, Lin, & Ross, 2002). This discrepancy is often referred to as the bias blindspot, where the perception of bias in self differs from the perception of bias in others. There is evidence that the least skilled tend to be poor at assessing their level of skill (Kruger & Dunning, 1999). Nonetheless, decision-making ability is a specific case. West et al. (2012) found no evidence that those with smaller blindspot scores had a different likelihood of committing a decision bias, nor that those with higher cognitive ability had lower blindspot scores. The question remains regarding levels of awareness on the existence of decisions biases and self-awareness on the frequency of biased decision-making. Crucially, due to the diversity of demographic factors, the question posed in this experiment did not ask subjects to compare themselves to a specific group of peers, but the average person. Direct comparison with previous research should be done with caution.

In line with an experiment conducted by Morewedge et al. (2015), subjects were asked to what extent did they agreed with the following two statements: (1) *I exhibit biases when* *making decisions*; (2) *The average person exhibits biases when making decisions.* Answers were recorded on a 5 point Likert scale ranging from (1) “strongly disagree” to (5) “strongly agree”. The score was calculated by subtracting the answer from statement (2) from that of statement (1). The order in which the two statements were presented was random. The variable *blindspot* takes values between “-5” and “5” points.

3.5. Explanations of decision biases

Brief verbal explanations of the six concepts linked to each of the decision tasks were presented to the subjects assigned to the treatment group. These explanations aimed at inducing shallow levels of knowledge of the decision biases. This experimental manipulation attempted to simulate awareness in a format similar to the one found in non-academic mediums, provided they were scientifically accurate. Simple language was used in a short text format. Below is a description of each explanation, separated by paragraph. Further discussion regarding the consequences of the language used is done in section 5.

Sunk-cost fallacy

The Sunk Cost Fallacy describes our tendency to follow through on an endeavour if we have already invested time, effort or money into it, even if the benefits from now on do not outweigh the costs from now on.

Allais paradox

The Allais Paradox occurs when people’s preferences result in inconsistent choices between two related gamble pairs.

Present bias

Present bias refers to the tendency of people to give stronger weight to payoffs in the present time when considering trade-offs between two moments.

Ellsberg paradox

Ambiguity aversion is related to an unreasonable fear of the unknown, leading to a tendency to favour uncertainty with known probabilities over uncertainty with unknown probabilities.

Positive/negative framing

The framing bias occurs when our decisions are influenced by the way information is presented. Identical information may be more or less attractive depending on what features are highlighted.

Anchoring and adjustment

Anchoring is a particular form of bias whereby initial exposure to a number serves as a reference point and influences subsequent judgments.

3.6. Procedure

Subjects were recruited primarily via social media. The platforms used to advertise the survey included WhatsApp, Facebook, Instagram, and LinkedIn. A particular effort was made to reach potential subjects with the specificity of having an academic background in behavioral economics. This was achieved by contacting people individually through the LinkedIn platform, where academic background is usually displayed.

On the initial page of the survey, subjects were informed of the voluntary and anonymous nature of their participation in the experiment. Once subjects proceeded, they were assigned to one of the two possible groups (*Treatment* or *Control*). Each decision task was asked on a separate page. In the treatment group, the explanation of the concept associated with each task was presented on a page preceding the task. After completing the decision tasks, the bias blindspot question was posed, followed by 5 questions regarding demographic content where subjects reported their age, gender, geographic location, education level, and whether they had formal education in behavioral economics. Next, they went through the opt-in section regarding the lottery incentive. The last page thanked subjects for their participation.

3.7. Analysis

In this section, the methods of analysis of the potential effect of treatment and/or behavioral economics background in decision performance are laid out. The methodology is explained in a separate section per decision task. Tests evaluating model assumptions are included in appendix C.

Allais paradox

To analyse the possible effect of treatment on the frequency of violation of normative theory in the Allais paradox decision task, a 2x2 Fisher's exact test is conducted. To analyse the possible differences in the probability of showing inconsistent choices due to having a formal education in behavioral economics (BE), logistic regression models controlling for relevant demographic variables are run. This is done in every task analysis, since this variable is not randomized, and failing to control for the relevant variables could lead to confounding results.

Sunk-cost fallacy

Similarly, to analyse the possible effect of treatment on the frequency of commitment of the sunk-cost fallacy, a 2x2 Fisher's exact test is conducted. To analyse the possible differences in the likelihood of committing the fallacy due to having a formal education in BE, logistic regression models controlling for relevant demographic variables are run.

Present bias

Likewise, to analyse the possible effect of treatment on the frequency of behaving in accordance to present bias, a 2x2 Fisher's exact test is conducted. To analyse the possible differences in the likelihood of displaying present biased choices due to having a formal education in BE, logistic regression models controlling for relevant demographic variables are run.

Ellsberg paradox

Again, to analyse the possible effect of treatment on the frequency of violation of normative theory in the Ellsberg decision task, a 2x2 Fisher's exact test is conducted. To analyse the possible differences in the likelihood of displaying choices that violate savage's axioms due to having a formal education in BE, logistic regression models are performed controlling for relevant demographic variables.

Positive/Negative attribute framing

To analyse the possible effect of treatment on the recommendation intentions displayed in the framing effect decision task, a two-way ANOVA is conducted. To analyse the potential impact of having education in behavioral economics on the effect of positive/negative attribute framing, ordered logistic regression models are performed controlling for relevant demographic variables.

Anchoring and adjustment

To analyse the possible effect of treatment on the river length estimations given the anchor conditions, a two-way ANOVA is conducted. To analyse the possible differences in anchoring and adjustment effects due to having a formal education in BE, an OLS regression is performed controlling for relevant demographic variables.

4. Results

This section contains the results of the analysis regarding the potential effect of knowledge of decision theory on decision-making tasks. The statistical analysis is presented and its relation to the hypotheses of this paper is outlined. Each decision task is analysed separately. Within each decision task analysis, two parts exist. One part presents the results regarding the possible effects of the experimental conditions, while another part presents the results regarding the possible effects of having a formal education in behavioral economics. At the end of the section, an overview of the results is provided. The detailed sets of choices that are not presented in this section are in appendix B.

4.1. Results per decision task

Allais paradox and Treatment

This segment lays out the findings of the analysis about the possible effect of informing individuals of the existence of the Allais paradox decision bias on the frequency of behaving in accordance with it. Given the Fisher's exact test results, the null hypothesis of no differences between the treatment group and control group is not rejected at a 5% significance level ($p = 0.34$, Fisher's exact test). This result provides no evidence in support of H1, where informing people of the existence of the bias would have a debiasing effect. The proportions are in table 2.

Table 2: Allais paradox – Violation of EUT per condition

	Control group	Treatment group
Violation of EUT	67	59
No Violation	49	50
Number of observations	116	109

1-sided Fisher's exact (p = 0.34)

Allais paradox and BE

This segment lays out the findings of the analysis about the possible effect of having a formal education in behavioral economics on the frequency of violating EUT in the Allais paradox decision task. The proportions are in Table 3. The result of Fisher's exact test does not allow for the rejection of the null hypothesis of no differences between subjects with a formal background in BE and those without such background at a 5% significance level (p = 0.13, Fisher's exact test). Remarkably, a higher proportion of those with BE violated EUT than those without such education. The percentage of subjects who made inconsistent choices was 60.2% for those with BE and 51.2% for and those without, respectively.

Table 3: Allais paradox – Violation of EUT and BE

	No BE	BE
Violation of EUT	59	65
No Violation	55	43
Number of observations	114	108

1-sided Fisher's exact (p = 0.13)

The results of the logistic regression models are in table 4, where the binary dependent variable represents the violation of EUT.

Table 4: Allais paradox - Logistic regression models of violation of EUT

Variables	(1) allviolation	(2) allviolation	(3) allviolation	(4) allviolation	(5) allviolation
BE	0.343	0.341	0.378	0.342	0.201
	(0.272)	(0.272)	(0.275)	(0.279)	(0.292)
Treatment		-0.132	-0.152	-0.128	-0.112
		(0.271)	(0.275)	(0.277)	(0.283)
Age			-0.0319	-0.0334	-0.0131
			(0.0363)	(0.0365)	(0.0502)
Male				0.233	0.311
				(0.282)	(0.290)
Education Level					
- Bachelor					1.124*
					(0.667)
- Masters					0.865
					(0.685)
- Ph.D./Doctorate					0.821
					(1.396)
Constant	0.0702	0.136	0.945	0.861	-0.567
	(0.187)	(0.232)	(0.961)	(0.968)	(1.379)
Observations	222	222	218	218	216

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of the logistic regression models confirm that having BE has no significant effect on the probability of acting in accordance with EUT when presented with the Allais paradox decision task used in this experiment. The results provide no evidence in support of H2, where individuals with formal education in behavioral economics would be less prone to biased decision-making than individuals without it.

Sunk cost fallacy and treatment

This segment lays out the findings of the analysis about the possible effect of informing individuals of the existence of the sunk cost fallacy on the frequency of behaving in accordance with it. Given the Fisher's exact test results, the null hypothesis of no differences between the treatment group and control group is not rejected at a 5% significance level (p = 0.34, Fisher's exact test). This result provides no evidence in support of H1, where informing people of the existence of a bias would have a debiasing effect. As are in Table 5, the absence of an effect is clear, given the notable similarity in the proportion of subjects committing the sunk cost fallacy in both conditions.

Table 5: Sunk-cost fallacy per conditions

	Control group	Treatment group
Fallacy	28	29
No fallacy	88	80
Number of observations	116	109

1-sided Fisher's exact (p = 0.34)

Sunk cost fallacy and BE

This segment lays out the findings of the analysis about the possible effect of having a formal education in behavioral economics on the frequency of behaving in accordance with the sunk cost fallacy. The proportions are in Table 6. The result of Fisher's exact test allows for the rejection of the null hypothesis of no differences between subjects with a formal background in BE and those without such background at a 5% significance level (p = 0.01, Fisher's exact test).

Table 6: Sunk cost fallacy and BE

	No BE	BE
Fallacy	36	19
No fallacy	78	89
Number of observations	114	108

1-sided Fisher's exact (p = 0.01)

The results of the logistic regression models are in table 7, where the binary dependent variable represents behaving as per the sunk-cost fallacy.

Table 7: Logistic regression models of sunk cost fallacy

Variables	(1) skf	(2) skf	(3) skf	(4) skf	(5) skf	(6) skf
BE	-0.771**	-0.769**	-0.798**	-0.737**	-0.680**	
	(0.323)	(0.323)	(0.325)	(0.330)	(0.347)	
Treatment		0.184	0.107	0.0731	0.0819	
		(0.315)	(0.318)	(0.320)	(0.328)	
Age			-0.0576	-0.0548	-0.0635	-0.0628
			(0.0510)	(0.0509)	(0.0588)	(0.0591)
Male				-0.378	-0.426	-0.429
				(0.324)	(0.337)	(0.338)
Education level						
- Bachelor					-0.348	-0.370
					(0.658)	(0.660)
- Masters					-0.839	-0.859
					(0.696)	(0.697)
- Ph.D./Doctorate					1.568	1.605
					(1.528)	(1.541)
1.BE						-0.487
						(0.484)
1.Treatment						0.231
						(0.422)
1.BE#1.Treatment						-0.378
						(0.670)
Constant	-0.773***	-0.867***	0.665	0.781	1.472	1.394
	(0.201)	(0.259)	(1.311)	(1.308)	(1.548)	(1.557)
Observations	222	222	218	218	216	216

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Based on the results of the logistic regressions it is estimated that, on average, having a formal education in behavioral economics decreases the probability of behaving in accordance with the sunk-cost bias, ceteris paribus. The effect is statistically significant at a 5% significance level. These results provide evidence in support of H2, where individuals with formal education in behavioral economics would be less prone to biased decision-making than individuals without it. There was no significant effect of the interaction between the variable BE and the condition Treatment.

Present Bias and Treatment

Given the Fisher's exact test results, the null hypothesis of no differences between the treatment group and control group is not rejected at 5% significance level (p = 0.34, Fisher's exact test). This result provides no evidence in support of H1, where informing people of the existence of the present bias would have a debiasing effect. The proportions are in table 8.

Table 8: Present bias per condition

	Control group	Treatment group
Present bias	25	27
No Present bias	91	82
Number of observations	116	109

1-sided Fisher's exact ($p = 0.34$)

Present bias and BE

This segment lays out the findings of the analysis about the possible effect of having a formal education in behavioral economics on the frequency of making choices consistent with the present bias. The proportions are in Table 9. The result of Fisher's exact test does not allow for the rejection of the null hypothesis of no differences between subjects with a formal background in BE and those without such background at a 5% significance level ($p = 0.47$, Fisher's exact test). The percentage of subjects who made biased choices was 24.1% for those with BE and 22.8% for and those without, respectively.

Table 9: Present bias and BE

	No BE	BE
Present bias	26	26
No Present bias	88	82
Number of observations	114	108

1-sided Fisher's exact ($p = 0.47$)

The results of the logistic regression models are in table 10, where the dependent variable represents behaving as per the present bias.

Table 10: Present bias - Logistic regression models

Variables	(1) presentbias	(2) presentbias	(3) presentbias	(4) presentbias	(5) presentbias
BE	0.0706	0.0734	0.00303	0.0364	-0.0381
	(0.317)	(0.317)	(0.321)	(0.326)	(0.338)
Treatment		0.149	0.141	0.123	0.147
		(0.317)	(0.321)	(0.323)	(0.326)
Age			-0.0477	-0.0468	-0.0207
			(0.0513)	(0.0514)	(0.0699)
Male				-0.194	-0.150
				(0.328)	(0.334)
Education Level					
-Bachelor					0.466
					(0.831)
-Master					0.499
					(0.856)
-Ph.D./Doctorate					-
Constant	-1.219***	-1.295***	-0.0553	0.0191	-1.064
	(0.223)	(0.278)	(1.319)	(1.324)	(1.866)
Observations	222	222	218	218	212

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of the logistic regression models confirm that having BE has no significant effect on the probability of making present biased choices in the task used in this experiment. The results provide no evidence in support of H2, where individuals with formal education in behavioral economics would be less prone to biased decision-making than individuals without it.

Ellsberg paradox and treatment

Given the Fisher's exact test results, the null hypothesis of no differences between the treatment group and control group is rejected at a 1% significance level (p = 0.01, Fisher's exact test). This result provides evidence in support of H1, where informing people of the existence of a bias would have a debiasing effect. The proportions and test results are in table 11.

Table 11: Ellsberg Paradox – Violation of EUT per condition

	Control group	Treatment group
Violation of axiom	71	47
No Violation	45	62
Number of observations	116	109

1-sided Fisher's exact (p = 0.01)

Ellsberg paradox and BE

This segment lays out the findings of the analysis about the possible effect of having a formal education in behavioral economics on the frequency of violating the sure thing principle in the Ellsberg paradox decision task. The proportions are in Table 12. The result of the Fisher's exact test does not allow for the rejection of the null hypothesis of no differences between subjects with a formal background in BE and those without such background, at a 5% significance level (p = 0.15, Fisher's exact test). The percentage of subjects who made choices violating the sure thing principle was 49% for those with BE and 57% for and those without, respectively.

Table 12: Ellsberg paradox and BE

	No BE	BE
Violation of axiom	65	53
No Violation	49	55
Number of observations	114	108

1-sided Fisher's exact (p = 0.15)

The results of the logistic regression models are in table 13, where the dependent variable represents the violation of EUT.

Table 13: Ellsberg paradox - Logistic regression models

Variables	(1) ellsbergviolation	(2) ellsbergviolation	(3) ellsbergviolation	(4) ellsbergviolation	(5) ellsbergviolation	(6) ellsbergviolation
BE	-0.320	-0.348	-0.456	-0.635**	-0.634**	
	(0.270)	(0.276)	(0.282)	(0.297)	(0.312)	
Treatment		-0.814***	-0.877***	-0.821***	-0.896***	
		(0.276)	(0.282)	(0.289)	(0.296)	
Age			0.0596	0.0559	0.00313	0.00321
			(0.0434)	(0.0443)	(0.0562)	(0.0562)
Male				0.934***	0.922***	0.924***
				(0.297)	(0.304)	(0.304)
Education level						
- Bachelor					-0.267	-0.259
					(0.680)	(0.682)
- Master					0.260	0.267
					(0.709)	(0.711)
- Ph.D./Doctorate					1.141	1.126
					(1.577)	(1.574)
1.BE						-0.705
						(0.439)
1.treatment						-0.965**
						(0.419)
1.BE#1.treatment						0.136
						(0.585)
Constant	0.283	0.702***	-0.692	-1.043	0.334	0.362
	(0.189)	(0.242)	(1.116)	(1.143)	(1.496)	(1.502)
Observations	222	222	218	218	216	216

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of the logistic regression models confirm the statistically significant effect of *Treatment,* at the 1% significance level. Regarding deeper levels of knowledge of decision theory, the regression models indicate that having BE background has a significant effect on the probability of acting in accordance with normative theory when presented with the Ellsberg paradox decision task used in this experiment. It is estimated that, on average, having a formal education in behavioral economics, compared to not having such education, decreases the probability of violating savage's axioms when presented with this Ellsberg paradox decision task, ceteris paribus. This effect is significant at the 5% significance level. The results provide evidence in support of H2, where individuals with formal education in behavioral economics would be less prone to biased decision-making than individuals without it. The interaction between *Treatment* and *BE* shows no significant effect at any of the usual significance levels.

Notably, gender is a highly significant variable. Based on the logistic regression models it is estimated that, on average, being male, compared to being female, increases the probability of violating the sure thing principle when presented with the Ellsberg paradox decision task, ceteris paribus.

Positive/Negative attribute framing and Treatment

A two-way ANOVA predicting the recommendation intentions from the treatment group and the framing condition showed a non-significant interaction at any of the usual significance levels ($F(1, 225) = 0.73$, $p = 0.39$). The effect of *Treatment* was found to be non-significant ($F(1, 225) = 0.16$, $p = 0.69$). These results provide no evidence in support of H1, where informing people of the existence of a bias would have a debiasing effect.

The framing effect was significant at the 1% significance level, ($F(1, 225) = 8.76$, $p = 0.003$), confirming that the mean recommendations were inferior in the negative framing condition compared to the positive framing condition in a statistically significant manner. The mean recommendation intentions regarding the hypothetical driving instructor scenario are in table 14.

Table 14: Means of recommendation intentions as a function of framing

Framing	Overall sample		
	M	(SD)	n
Positive	5.4	(0.9)	114
Negative	5.0	(1.2)	111
Effect size *(d[CI])*	0.4	[0.13, 0.66]	-
t (df;p)	5.2	(223;<.004)	-

Positive/Negative attribute framing and BE

Given that the Likert scale was used in this decision task (Likert, 1932), an ordered logistic regression was run in order to analyse the potential impact of having education in behavioral economics on the effect of positive/negative attribute framing. The results are in table 15.

Table 15: Framing bias - Ordered logistic regression models

Variables	(1) flevel	(2) flevel	(3) flevel	(4) flevel	(5) flevel
Negativeframing	-0.676***	-0.676***	-0.637**	-0.634**	-0.573**
	(0.252)	(0.252)	(0.254)	(0.254)	(0.257)
BE	-0.0440	-0.0440	-0.0964	-0.0754	-0.0411
	(0.249)	(0.249)	(0.252)	(0.255)	(0.268)
Treatment		-0.000377	-0.0121	-0.0228	0.0169
		(0.249)	(0.251)	(0.252)	(0.257)
Age			0.0136	0.0145	-0.0211
			(0.0342)	(0.0341)	(0.0454)
Male				-0.132	-0.0909
				(0.258)	(0.264)
Education level					
- Bachelor					-0.572
					(0.592)
- Masters					-0.224
					(0.613)
- Ph.D./Doctorate					-0.522
					(1.182)
/cut1	-5.807	-5.807	-5.448	-5.494	-6.706
	(1.021)	(1.029)	(1.346)	(1.347)	(1.600)
/cut2	-4.178	-4.178	-3.819	-3.865	-5.075
	(0.492)	(0.507)	(1.006)	(1.008)	(1.326)
/cut3	-2.824	-2.824	-2.463	-2.511	-3.713
	(0.310)	(0.333)	(0.931)	(0.933)	(1.266)
/cut4	-1.692	-1.692	-1.386	-1.432	-2.657
	(0.247)	(0.275)	(0.912)	(0.914)	(1.249)
/cut5	-0.348	-0.348	-0.0138	-0.0587	-1.263
	(0.220)	(0.253)	(0.903)	(0.905)	(1.238)
/cut6	2.652	2.652	2.967	2.923	1.813
	(0.345)	(0.367)	(0.950)	(0.951)	(1.267)
Observations	222	222	218	218	216

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of the ordered logistic regression models show no evidence of BE having a significant effect on the recommendation intentions given the attribute framing conditions. The results provide no evidence in support of H2, where individuals with formal education in behavioral economics would be less prone to biased decision-making than individuals without it.

Anchoring and adjustment & Treatment

A two-way ANOVA predicting river length estimates based on anchors and experimental conditions showed no significant interaction at any of the usual significance levels ($F(1, 216)$

= 0.36, p = 0.55). The effect of *Treatment* was found to be non-significant at any of the usual significance levels ($F(1, 216) = 0.16$, $p = 0.61$). These results provide no evidence in support of H1, where informing people of the existence of a bias would have a debiasing effect.

The anchoring effect was significant at the 1% significance level, ($F(1, 216) = 70.06$, $p < 0.001$), confirming that the mean estimates were significantly inferior given the low anchor when compared to the estimates given the high anchor. The mean river length estimates segmented by experimental condition and academic background are in table 16.

Table 16: Mean estimates of river length as a function of anchors

Riverstimate (Km)	Total	Conditions		BE	
		Control	Treatment	BE	NoBE
Low anchor					
Mean	1314.9	1445.8	1155.8	1446.2	1218.3
(SD)	(1467.6)	(1681.4)	(1157.8)	(1452)	(1502.7)
High anchor					
Mean	3507.6	3494.1	3519.7	3164	3695.1
(SD)	(2314.2)	(2611.1)	(2036.1)	(2766.9)	(1625)
Total					
Mean	2400.7	2386.9	2415.1	2280.1	2478.8
(SD)	(2220.6)	(2380.5)	(2052.8)	(2344.6)	(1994.4)

In order to analyse the possible differences in estimates due to having formal education in BE, an OLS regression was performed controlling for the relevant variables. The results are in table 17.

Table 17: Anchoring and adjustment: OLS regression models

Variables	(1) rivestimate	(2) rivestimate	(3) rivestimate	(4) rivestimate	(5) rivestimate
Lowanchor	-2,406***	-2,402***	-2,324***	-2,279***	-2,148***
	(166.3)	(167.9)	(165.3)	(227.5)	(240.7)
BE	-261.3	-260.4	-252.1	-265.2	-255.1
	(296.4)	(295.5)	(296.3)	(300.1)	(313.0)
Treatment		34.67	117.4	125.8	137.6
		(291.7)	(293.0)	(289.5)	(298.2)
Age			14.84	14.33	69.69
			(37.10)	(37.28)	(59.13)
Male				88.78	56.90
				(300.7)	(309.5)
Education Level					
- Bachelor					209.5
					(407.8)
- Masters					-145.2
					(415.0)
- Ph.D./Doctorate					-1,032
					(1,244)
Constant	2,565***	2,547***	2,085**	2,051**	630.8
	(189.3)	(231.5)	(961.5)	(964.1)	(1,460)
Observations	215	215	211	211	209
R-squared	0.030	0.030	0.026	0.027	0.036

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of the ordinary least square regression models show no evidence of BE having a significant effect on the estimates made given the anchors provided. The results provide no evidence in support of H2, where individuals with formal education in behavioral economics would be less prone to biased decision-making than individuals without it.

4.2. Overview of results

Six decision tasks were posed to subjects. Out of these, surface knowledge had a significant effect exclusively in the Ellsberg paradox task. Deeper knowledge, represented by formal education in behavioral economics, had a significant effect solely in the Ellsberg paradox task and in the sunk cost fallacy task. An overview of the results per task in relation to each of the two hypotheses is provided in table 18.

Table 18: Overview of results

		H1: *Treatment*	H2: *BE*
Ellsberg Paradox	Statistical differences	Yes***	Yes**
	Conform hypothesis	Yes	Yes
Sunk cost fallacy	Statistical differences	No	Yes**
	Conform hypothesis	No	Yes
Present bias	Statistical differences	No	No
	Conform hypothesis	No	No
Allais paradox	Statistical differences	No	No
	Conform hypothesis	No	No
Anchoring and adjustment	Statistical differences	No	No
	Conform hypothesis	No	No
Attribute Framing	Statistical differences	No	No
	Conform hypothesis	No	No

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

4.3. Relation with bias blindspot

Most subjects did not rate themselves as either more or less biased in decision-making than the average person. Of the 225 observations, 134 (60%) have a null score regarding the bias blindspot. Solely 8 (3.5%) of subjects considered themselves to be more biased in decision-making than the average individual. The remaining 83 (36.9%) considered themselves as less biased, with 64 (28.4%) having a score of 1 point, 15 (6.7%) of 2 points, and 4 (1.8%) of 3 points. The frequencies are shown in table 19.

Table 19: Bias blindspot – Score frequencies

Bias blindspot score	Total	
	Observations	Frequency
-3	1	0.4%
-2	2	0.9%
-1	5	2.2%
0	134	60%
1	64	28.4%
2	15	6.7%
3	4	1.8%

The difference in the bias blindspot score between those in the control group (*M* = 0.5; *SD* = 0.8) and those in the treatment group (*M* = 0.3; *SD* = 0.8) was significant at the 10% significance level ($t(223) = 1.9400$; $p<0.05$). Regarding the differences in bias blindspot scores due to having a formal education in decision theory, no significance was found at any of the usual significance levels ($t(220) = -0.96$; $p<0.34$). The mean scores of bias blindspot discriminated by experimental condition and education background are in table 20.

Table 20: Bias blindspot mean scores - Condition and BE

Bias blindspot score	Total	Conditions		BE	
		Control	Treatment	BE	NoBE
Mean	0.4	0.5	0.3	0.5	0.4
(SD)	(0.8)	(0.8)	(0.8)	(0.8)	(0.8)

In line with previous research, the correlation between the blindspot score and the frequency of committing decision biases was found not to be relevant in terms of magnitude, nor was it statistically significant ($r(220) = -0.02$, $p = 0.82$).

5. Summary and discussion

This paper aimed to analyse how knowledge of decision theory impacts decision-making in the context of decision biases. The research started by reviewing literature related to this matter. Two hypotheses were formed. The first hypothesis was concerning the expected effects of awareness of decision theory concepts on decision-making. The second hypothesis was regarding the expected effects of having a formal education in decision theory on decision-making. To address these, an online experiment was designed with six decision tasks where sub-optimal decisions have been systematically recorded. The concepts associated with such tasks are an integral part of decision theory and are taught in formal education degrees. The tasks used were linked to the Allais paradox, Ellsberg paradox, Sunk-cost fallacy, Present bias, Anchoring and adjustment bias, and Positive/Negative framing bias.

Upon agreeing to participate in the experiment, subjects were randomly assigned to one of two groups, *control* or *treatment.* The only difference between the groups was that before each task, an explanation of the bias and/or violation of normative theory associated with the decision task was presented. Among other relevant demographic variables, it was controlled for whether subjects had or were currently pursuing formal education in behavioral economics. Statistical methods used included Fisher's exact test, two-way ANOVA, binary logistic regression, ordered logistic regression, and ordinary least squares regression. Of the six decision tasks, no evidence in support of either of the two hypotheses was found for the cases of the Allais paradox, Present bias, Anchoring and adjustment bias, and Positive/Negative framing bias. For these decision tasks, within the context of this experiment, no indication of knowledge of decision theory having an impact on decision performance was found. For the Ellsberg paradox and the sunk-cost fallacy decision tasks, evidence was found in support of the 2nd hypothesis were having a formal education in behavioral economics would reduce biased decision-making. Of the total set of decision tasks, data supporting the first hypothesis were found only regarding the Ellsberg Paradox decision task. For the most part, the findings do not support the hypotheses developed in this paper. These are addressed first per decision task, followed by a general discussion of the overall results.

Allais paradox

The case of the Allais paradox (Allais, 1953) is of particular interest given that it is at the historical core of behavioral economics. Remarkably, formal education in behavioral economics did not affect decisions violating Savage's axiom. Looking at the frequency, those with such education actually violated EUT slightly more often than those without. This is in contrast to the conclusions of Van de Kuilen & Wakker (2006) regarding learning and the Allais paradox. The authors found evidence indicating that learning leads behavior to converge to EUT. Importantly, the authors concluded that it was learning by experience, not by thought alone, that led to such results. One might reasonably have expected that those with BE background, given the focus on the study of decision making, would have had a level of understanding somewhat similar to that acquired by subjects during such an experiment. It appears that this is not the case. It can be speculated that the difference in results is due to the distinct, significant differences in experimental design. Apart from other dissimilarities, there were no proper incentives in the experiment done in this thesis, nor was there learning by experience. These differences are critical to the overall results of this thesis and are addressed further in the general discussion of the results.

Sunk-cost fallacy

In the case of the sunk-cost fallacy task, treatment had no significant effect. However, formal training in behavioral economics did reduce the frequency of committing the fallacy. Part of the original paper in which the decision task used in this paper was developed is closely related to the present analysis. Arkes & Blumer (1985) tested for possible differences in the frequency of committing the fallacy among psychology students who had taken a course in economics. They found no significant difference between those who had taken such a course and those who had not. In an introductory economics course, the fallacy might be mentioned once. It could be argued that the psychology students may have had only a superficial level of knowledge, even though it was in the context of formal education. This would be in line with the findings from this thesis. It could be argued that those subjects were merely aware of the concept, whereas those who have degrees in classical economics, accounting, and BE potentially have a deeper understanding of cost-benefit analysis, as it is an integral part of economic thinking. This is consistent with research showing that training in cost-benefit analysis can mitigate this fallacy (Larrick, Morgan, & Nisbett, 1990). It appears that in the context of the sunk-cost decision task, there is a significant difference between levels of knowledge about decision theory, with a deeper level of knowledge having a debiasing effect, while mere awareness not.

Present Bias

Notably, the example used in the present bias decision task has an unrealistically high discrepancy in returns. Regardless, the behavior of those with behavioral economics education did not differ significantly from those without such education. Similarly, presenting the explanation of the present bias had no effect. Preferences for immediate rewards have been consistently documented in research, yet the complete lack of effect of knowledge finds no immediate support in research. Some anecdotal evidence may lead to speculation. When in an informal conversation with ex-subjects of the study who had BE education, a common line of thought came up. The statement was along the lines of "*Even though I was aware of the biases, I still acted as if I were in a real-life scenario, where my preferences often went against the norm*". Naturally, this statement could be applied to any of the decision tasks.

It is plausible that in this context, regardless of knowledge, preferences do not change because of the connexion with inherent uncertainty about the future compared to the present.

It can be argued that the future tends to always involve some degree of risk. Even if they are assured that they will get the money, people are often afraid that something might happen. It could be argued that since in the future the probability of not getting the money is unknown, ambiguity aversion could play a role leading to the present being the preferred option. Further speculation is unsupported, but it is possible that such a preference is rooted in stronger underlying psychological forces and therefore cognitive understanding has little influence.

Ellsberg paradox

The Ellsberg paradox decision task was the only task in which the results supported H1. As might be expected, if the results supported H1, they would also supported H2. Both formal education in behavioral economics and awareness of the concept of ambiguity aversion had a significant effect. It is not directly clear why in this particular task treatment had an effect, yet the results are consistent with those from research. Jia, Furlong, Gao, Santos, & Levy (2020) found evidence that learning about the Ellsberg paradox reduced ambiguity aversion. In their paper, subjects learned about the paradox and their own decisions by computing the objective probability of winning the ambiguous lotteries, or by observing such computations. Despite the differences in experimental design, the results are consistent. This is also consistent with the results of Güney & Newell (2015), where learning probability distributions through both experience and description had an effect, with the former being significantly stronger. It seems likely that individuals with an academic background in behavioral economics have a greater understanding of probability distributions in the context of the task, which partially explains the results. Nonetheless, the treatment only informs subjects about the explanation of ambiguity aversion, it does not address the probability distributions, nor does it increase subjects' probabilistic understanding.

A possible explanation can be derived from the evidence of the remaining decision tasks, the relevant literature, and anecdotal inputs from ex-subjects. Within the decision tasks where there are individually normatively "poor" answers (Ellsberg paradox, Allais paradox, Sunk cost fallacy, Present bias), it could be argued that the Ellsberg paradox decision task is the furthest from a scenario experienced in everyday life. The argument is that in tasks closer to everyday experience, inherent preferences are stronger and therefore less susceptible to being influenced by potentially changing views, such as information about normative theory. For a question involving an urn, 3 coloured balls, and hypothetical betting, individuals may be more open to seeking a normatively correct answer than in a more familiar setting. A question involving a travel preference (sunk-cost-fallacy task), getting money now or later (present-bias task), and getting money for sure (Allais paradox task) is more directly related to daily life experience, easier to conceptualize, and perhaps associated with stronger preferences. Indeed, less familiar decision contexts require more mental processing (Roller, 2011). Although the treatment aimed to be an impartial explanation of decision theory concepts, given that it was presented immediately before a decision-making task and referred to what is normatively correct, it could be argued that such an explanation may be seen by subjects as having some similarities to possible advice. Research shows that people tend to overweight advice on difficult decision tasks (more mental processing) and underweight advice on easier tasks (Gino & Moore, 2007). Although this is based on assumptions, as less familiar tasks may be considered more complex, this could potentially explain some of the differences in results.

Notably, gender differences were found in this decision task, with female subjects being less likely to be ambiguity averse. Although there are findings in the literature regarding gender differences in risk preferences (Borghans, Heckman, Golsteyn, & Meijers, 2009), there do not appear to be any regarding ambiguity aversion.

Anchoring and adjustment

The anchoring and adjustment effect has been observed in a variety of contexts and has been shown to be strong and widespread (Furnham & Boo, 2011). Many attempts to reduce the anchoring bias have had either little or no effect. The most effective technique seems to be the consider-the-opposite strategy (Mussweiler & Strack, 2000; Mussweiler, Strack, & Pfeiffer, 2000). More recently, Morewedge et al. (2015) demonstrated success in mitigating the bias through a one-time training debiasing intervention. This took the form of interactive games and video-based training in which subjects were informed not only of the bias but also of methods to mitigate it, including the consider-the-opposite strategy. The results of the experiment conducted as part of this thesis do not support either of the stated hypotheses. It appears that knowledge of this bias does not reduce its effect. This is consistent with the conclusions found in the majority of the literature, where theoretical knowledge alone appears to have no impact.

Positive/negative framing

The data found does not support either of the hypothesis stated in this thesis. Relatively little research regarding the debiasing effect of informational warning has been conducted for the case of framing, although there appears to have a significant, small debiasing effect (Cheng & Wu, 2010). This was not the case in the scope of this thesis. Regarding formal education, the closest literature regards the effect of statistical background with better decision-making in the presence of framing (Peters, Västfjäll, Slovic, Mertz, Mazzocco, & Dickert, 2006). Likewise, this was not found in this thesis.

General discussion

In summary, the evidence presented in this paper suggests that there is a gap between knowledge and behaviour when it comes to decision theory. Of the six decision tasks examined, surface knowledge had a significant effect in only one task, while deeper knowledge had an effect in two tasks. The extent to which this gap exists remains to be explored given the wealth of potential research on this topic.

A tentative explanation of the overall results relates to the definition of knowledge itself. The concept is described as having two sources, either being obtained by experience or study (Cambridge, 1995). Coherently, within Epistemology, a distinction is made between the understanding of facts (descriptive knowledge) from skills (procedural knowledge) (Stanley & Willlamson, 2001). Similarly, in the cognitive science literature procedural knowledge is distinguished from declarative knowledge, where the former is knowledge exercised in performing a task, while the latter is knowledge about specific facts or propositions (Ten Berge & Van Hezewijk, 1999).

This is closely related to the distinction made in the experimental economics literature, where learning by thinking is separated from learning by experience (Myagkov & Plott, 1997). It can be suggested that learning by thinking corresponds to descriptive knowledge while learning by experience corresponds to procedural knowledge. In this paper, the effect of descriptive knowledge was investigated. The experimental treatment condition made subjects aware of decision-theoretic facts. Having formal education in behavioral economics was also analysed, which consists mainly of the acquisition of descriptive knowledge. In the survey, there was no feedback, nor any consequence of the decisions made. This difference could explain why the results of this paper are not consistent with some of the related literature. The documented successful reduction of normative theory violations tends to occur in a context where there is learning through experience (e.g., Nielsen & Rehbeck, (2020); Van de Kuilen & Wakker (2006)). Consistent with this premise, recent successful debiasing interventions through training have done so with a focus on learning through experience where there is feedback and repetition of decisions (Clegg et al., 2014; Morewedge et al., 2015). This is consistent with what Larrick (2004) predicted when he outlined the interest in understanding whether training in behavioral theory has a debiasing effect. The author speculated, "*courses that contain behavioral decision research may miss an opportunity to improve people's intuitions if they do nothing more than demonstrate the flaws. Without accompanying recognition skills and decision tools, it is unlikely that "understanding" alone would be sufficient"* (Koehler & Harvey, 2004, p. 326). It seems plausible that merely studying decision errors without acquiring procedural knowledge is not sufficient to produce a significant and consistent change in decision-making. The data from this thesis supports this premise.

Limitations

The limitations inherent to this study are important to be discussed. First of all, the specificity of the experiment. For the analysis of each decision bias/violation of normative theory, one decision task was selected among several other potential examples used in the literature. It is plausible that the results would have been affected if other tasks had been selected. Small differences in decision environments often affect results (Alekseev, Charness, & Gneezy, 2017). Concerning the variable representing formal education in behavioral economics, a note of specificity must also be made. Although not explicitly controlled for, the subjects with such education had acquired it (or were in the process of doing so) at Erasmus University Rotterdam. It is plausible that curricula regarding behavioral economics degrees differ across institutions in ways that could influence the results. Furthermore, although subjects who were currently pursuing such a degree were in the final block at the time of the survey, some students were likely doing courses via resits, which was not controlled for.

The experimental design had clear limitations, namely regarding the incentive structure. Research shows that incentives can mitigate irrational behavior caused by a lack of elementary understanding and/or motivational deficits (Camerer & Ho, 1999; Myagkov & Plott, 1997). The financial constraints of this work did not allow for more appropriate incentive mechanisms.

On average, the time taken to complete the survey was 2.2 minutes longer for subjects in the treatment group than for subjects in the control group. Although seemingly a small difference, it is possible that the higher cognitive effort required to read the additional material affected subjects in the treatment group, as cognitive load influences decision making (Deck & Jahedi, 2015).

There was a great deal of variability regarding the language used in the explanations presented to those in the treatment group. This occurred both in terms of length and in terms of content. In some cases, the first-person point of view was used (Sunk-Cost fallacy, Positive/Negative framing), and in others, the third-person perspective was used (Allais paradox). The term "bias" was used in only 3 of the cases (Present bias, Positive/Negative framing, Anchoring and adjustment), while other terms were used in the remaining cases. In the only case where treatment had a significant effect, the wording “unreasonable fear” was used, which may carry a significantly stronger negative connotation. Some of the concepts were presented in a seemingly vague manner (e.g., Allais paradox), while others in a more specific format (e.g., Sunk-cost fallacy). Alekseev et al. (2017) pointed out the impact that small differences in language use can have on results. In the case of this work, the differences are relatively large and undoubtedly a significant limitation. It would be crucial for further research to use a more consistent type of language where variability in the structure of conceptual explanations is minimal.

The experimental design was intended to induce awareness of a decision-theoretic concept. Of course, not only did it do so, but there was likely an immediate association with the decision task that followed. This is a limitation in terms of external validity. A person who is aware of a decision bias does not necessarily identify it when presented with a decision in which it may occur, contrary to seems highly likely in the case of this experiment.

The theoretical approach in this thesis includes statistical/numerical reasoning as part of the knowledge acquired in the study of decision theory. Performance on decision tasks has often been shown to be correlated with statistical/numerical reasoning and general cognitive ability (Stanovich & West, 2008; Toplak, West, & Stanovich, 2011). A different approach could be taken, controlling for such cognitive abilities, thereby isolating decision-theoretic knowledge from these variables. Moreover, there is some evidence that the type of education influences performance on decision tasks (Larrick, Morgan, & Nisbett, 1990). Individuals with an academic background in finance/business/economics may have significantly different performance than individuals with a background in law, for example. It is also plausible that those studying psychology are more likely to be aware of certain cognitive biases than their peers. It would be relevant for future research to control for the education type, possibly even comparing traditional economics education with a behavioral focused one.

Although this thesis considered many of the common sets of choices in the decision tasks investigated as decision biases and considered these biases as suboptimal, this is not done consistently throughout the literature. There are disagreements as to what decisions can be considered as “biased” (Besharov, 2004) as well as if a biased decision is “poor” (Orasanu, Calderwood, & Zsambok, 1993). Cognitive biases developed as part of the evolutionary process, and there is evidence showing they are advantageous in certain contexts (Haselton, Nettle, & Murray, 2015). Even in relation the some of the specific decision tasks used in this paper, there is debate as to if the common choices are irrational, namely in the case of the Allais paradox (Mongin, 2019; Weber, 1998), Ellsberg paradox (Al-Najjar & Weinstein, 2009; Gibbard, 1990; Pope, 1991; Schmeidler, 1989) and Present bias (Farmer & Geanakoplos, 2009; Horvath & Sinha, 2013). This lack of consensus is one of the main limitations of the paper at hand.

Although two general hypotheses were stated in this study, these were tested per decision task, leading to a total of 12 separate statistical queries. Testing a large number of hypotheses may create a significant possibility of a false positive (Lytsy, 2017). Regarding time, although previously mentioned, it is important to highlight that the effect of treatment was analysed in an immediate setting. The findings may be different if subjects have more time to make and contemplate their decisions.

6. Conclusion

Of the six decision tasks analysed, surface knowledge had a significant effect in only one, while deeper knowledge had in two. In general, knowing decision theory does not appear to consistently reduce the frequency of decision biases. This is regardless of whether this knowledge is at a level of mere awareness of concepts or at a level of higher education. A gap exists between knowing about normative decision-making and behaving in accordance with it. This may be because the knowledge evaluated was purely theoretical. Comprehending decision theory and experiencing decision-making may be essentially different in terms of their effect on decision performance. Perhaps libertarian paternalism can have one more argument in its support if even highly educated individuals in accredited institutions seem almost as prone to decision biases as their peers. Nonetheless, the results of this work can open up further investigation into exactly what kind of knowledge is needed to reduce decision biases, especially biases that are of undoubtedly negative consequences. Perhaps there is an argument to be made in support of a specific debiasing program where descriptive knowledge would be part of academic curricula, business education, policy-making, and other areas. Although not always negative, the impact of decision biases in the affairs of the world need not be outlined to support further research.

In summary, knowledge of decision theory may influence decision-making in certain contexts, but it does not appear to be sufficient to consistently mitigate decision biases regarding the tasks studied in this thesis.

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8. Appendix

8.1. Appendix A: Survey design

Introductory Page

Welcome!

Participation in this survey is anonymous and voluntary.

Throughout the survey you may receive information containing particular definitions. Questions will be posed which may be in a quiz format, may regard hypothetical scenarios, and may require your concentration.

Please answer truthfully, and please always try to answer as if you were in a real-life scenario.

The survey takes an estimated 7 minutes to complete.

A great thank you for participating.

Decision tasks

Sunk-cost fallacy

This is a hypothetical format question. There are no right or wrong answers. Please try to answer as if you were in a real-life scenario.

Assume that you have spent €100 on a ticket for a weekend trip to Michigan. Several weeks later you buy a €50 ticket for a weekend trip to Wisconsin.

You think you will enjoy the Wisconsin trip more than the Michigan trip. As you are putting your just-purchased Wisconsin trip ticket in your wallet, you notice that the Michigan trip and the Wisconsin trip are for the same weekend!

It's too late to sell either ticket, and you cannot return either one.

You must use one ticket and not the other.

Which trip will you go on?

€50 trip to Wisconsin	€100 trip to Michigan

Allais paradox

This is a hypothetical format question. There are no right or wrong answers. Please try to answer as if you were in a real-life scenario.

Suppose you were offered the alternatives below:

Which option do you prefer?

80% chance of winning €4,000	100% chance of winning €3,000

Suppose you were offered the alternatives below:

Which option do you prefer?

20% chance of winning €4,000	25% chance of winning €3,000

Present bias

This is a hypothetical format question. There are no right or wrong answers. Please try to answer as if you were in a real-life scenario.

Suppose you were offered the alternatives below:

Which option do you prefer?

A payment of €100 today	A payment of €120 in 1 month

Suppose you were offered the alternatives below:

Which option do you prefer?

A payment of €120 in 12 months	A payment of €120 in 13 months

Ellsberg paradox

This is a hypothetical format question. There are no right or wrong answers. Please try to answer as if you were in a real-life scenario.

Suppose an urn contains 90 balls.

Every ball has one colour (red, black, or yellow).

30 balls are red.

Of the other balls, you are not told how many are black and how many are yellow, only that together they total 60 balls.

Suppose you are going to draw a ball at random from the urn, and gamble on the colour of that ball:

Which option do you prefer?

Win €100 if ball is red	Win €100 if ball is black

Which option do you prefer?

Win €100 if ball is red or yellow	Win €100 if ball is black or yellow

Positive/Negative framing

Negative version

This is a hypothetical format question. There are no right or wrong answers. Please try to answer as if you were in a real-life scenario.

Suppose you know a driving instructor.

On average, 15% of her students **fail** their driving test the first time they take it.

Would you recommend this driving instructor to someone you know?

Extremely unlikely	Very unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Very likely	Extremely likely

Positive version

This is a hypothetical format question. There are no right or wrong answers. Please try to answer as if you were in a real-life scenario.

Suppose you know a driving instructor.

On average, 85% of her students **pass** their driving test the first time they take it.

Would you recommend this driving instructor to someone you know?

Extremely unlikely	Very unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Very likely	Extremely likely

Anchoring and adjustment

High anchor version

This is a quiz format question. Please answer to the best of your abilities.

Do you think the Mississippi's river length is greater or less than 3200km?

Greater	Less

What do you think is the Mississippi's river length? (Km)

Low anchor version

This is a quiz format question. Please answer to the best of your abilities.

Do you think the Mississippi's river length is greater or less than 115km?

Greater	Less

What do you think is the Mississippi's river length? (Km)

Bias blindspot

To what extent do you agree with the following statements?

I exhibit biases when making decisions

Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree

The average person exhibits biases when making decisions

Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree

Demographic questions

What is your age?

What is your gender?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

What is the highest level of education you have obtained so far?

- Some high school or less
- High school diploma
- Bachelor
- Masters
- PhD/Doctorate
- Prefer not to say

Have you completed, or are you currently pursuing, a degree in the field of behavioral economics?

- No

- Yes
- Prefer not to say

Do you currently live in the Netherlands?

- Yes
- No
- Prefer not to say

Random lottery incentive

If you wish, insert your email address to apply for a randomly assigned amazon gift-card (20€).

Your data will only be used for the purpose of assigning the prize, after which it will be deleted.

8.2. Appendix B: Sets of choices

Allais paradox

- A1A2: *100% chance of winning €3,000 & 20% chance of winning €4,000*
- A1B2: *100% chance of winning €3,000 & 25% chance of winning €3,000*
- B1A2: *80% chance of winning €4,000 & 20% chance of winning €4,000*
- B1B2: *80% chance of winning €4,000 & 25% chance of winning €3,000*

Table 21: Pairs of choices – Allais paradox

Sets of choices: frequencies	Overall sample	Conditions		BE	
		Control	Treatment	BE	NoBE
A1A2	124	65	59	64	58
A1B2	80	37	43	30	49
B1A2	19	12	7	13	6
B1B2	2	2	0	1	1

Present Bias

- A1A2: *A payment of €100 today & A payment of €100 in 12 months*
- A1B2: *A payment of €100 today & A payment of €120 in 13 months*
- B1A2: *A payment of €120 in 1 month & A payment of €100 in 12 months*
- B1B2: *A payment of €120 in 1 month & A payment of €120 in 13 months*

Table 22: Pairs of choices – Present bias

Sets of choices: frequencies	Overall sample	Conditions		BE	
		Control	Treatment	BE	NoBE
A1A2	23	14	10	5	18
A1B2	52	25	27	26	26
B1A2	11	7	4	6	5
B1B2	138	70	68	67	71

Ellsberg Paradox

- A1A2: *Win €100 if ball is red & Win €100 if ball is red or yellow*
- A1B2: *Win €100 if ball is red & Win €100 if ball is black or yellow*
- B1A2: *Win €100 if ball is black & Win €100 if ball is red or yellow*
- B1B2: *Win €100 if ball is black & Win €100 if ball is black or yellow*

Table 23: Pairs of choices - Ellsberg paradox

Sets of choices: frequencies	Overall sample	Conditions		BE	
		Control	Treatment	BE	NoBE
A1A2	76	29	47	41	33
A1B2	106	65	41	48	58
B1A2	12	6	6	5	7
B1B2	31	16	15	16	14

8.3. Appendix C: Statistical models

8.3.1. Model assumptions

Logistic regression models

The logistic regression method has four main assumptions that must be met in order to ensure that results are valid (Peng, Lee & Ingersoll, 2002). These are:

1. All observations must be independent
2. The number of observations must be sufficient for analysis
3. There must be no specification error
4. There must be no Multicollinearity

1. All observations must be independent

Due to the nature of the experimental design used in this thesis, the first assumption is met regarding all models, for all observations are independent.

2. The number of observations is sufficient for analysis

Hosmer and Lemeshow (2004) provide a guideline for the minimum number of cases per independent variable being 10, therefore this assumption is met for all models.

3. Specification error

The STATA software *Linktest* command can be used to detect specification error (Torres-Reyna, 2007). The logic behind *linktest* is that if the model were to be properly specified, no additional statistically significant predictors should be found. If the variable "*_hatsq*" is found not to be significant, one fails to reject the null hypothesis that the model is correctly specified. Below the test results are shown.

Ellsberg paradox

Since the variable is not significant at any of the usual significance levels, the assumption is considered to be met, concerning the model used for the Ellsberg paradox task. The results of the test are in table 24.

Table 24: Linktest and specification error – Ellsberg paradox

Variables	ellsbergviolation
_hat	0.916***
	(0.220)
_hatsq	0.379
	(0.26)
Constant	-.017
	(0.186)
Observations	215

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The same test was run concerning the Allais paradox, Sunk-cost fallacy and Present bias tasks and the logistic models used. No evidence of a specification error was found in any of these cases.

4. There must be no multicollinearity

One possible manner of testing for multicollinearity is to run a *VIF* test (Brooks, 2008). Neter, Wasserman, and Kutner (1990) indicate that VIF higher than 10 suggests potential multicollinearity problems.

Given the results of the test present in table 25, no indication of a multicollinearity issue is found concerning the Ellsberg paradox task. The assumption is considered to be met.

Table 25: VIF test multicollinearity – Ellsberg paradox

Variables	VIF	1/VIF
BE	1.31	0.94
treatment	1.03	0.97
age	1.25	0.8
male	1.05	0.94
educ	1.29	0.77
Mean VIF	1.14	

The same test was run concerning the Allais paradox, Sunk-cost fallacy, and Present bias logistic models. No evidence of a multicollinearity problem was found.

Ordered logistic regression model

The ordered logistic regression method has four main assumptions that must be met in order to ensure that results are valid (Williams, 2018). These are:

1. The dependent variable is measured on an ordinal level.
2. One or more of the independent variables are either continuous, categorical, or ordinal.
3. There must be proportional odds.
4. There must be no multicollinearity.

Positive/Negative framing bias

The dependent variable is measured on an ordinal level.

Since the dependent variable was measured using the Likert scale, this assumption is met.

One or more of the independent variables are either continuous, categorical, or ordinal.

Since there are both continuous (age) and categorical (e.g. gender) variables, this assumption is met.

There must be proportional odds.

Using the *Gologit2* command to run the ordered logistic regression, allows for the *Wald* test to be conducted in order to evaluate if the proportional odds assumption is met (Williams, 2005). Given the results (Wald $\chi 2(1, N = 215) = 0.06$; $p= 0.81$) the assumption is considered to be met.

There must be no multicollinearity

Because of the results of the test present in table 26, no indication of a multicollinearity issue was found. The assumption is considered to be met.

Table 26: VIF test for multicollinearity

Variables	VIF	1/VIF
BE	1.07	0.94
treatment	1.03	0.97
age	1.25	0.80
male	1.06	0.94
educ	1.30	0.77
dfailed	1.02	0.98
Mean VIF	1.12	

Ordinary least squares regression

The OLS regression method has five main assumptions that must be met in order to ensure that the method is valid and is the best linear unbiased estimator (Brooks, 2008). These are:

1. The error terms should be normally distributed (Normality)
2. The model is linear in parameters (Linearity)
3. There is homoscedasticity.
4. There is no multicollinearity.
5. There is no autocorrelation.

The error terms should be normally distributed (normality)

Given that the sample size is sufficiently large (>200), the normality assumption is not needed since the Central Limit Theorem ensures that the distribution of disturbance term will approximate normality (Hoeffding & Robbins, 1948).

Linearity among parameters

It is possible to detect non-linearity by plotting the standardized residual values against standardized fitted values (Osborne & Waters, 2002). It was concluded that the error terms follow a normal distribution. Importantly, this conclusion is subjective, as it relies on visual interpretation (Hayashi, 2000).

Homoscedasticity

Running a Cameron & Trivedi's decomposition IM-test (Cameron & Trivedi, 2010) allows to test this assumption. Evidence of heteroskedasticity was found. Therefore, the OLS estimations would still be consistent and unbiased, but not the best. To address this limitation, the regression was run with robust standard errors.

Multicollinearity

To address this assumption, the *VIF* test can be used (Brooks, 2008). Given the results of the test present in table 27, no indication of a multicollinearity issue is found. The assumption is considered to be met.

Table 27: VIF test for multicollinearity

Variables	VIF	1/VIF
educ	1.41	0.71
age	1.39	0.71
male	1.20	0.83
BE	1.14	0.87
treatment	1.10	0.91
dlowanchor	1.07	0.93
Mean VIF	1.22	

Autocorrelation

Since this analysis was done with cross-sectional data, serial autocorrelation cannot be an issue. There is also no reason to expect spatial autocorrelation. Therefore this assumption is considered to be met.

8.3.2. Sample size calculations

Fisher's Exact tests

McDonald (2014) recommended using the Fisher's exact test for sample sizes that are less than 1,000, while the Chi-square test for larger samples. To validate via an a priori sample size calculation, using proportions 0.6 and 0.7, with 80% power (alpha = .05, one-tailed), G*Power suggests 84 subjects per group (N = 168) would be necessary to test for "Inequality of proportions of two independent groups (Fisher's exact)".

t-tests

In order to detect an effect size of Cohen's d = 0.5 with 80% power (alpha = .05, two-tailed), G*Power suggests we would need 86 subjects per group (N = 172) in an independent samples t-test". The effect size was set to d = 0.5, being the medium effect size convention (Cohen, 2013)

Two-way ANOVA

In order to detect an effect size of Cohen's d = 0.25 with 80% power (alpha = .05), G*Power suggests we would need a total sample size of 82 in "ANOVA, between factors test". The effect size was set to d = 0.25, as per a similar paper (Gamliel & Kreiner, 2013).

Ordinary least squares model

In order to detect an effect size of Cohen's f2 = 0.15 with 80% power (alpha = .05; 6 predictors) G*Power suggests we would need a total sample size of 98 subjects in an Linear multiple regression fixed model". The effect size was set to f2= 0.15, being the medium effect size convention (Cohen, 2013).