

Nijmegen School of Management
Department of Economics and Business Economics
Master's Thesis Economics (MAN-MTHEC)

Framing effect (price vs. return)

on risk-taking behavior

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Nijmegen, 30 June 2025

Program: Master's Program in Economics
Specialisation: Economics, Behavior & Policy
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1 Abstract

This paper investigates whether the framing of investment options, specifically presenting choices in term of prices versus returns, affects risk-taking behavior among individual investors. To examine this question, an experiment was conducted in which participants were randomly assigned to one of the two treatment groups. One group received investment scenarios framed in prices, while the other group received identical scenarios framed in returns. Each participant answered eight investment questions, allocating hypothetical capital between a higher-risk and lower-risk stock in each investment question. Risk-taking behavior was measured as the average amount allocated to the high-risk stock across all eight investment questions. The analysis involved an independent samples t-test, multiple regression models (including relevant control variables), a panel data regression and a multivariate multiple linear regression. Across all statistical methods, the direction of the framing effect was consistent. Participants exposed to price framing tended to allocate more to the high-risk stock than those exposed to return framing. However, in none of the analyses did this difference reach statistical significance at the conventional 0.05 p-value threshold. Therefore, the results of this paper indicate that the price versus return framing does not have a significant effect on risk-taking behavior, in this experimental context.

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2 Introduction

In today's complex financial environment, understanding the factors that influence financial decision-making is of great importance. Individuals are constantly faced with decisions that involve varying degrees of risk, such as investments in stocks, bonds, cryptocurrencies and other financial assets. These decisions often involve uncertain outcomes. If different framing techniques, such as price versus return framing, can lead individuals to make riskier or more conservative choices, the implications for their financial well-being could be huge. Investigating whether the framing of investment options influences financial decision-making is therefore crucial.

Understanding the role of framing in risk-taking behavior is essential, not only for investors, but also for financial advisors, policymakers and other stakeholders. By determining whether specific framing techniques impact investor behavior, this research could help reduce poor financial decision-making, improve financial literacy and contribute to more effective and responsible financial decision-making. If investors are aware of how framing influences their choices, they also may be better able to make rational decisions. This may be especially important for individuals with limited financial knowledge, who may be more vulnerable to framing effects. Ultimately, by exploring how framing shapes financial decision-making and effectively communicating this evidence to investors and all other stakeholders, this study could potentially contribute to reducing the risk of financial missteps and enhance the overall quality of financial decision-making of investors and other stakeholders. Therefore, investigating whether specific framing techniques affect the financial decision-making of individuals, is socially relevant.

This paper digs deeper into this topic. It investigates how the framing of investment options, specifically the distinction between price framing and return framing, influences individuals' risk-taking behavior in financial decision-making. The paper aims to answer the following research question:

How does the framing of investment options (price vs. return) affect risk-taking behavior in investors?

This paper contributes to the field of behavioral finance and economics. Framing effects in decision-making is a topic that is studied quite intensively (for example: Balart et al., 2020.,

Mishra and Fiddick, 2012. & Glaser et al., 2007). However, the specific effects of the price versus return framing, specifically on risk-taking behavior in financial decision-making, isn't studied quite well. There is little (Huber & Huber, 2019 and Stössel & Meier, 2015) to no research devoted to this specific topic. This paper addressed this gap by conducting an experiment to directly compare the effects of these two types of framing on risk-taking behavior. The findings fill in the existing literature gap, which defines the academic relevance of the paper.

To investigate how the framing of investment options (prices vs. returns) affects risk-taking behavior, this paper conducted an experiment using a self-designed Qualtrics survey. Participants were randomly assigned to one of the two treatment groups. One treatment group is exposed to price-framed investment questions and the other treatment group is exposed to return-framed investment questions. Both treatment groups get the same questions, but framed in a different way, depending on the treatment group. Every participant will be asked a series of 8 investment questions, with one higher-risk option and one lower-risk option presented in each investment question. To assess whether there is a significant framing effect on risk-taking behavior an independent samples t-test, multiple regression analyses, a panel data regression and a multivariate multiple linear regression were conducted. Across all analyses, a comparable trend was observed, participants in the price framing treatment group generally allocated more to the high-risk stock than those in the return-framing treatment group. However, none of the statistical test revealed a significant difference between the treatment groups at the conventional p-value threshold of 0.05. Therefore, the study concluded that the framing of investment options (price vs return) does not have a significant effect on risk-taking behavior.

3 Theoretical background

3.1 Literature review

Human behavior is shaped by a wide range of factors, including (among others) psychological, social, biological and contextual influences. Risk-taking behavior, as a specific form of decision-making, is no exception. It is influenced by numerous determinants (Figner and Weber, 2011).

An individual's willingness to take risks, for instance in investment decisions, may differ from their actual risk-taking behavior. This distinction reflects the difference between risk preference and actual risk-taking behavior. Nevertheless, literature suggests a positive correlation between (self-reported) risk preference and actual risk-taking behavior (Tavor, 2019). Empirical findings of the paper of Tavor (2019) indicate that individuals who report higher levels of risk aversion tend to exhibit more risk-averse behavior in practice. This suggests that self-reported risk preferences may play a meaningful role in potentially shaping actual risk-taking behavior and are therefore important to consider in analyses of financial decision-making.

Another factor that has been found to play an important role in risk-taking behavior is age. The literature generally indicates that risk-taking behavior varies systematically across different age groups. The study of Duell et al. (2017) reports that risk-taking behavior tends to follow an inverted U-shaped pattern over the life course, with the highest levels of risk-taking typically observed in the late adolescence. Furthermore, the study of Duell et al. (2017) revealed that males generally displayed higher levels of risk-taking behavior compared to females. These findings underscore the importance of both gender and age as essential factors that must be accounted for in the analysis of risk-taking behavior.

In addition to risk preference, age and gender, numerous other variables have been found to have a relation to risk-taking behavior. For instance, education level and occupation are significantly associated with risk-taking behavior (Parkash et al., 2014).

In addition to these individual characteristics that are associated with risk-taking behavior, various cognitive biases systematically influence decision-making behavior. For instance, the descriptive-experience gap. The descriptive-experience gap demonstrates that the way individuals acquire information has a significant impact on their behavior. People who learn about low-probability events through experience tend to underweight these unlikely outcomes. In contrast, when the same low probabilities are formulated in a descriptive format, individuals tend to overweight these probabilities (Haines et al., 2023). This difference suggests that the way people process probabilities depends on whether information is gained through direct experience or through description, leading to different behaviors involving risky-decisions.

Furthermore, the biases of overconfidence and loss aversion represent salient examples of cognitive distortions that influence individual behavior. Overconfidence bias refers to the systematic tendency of investors to overestimate their own abilities, which consequently leads to

an underestimation of associated risks. This cognitive bias often results in investors undertaking riskier investment decisions than would be justified by a rational assessment of potential outcomes (Chaudhary, 2025).

Loss aversion bias, on the other hand, denotes the phenomenon whereby individuals place greater weight on avoiding losses than on acquiring gains. The psychological impact of a loss is perceived as more severe than the positive effect of a comparable gain. As a result, investors tend to favor investments that minimize potential losses, even if such investments offer lower expected returns relative to alternatives with higher risk-adjusted yields (Chaudhary, 2025).

Overall, these biases evidently influence human behavior, particularly in the domain of risk taking. Individuals' risk-taking behavior is prone to such biases, which can meaningfully affect their decision-making processes. In addition to these biases, another concept of great importance in analyzing human decision-making is that of framing effects.

The framing effect is a fundamental and extensively researched phenomenon within behavioral finance and economics. It refers to a cognitive bias in which individuals' responses and decision-making processes are influenced by the manner in which a given scenario or information is presented, rather than by the inherent content or substance of the scenario itself (Gong, Zhang, Yang, Huang, Feng & Zhang, 2013). Research demonstrates that individuals' responses to a given problem can vary significantly depending on how the problem is presented. Specifically, when the same issue is described using different frames, people frequently exhibit distinct reactions, highlighting the influence of framing effects on decision-making processes (Frisch, 1993). A prominent example of a framing effect is the loss-gain frame. Specifically, people tend to exhibit distinct reactions to the same decision depending on whether the option is presented in terms of (potential) gains or (potential) losses (Gong, Zhang, Yang, Huang, Feng & Zhang, 2013).

The study by Balart et al. (2020) examines how the loss-gain frame impacts decision-making in risky situations, in a test-taking environment. The study shows that loss framing, where participants start with the maximum score and face penalties for both incorrect and unanswered questions in the experiment, significantly reduced the number of skipped questions, compared to the gain frame. This shift in behavior was primarily driven by risk aversion. While loss aversion is often considered a key motivator in decision-making, the authors argue that it was not the primary factor behind the increased engagement observed (Balart et al., 2020).

Instead, the loss framing increased participants' willingness to take risks, as they chose to answer more questions.

The study by Mishra and Fiddick (2012) further asserts the influence of the loss-gain frame on risk-taking behavior. The evidence presented indicates that individuals who are presented with decisions framed in terms of gains tend to exhibit greater risk aversion. In contrast, when decisions are framed as potential losses, individuals are more inclined to take risks. Thus, the manner in which information is framed, such as through the loss-gain frame, can have a substantial impact on the decision-making processes of individuals.

The study conducted by Glaser et al. (2007) reveals another intriguing framing effect, within the context of stock price forecasting. In their experiment, participants were asked to provide mean forecasts for stocks, with two distinct treatment groups exposed to different frames. One group was asked to forecast future stock prices, while the other treatment group was tasked with forecasting future stock returns. The results indicated a significant disparity between the two groups. Specifically, for stocks exhibiting an upward trend, the group exposed to return framing provided significantly higher forecasts of future stock returns compared to the price-framed group. Conversely, for stocks displaying a downward trend, the return-framed group predicted significantly lower future returns than the price-framed group. This finding highlights a pronounced framing effect, wherein the way in which information is framed (prices vs returns), substantially influenced the participants' decision-making. Glaser et al. (2007) emphasize the critical role that the framing of information, specifically the distinction between price and return frames, plays in impacting financial decision-making behavior.

Building on Glaser et al. (2007), which found that the framing effect (price vs return) depends on the trend direction. The paper of Glaser et al. (2019) also examines this price versus return framing, but more focused on the overall effect across different settings. Their study (Glaser et al., 2019) uses a broader set of experimental conditions and participant types and finds that return forecasts are generally higher than price-based forecasts, regardless of whether the trend is upward or downward. Both papers (Glaser et al., 2007 & Glaser et al., 2019) use similar experimental designs, where participants are split into groups and asked to give forecasts in terms of prices or returns. Both papers (Glaser et al., 2007 & Glaser et al., 2019) highlight the important role of framing (price vs return) in shaping financial expectations. Importantly, Markus Glaser is the first author on both studies, showing a consistent research interest in this area. Thus, while the

2007 paper (Glaser et al.) emphasizes how the framing effect (price vs return) varies depending on trend direction, the 2019 paper (Glaser et al.) highlights a general positive bias in return forecasts caused by the framing. Together, they provide a more complete understanding of how price versus return framing influences investor expectations and can also affect their investment behavior.

These earlier studies by Glaser et al. (2007) and Glaser et al. (2019) focus on how price versus return framing influences investors' expectations at the individual level. The paper of Hanaki et al. (2023) examines how these framing effects (price vs return) impact market behavior more broadly. Their results show that when participants forecast returns instead of prices, markets tend to become more unstable. This increased instability can contribute to the exacerbation or formation of bubbles and crashes in the financial markets, leading to potentially riskier market conditions. Thus, the way forecasts are elicited (price vs return) affects not only individual expectations, but also has potential implications for overall market risk and volatility.

The study by Huber and Huber (2019) also explores the effect of the price versus return frame. Specifically, the comparison between price and return charts on risk perception. Their findings indicate that assets are generally perceived as riskier when presented through return-based frames as opposed to price-based frames. This suggests that the framing of financial information, whether in terms of prices or returns, can significantly influence individuals' perception of risk, potentially affecting their subsequent decision-making processes.

Additionally, Stössel and Meier (2015) further examine how different graphical presentations of financial information, specifically price line charts versus return bar charts, affect investors' risk perception and risk-taking behavior. Their results also show that return-framing, typically displayed through return bar charts, leads to higher perceived risk and consequently more cautious investment decisions. Conversely, price framing tends to lower risk perception, which may encourage greater risk-taking. These findings reinforce the notion that the format of financial information presentation (price vs return) plays a crucial role in shaping both risk perception and investment behavior.

The existing literature provides robust evidence that the way in which scenarios, questions, choices or information are framed can substantially influence individual behavior and decision-making. Framing effects, particularly in the context of financial decision-making, can lead to shifts in risk attitudes. These effects are not limited to abstract or theoretical contexts, but

extend to real-world decisions. A prominent example of a framing effect is the price versus return framing. This framing effect has the potential to alter individuals' expectations and behavior, thereby underscoring the importance of framing in shaping financial decision-making.

This paper also examines framing effects, specifically the impact of price versus return framing on financial decision-making. However, it distinguishes itself from existing literature in several important ways. Firstly, the experimental design focuses explicitly on how price versus return framing influences risk-taking behavior, particularly in the context of actual investment choices between high-risk and low-risk options. This differs from studies like Huber and Huber (2019), which focus less on price versus return framing itself and more on how aspects of graphical presentation, such as the scale of the chart (narrow versus wide), affect how people perceive risk and expected returns, without directly examining how these factors influence actual risk-taking decisions. Secondly, unlike much of the prior work that investigates framing effects based on historical price and return information (Glaser et al., 2007 & Glaser et al., 2019), this thesis centers on the framing of future investment options, thereby providing more direct insights into decision-making under uncertainty. Finally, the methodology employed in this thesis incorporates controlled experimental manipulation of framing within a choice setting, allowing for the assessment of behavioral consequences, whereas some earlier studies have primarily measured perceptions or forecasts (Stössel & Meier, 2015 & Huber and Huber, 2019).

Therefore, this paper fills a gap in the literature by providing a focused examination of how price versus return framing impacts actual risk-taking behavior in investment decisions, going beyond changes in risk perception or expectations documented in prior research.

3.2 Hypothesis

Previous research has demonstrated that framing effects, specifically price versus return framing, significantly influence individuals' expectations and decision-making (Glaser et al., 2007 & Glaser et al. 2019). Moreover, assets presented through a return frame are generally perceived as riskier compared to those framed by price (Huber and Huber, 2019). Empirical evidence further indicates that return framing leads to heightened risk perception and consequently promotes more cautious investment decisions, potentially resulting in reduced risk-taking behavior. Conversely, price framing tends to lower perceived risk, which may encounter greater risk-taking among investors

(Stössel and Meier, 2015). Beyond individual behavior, price versus return framing has also been shown to impact broader market dynamics. For instance, when participants are asked to forecast returns rather than prices, financial markets tend to exhibit increased instability, which may contribute to the exacerbation or creation of bubbles and crashes, thereby potentially leading to riskier market outcomes (Hanaki et al., 2023) Therefore, it is evident that price versus return framing affects both individual and aggregate behaviors. Drawing on these findings, this study presents the following hypothesis:

There is a significant effect of the price versus return framing on the risk-taking behavior of investors.

4 Methodology

To investigate the effect of framing on risk-taking behavior, specifically the impact of price framing versus return framing, this study conducts an experimental design. The experiment will be administered via a self-designed Qualtrics survey, which serves as the data collection tool. Participants are randomly assigned to one of two treatment groups. Both treatment groups are presented with the same set of investment questions, but the framing of these questions differs. One group (the price-framed treatment group) receives investment questions framed in terms of price changes, while the other group (the return-framed treatment group) receives identical questions framed in terms of expected returns.

The investment questions require participants to allocate a sum of 1000\$ across two investment options, one higher-risk option and one lower-risk option. For example, a participant might invest \$299 in the higher-risk option and \$701 in the lower-risk option. The definition of the higher-risk and lower-risk options depends on the variance of the possible outcomes. Specifically, the higher-risk option is associated with the highest variance. In contrast, the lower-risk option is characterized by the lowest variance. The appendix provides an overview of the whole Qualtrics survey (Appendix A) and which stock is designated as the higher-risk option in each investment question (Appendix B).

An example of a price-framed treatment question is as follows:

“You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of 1000\$, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- Stock A: There is a 70% chance that the stock price will increase to 120\$ and a 30% chance that it will decrease to \$80.
- Stock B: There is a 50% chance that the stock price will increase to \$140 and a 50% chance that it will decrease to \$60. ‘

Participants in the return-framed treatment group receive identical questions, but framed in terms of expected returns. An example question for the return-framed treatment group is as follows:

“You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- Stock A: There is a 70% chance that the stock price will increase by 20% and a 30% chance that it will decrease by 20%.
- Stock B: There is a 50% chance that the stock price will increase by 40% and a 50% chance that it will decrease by 40%. ‘

Participants will answer a total of 8 investment questions, which are presented similarly for both treatment groups, but the framing (price or return) will vary according to the participants' assigned treatment. The investment questions are presented in a random order. The number of eight investment questions was chosen to ensure a comprehensive dataset without making the survey too time-consuming for participants. At the end of the survey, a verification question was also incorporated to assess whether respondents were paying attention while completing the survey.

Since participants are randomly assigned to one of the two treatment groups, we can assume that their average risk-taking behavior before the experiment (prior to the first investment question) is similar across the groups. Nevertheless, this paper still controls for any potential pre-existing differences in risk preferences. Participants will be asked to report their risk preferences before the investment questions begin. Specifically, they will answer the following question: “On a scale of 0 to 10, how willing are you to take risks in stock investments? (0 means no willingness to take risks in stock investments and 10 means you are very willing to take risks in stock investments)”. The self-reported risk preference will be included as a control variable in the analyses to account for potential baseline differences in risk preferences between the treatment groups.

Additionally, demographic information, including age, gender, education level and other relevant characteristics, will be collected at the end of the survey. These variables will be used as control variables in the analysis. Including these demographic controls will help account for any systematic differences between participants that could influence their risk-taking behavior, ensuring a more accurate assessment of the framing effect.

It is important to note, however, that some participants may not possess extensive financial knowledge. This could be a potential limitation, as their decisions might be influenced more by personal experience and intuition rather than financial expertise. To address this, I will include financial literacy questions in the survey to assess participants’ financial knowledge. This information will be included as control variables in the analysis, allowing to control for any differences in financial literacy that might affect participants’ risk-taking behavior.

The average amount allocated to the risky option (Higher-risk stock) across all 8 investment questions will serve as the measure of risk-taking behavior. To assess whether there is a significant difference in risk-taking behavior between the two treatment groups, a t-test is conducted. This test will compare the means of the risk-taking behavior variable between the price-framed and return-framed treatment groups. Before conducting the t-test, this study first assessed the distribution of the dependent variable (risk-taking behavior) to verify whether the data follows a normal distribution. The results showed that the data is normally distributed and that the sample size is larger than 100 participants. Therefore, this study proceeded with a t-test to compare the means of the two groups. This approach enhances the robustness of the statistical analysis.

In addition to performing a t-test, multiple regression analyses are conducted to properly account for all control variables in the analyses. In the regression models, risk-taking behavior (measured by the average amount allocated to the high-risk stock across the 8 investment questions) will serve as the dependent variable, while framing (treatment group) will be the independent variable. Framing will be coded as a binary variable. Furthermore, relevant control variables will be included in the regression models. The total set of control variables include risk preference, age, gender, employment status, education level, self-reported financial knowledge, tested financial knowledge, student status, country of residence and investing experience (an overview of all the control variable questions in the Qualtrics survey is shown in Appendix A). Including control variables will allow for an examination of whether there is a significant framing effect (price vs return) on risk-taking behavior, while controlling for potential confounders.

In addition to the t-test and regression analyses incorporating control variables, the analysis also includes a regression model with an interaction term for risk preference, a panel data regression a multivariate multiple linear regression. Overall, this application of multiple analytical approaches enhances the robustness and reliability of the findings regarding the framing effect.

5 Results

5.1 Descriptive statistics

A total of 128 individuals participated in the Qualtrics survey. Of these, three respondents did not provide informed consent and were therefore excluded from the dataset. In addition to these three, another 15 participants failed to complete the whole survey. These participants failed to complete one or more essential components of the survey, such as demographic questions and/or the investment questions. Their responses were excluded from the dataset to maintain consistency and analytical validity. Including incomplete data would have introduced missing values in key variables, limiting the comparability across participants and potentially biasing the results. Furthermore, because the dependent variable, average risk-taking, is based on the responses to all eight investment questions, incomplete data would compromise the reliability of the dependent variable. For these reasons, only fully completed responses were retained for the analysis. This

resulted in a final sample of 110 participants who both provided informed consent and completed the entire survey. Furthermore, all 110 respondents answered the verification correctly. The data from these 110 respondents were therefore used in all subsequent analyses. The distribution of all relevant sample characteristics for the final sample of 110 participants is presented in Table 1 below, including demographic variables, background characteristics and the treatment group assignment.

Variable	Category	Return-framed	Price-framed	Total
Treatment group		54 (49.1%)	56 (50.9%)	110
Gender	Male	36 (47.4%)	40 (52.6%)	76
	Female	18 (52.9%)	16 (47.1%)	34
Student status	No	21 (41.2%)	30 (58.8%)	51
	Yes	33 (55.9%)	26 (44.1%)	59
Highest completed education level	Primary School	0 (0%)	1 (100%)	1
	Secondary School	12 (54.5%)	10 (45.5%)	22
	MBO	2 (22.2%)	7 (77.8%)	9
	HBO	13 (56.5%)	10 (43.5%)	23
	Bachelor's degree (WO)	11 (45.8%)	13 (54.2%)	24
	Master's degree (WO)	15 (50%)	15 (50%)	30
	PhD or higher	1 (100%)	0 (0%)	1
Employment status	Full-time employed	16 (45.7%)	19 (54.3%)	35
	Part-time employed	24 (53.3%)	21 (46.7%)	45
	Self-employed	3 (60%)	2 (40%)	5
	Unemployed (seeking employment)	3 (33.3%)	6 (66.7%)	9
	Retired	2 (25%)	6 (75%)	8
	Unemployed (not seeking employment)	6 (85.7%)	1 (14.3%)	7
	Other	0 (0%)	1 (100%)	1
Country of residence	Netherlands	54 (50.9%)	52 (49.1%)	106
	Belgium	0 (0%)	1 (100%)	1
	France	0 (0%)	1 (100%)	1
	Other	0 (0%)	2 (100%)	2
Investing experience	No experience	16 (44.4%)	20 (55.6%)	36
	Limited experience	22 (52.4%)	20 (47.6%)	42
	Moderate experience	13 (54.2%)	11 (45.8%)	24
	Extensive experience	3 (42.9%)	4 (57.1%)	7
	Professional experience	0 (0%)	1 (100%)	1
Self-reported financial knowledge	Very limited	10 (45.5%)	12 (54.5%)	22
	Basic understanding	17 (48.6%)	18 (51.4%)	35
	Moderate understanding	17 (58.6%)	12 (41.4%)	29
	Advanced understanding	10 (43.5%)	13 (56.5%)	23
	Expert knowledge	0 (0%)	1 (100%)	1
Tested financial knowledge	Correct	33 (54.1%)	28 (45.9%)	61
	Wrong 1	13 (44.8%)	16 (55.2%)	29
	Wrong 2	8 (40%)	12 (60%)	20
Age	18 - 25 years old	31 (52.5%)	28 (47.5%)	59
	26 - 35 years old	9 (60%)	6 (40%)	15
	36 - 45 years old	2 (40%)	3 (60%)	5
	46 - 55 years old	8 (50%)	8 (50%)	16
	56 - 65 years old	2 (33.3%)	4 (66.7%)	6
	66 years and older	2 (22.2%)	7 (77.8%)	9
Risk Preference	Mean (SD)	5.31 (2.36)	4.88 (2.22)	5.09 (2.29)

Table 1: Sample characteristics by treatment group (including all control variables and independent variable)

Note: For each variable, the absolute number indicates the number of participants in that treatment group, while the percentages in the parentheses reflect the proportion of participants within that category who are assigned to each treatment group.

Table 1 displays the distribution of all demographic variables, background characteristics and the treatment group assignment, for the final sample of 110 participants. These variables comprise all the control variables as well as the independent variable (treatment group), used in the analyses. For each variable, Table 1 reports both the absolute count per treatment group and, in the parentheses, the percentage of the participants within each category assigned to that treatment group. This overview enables a clear comparison of sample characteristics between the two treatment groups (price vs return framed) and provides insight into the composition of the sample within each category.

As presented in Table 1, of the 110 participants, 54 were randomly assigned to the return-framed treatment group and 56 to the price-framed treatment group. Of the 110 participants included in the final sample, the majority were male. 76 were identified as male and 34 as female. Although the overall sample is not gender-balanced, the distribution of gender is relatively equal across the two treatment groups. The return-framed group consists of 36 males and 18 females, while the price-framed group includes 40 males and 16 females. The majority of participants fall within the 18-25 age category, as can be seen in Table 1. Reflecting a predominantly younger sample. Of the 110 respondents, 59 indicated that they were currently enrolled as students, while the remaining 51 were not.

As outlined in the methodology section, participants were asked at the beginning of the survey to self-report their willingness to take risks in the context of stock investments. As presented in Table 1, the mean value of risk preference is higher in the return-framed treatment group (5.31), compared to the price-framed treatment group (4.88). Additionally, the distribution of these self-reported risk preference scores, broken down by treatment group, is presented in graph 3 in Appendix C. A closer inspection of the graph reveals that participants in the price-framed treatment group are more frequently represented at the lower end of the risk preference scale compared to the return-framed participants. For example, at risk preference score 3, the number of price-framed participants noticeably exceeds that of the return-framed participants. Conversely, at high-risk preference scores, the return-framed group tends to occur more frequently or equally often compared to the price-framed group. This pattern aligns with the results shown in table 1, where the return-framed participants, on average, report a greater willingness to take financial risks than those in the price-framed treatment group. However, the difference in mean risk preference scores between the treatment groups is not statistically

significant, as shown in Table 2. This indicates that there is no significant difference in the average level of risk preference between the participants assigned to the return-framed and price-framed treatment group.

Overall, the distributions appear to be relatively similar between the two treatment groups across all control variables. No major discrepancies are observed, indicating that the random assignment was effective in balancing these characteristics. However, to formally assess potential distributional imbalance between the price-framed and return-framed treatment groups, an independent samples t-test was conducted for the continuous variable risk preference and chi-squared tests were performed for the other nine categorical control variables. The resulting p-values are reported in table 2 and serve as indicators of the extent to which each variable's distribution differs between the treatment groups.

As shown in table 2, the variables Student status, employment status, country of residency, self-reported risk preference and Tested Financial Knowledge exhibit the greatest distributional imbalance between the two treatment groups, in that order. However, all p-values are well above the 0.05 significance threshold, indicating that these differences are not statistically significant. This suggests that all the control variables are relatively evenly distributed across the treatment groups and that the random assignment of the participants to the two treatment groups was largely successful.

Variable	Test	P-value
Age	Chi-squared	0.4985
Gender	Chi-squared	0.7384
Student	Chi-squared	0.1762
Education	Chi-squared	0.4835
Employment status	Chi-squared	0.2242
Country of residence	Chi-squared	0.2612
Investing experience	Chi-squared	0.77
Self-reported financial knowlegde	Chi-squared	0.6575
Tested Financial knowledge	Chi-squared	0.4761
Risk preference	T-test	0.3173

Table 2: Output of the t-test and chi-squared tests for distribution differences between treatment groups

Supplementary figures illustrating the distribution of control variables across treatment groups can be found in Appendix C.

As discussed in the literature review, a positive correlation is generally observed between individuals' risk preferences and their actual risk-taking behavior (Tavor, 2019). In this study, participants in the return-framed treatment group reported a higher average risk preference than those in the price-framed treatment group, but this difference was not statistically significant and does not seem to be fully reflected in their actual investment behavior.

In this study, as a measure of risk-taking behavior, the average amount allocated to the high-risk stock across the eight investment questions was calculated for each participant. Subsequently, the mean of these individual averages was computed for each treatment group. Interestingly, the price-framed treatment group exhibited a slightly higher mean level of risk-taking behavior than the return-framed treatment group (shown in table 3). In other words, although return-framed participants indicated higher levels of self-reported risk preference (on average), price-framed participants appear to actually engage in higher risk-taking behavior on average. This discrepancy between risk preferences and actual risk-taking behavior may indicate a framing effect. In which participants who are exposed to price framing are more inclined to take risks despite reporting lower willingness to take risks.

However, other factors, such as age, gender, financial knowledge and investing experience, may also influence risk-taking behavior. Therefore, in order to isolate the effect of framing, these potential confounding variables will be included as control variables in the regression analyses, presented later in this study.

Variable	Return-framed	Price-Framed
Q1	386.48 (252.6)	452.3 (256.13)
Q2	385.11 (262.87)	458.46 (240.96)
Q3	460.39 (281.36)	444.57 (244.01)
Q4	376.2 (277.55)	419.48 (277.5)
Q5	343.61 (288.08)	406.75 (269.02)
Q6	451.07 (280.49)	542.89 (273.02)
Q7	334.35 (250.14)	439.75 (254.93)
Q8	351.28 (266.29)	364.75 (245.91)
Risk-Taking Behavior	386.06 (172.93)	441.12 (155.83)

*Table 3: Mean (SD) High-Risk allocations per investment question and overall risk-taking by treatment group
Note: Q1-Q8 represent the mean amount allocated to the high-risk stock for each respective investment question.*

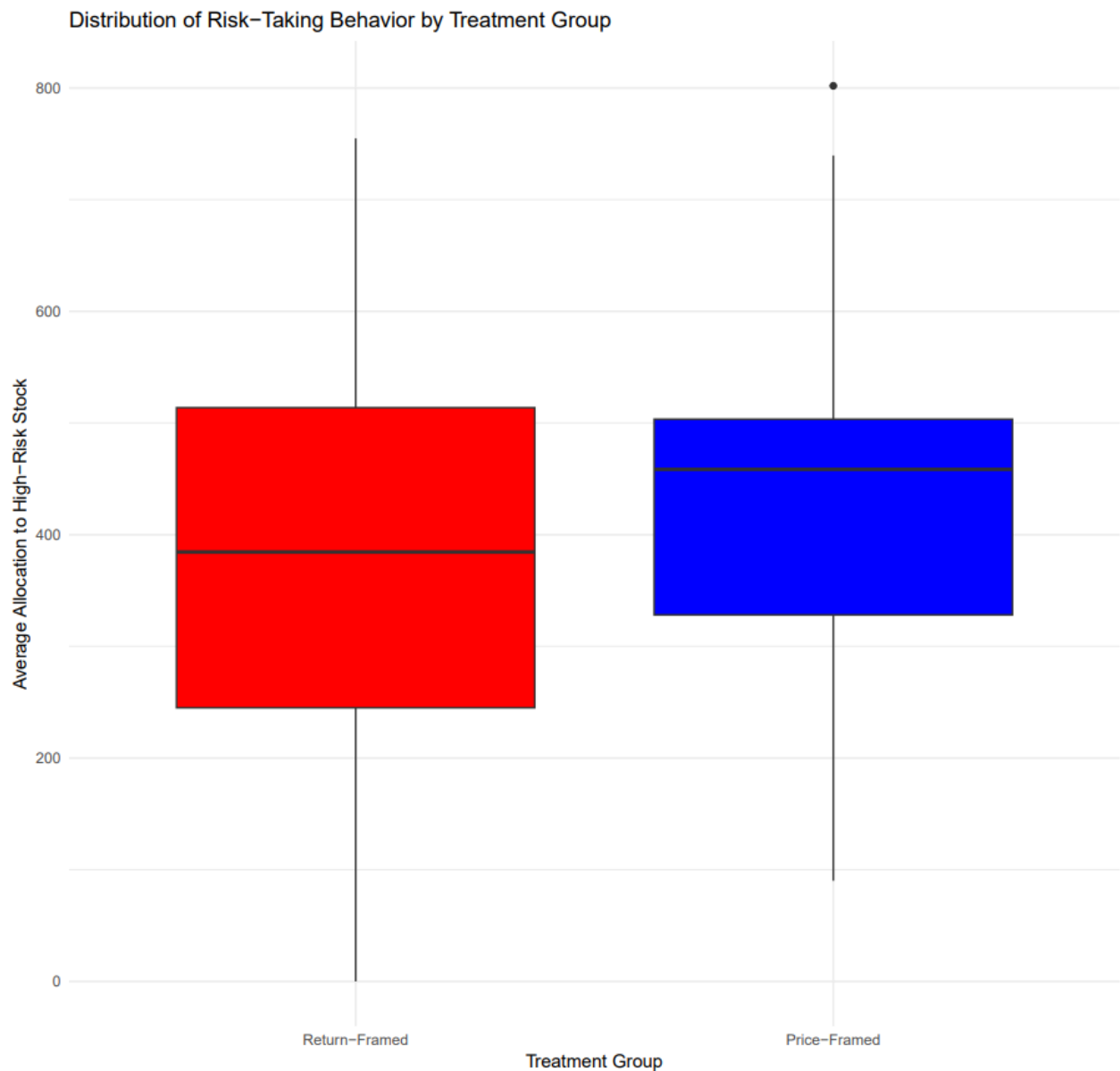


Figure 1: Boxplot Risk-taking behavior variable by treatment group

The boxplot presented in figure 1, illustrates the distribution of the risk-taking behavior variable (measured as the average amount allocated to the high-risk stock across eight investment questions) across the two treatment groups. The median level of risk-taking behavior is notably higher in the price-framed treatment group compared to the return-framed treatment group. Furthermore, the variability in risk-taking behavior is greater within the return-framed treatment group, indicating more diverse risk-taking behavior within the return-framed treatment group. The findings of the boxplot are consistent with previous analyses, which demonstrated a higher average level of risk-taking behavior in the price-framed group, thereby supporting the potential existence of a framing

effect, whereby price framing leads to increased risk-taking behavior. Of course, additional statistical analyses are required to confidently confirm the presence of a framing effect.

Furthermore, it is of interest to examine whether the potential framing effect varies across individual investment questions. While a potential general framing effect, where price framing potentially leads to increased risk-taking behavior, may be presented at the aggregate level, it is unclear if this potential framing effect holds consistently across all eight investment questions. Therefore, it is valuable to compare the amount allocated to the high-risk stock for each investment question, individually. To assess whether the treatment group means per individual question differ and whether these differences consistently point in the same direction. Figure 2 below provides a graphical representation of (part of) the data presented in Table 3.

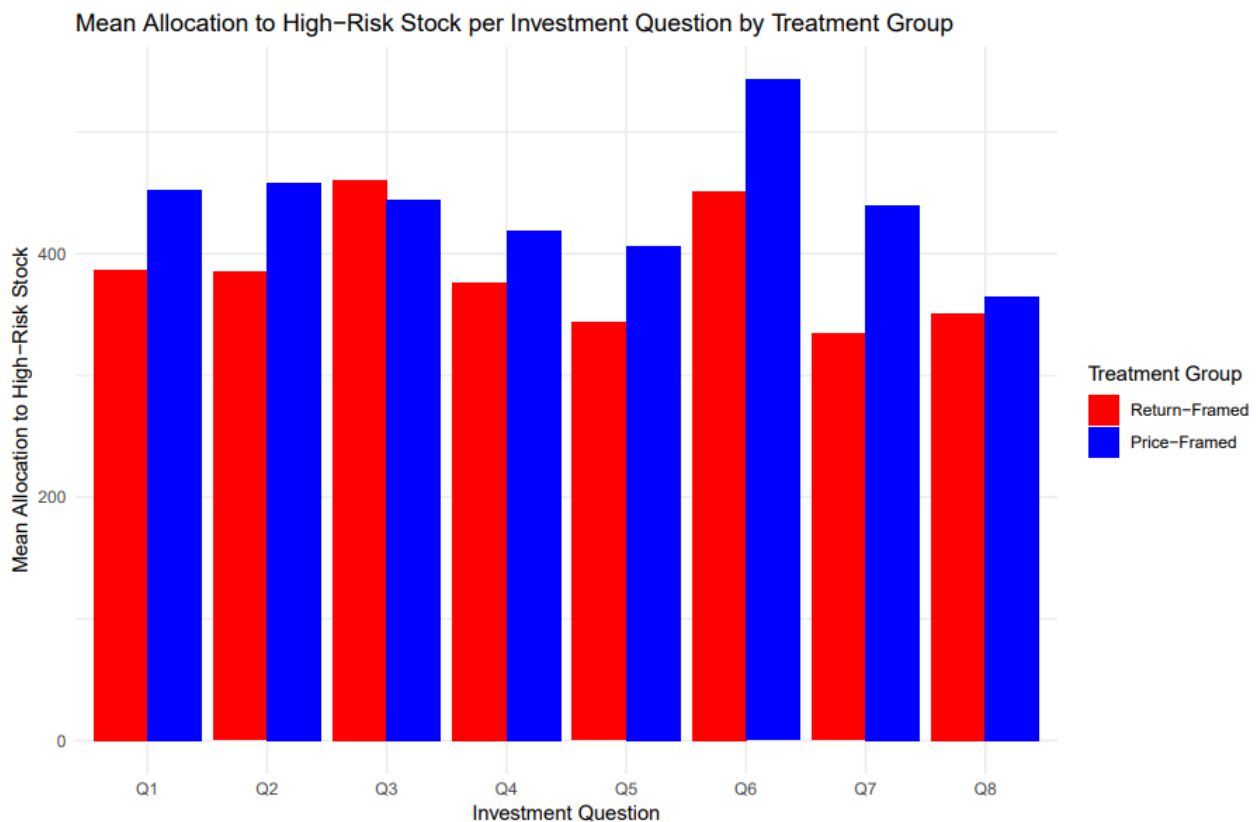


Figure 2: Mean values of allocation to the high-risk stock per individual investment question by treatment group

Interestingly, when examining the mean allocation to the high-risk stock for each investment question individually, figure 2 shows, that only in investment question 3 did participants in the

return-framed treatment group allocate, on average, more to the high-risk stock compared to those in the price-framed treatment group. Besides, this difference was relatively small. For the remaining seven investment questions, the mean allocation to the high-risk stock was consistently higher in the price-framed treatment group. These results align with the potential framing effect observed at the aggregate level.

5.2 Statistical analyses

5.2.1 Independent Samples t-test

To further explore the potential framing effect, more rigorous statistical analyses are required.

This study begins with an independent samples t-test, where risk-taking behavior (measured as the average amount allocated to the high-risk stock across all eight investment questions), serves as the dependent variable and the treatment group functions as the independent variable.

However, prior to performing the t-test comparing risk-taking behavior across the return-framed and price-framed treatments, Levene’s test was conducted to assess the equality of variances. The test resulted in a p-value above the 0.05 threshold, indicating no significant difference in variances between the two treatment groups. Given that the assumption of equal variances holds, the standard independent t-test is conducted to compare the mean risk-taking behavior between the two treatment groups.

Treatment group	Mean
Return-Framed	386.06
Price-Framed	441.12
P-value	0.08201

Table 4: Standard independent t-test Risk-Taking Behavior

The results of the t-test, presented in table 4, indicate that the mean risk-taking behavior differs weakly significantly between the two treatment groups. The p-value of 0.08 approaches the significance threshold of 0.05. Notably, the mean risk-taking behavior is higher in the price-framed treatment group compared to the return-framed treatment group. This weakly significant difference suggests the presence of a tentative framing effect, whereby participants exposed to

price framing exhibit increased risk-taking behavior. Although the t-test offers a straightforward comparison of the mean risk-taking behavior between the treatment groups, it does not account for differences between the treatment groups participants or other influencing factors. Such pre-existing differences could confound the observed effect of framing on risk-taking behavior. Therefore, regression analyses are necessary to control for certain variables and better isolate the framing effect.

5.2.2 Regression analyses

Term	Estimate	Std.error	P-value
(Intercept)	228.52	200.66	0.26
Treatment group (Price-Framed)	48.45	33.62	0.15
Risk Preference	18.43	7.51	0.02
Age (26 - 35 years)	-15.91	65.66	0.81
Age (36 - 45 years)	27.44	92.49	0.77
Age (46 - 55 years)	-7.52	64.98	0.91
Age (56 - 65 years)	40.15	98.66	0.69
Age (66 years and older)	40.1	114.55	0.73
Gender (Female)	59	42.95	0.17
Student (Yes)	32.69	84.81	0.7
Secondary School (education level)	86.71	182.17	0.64
MBO (education level)	89.28	181.58	0.62
HBO (education level)	53.44	174.8	0.76
Bachelor's degree (WO) (education level)	45.94	177.62	0.8
Master's degree (WO) (education level)	46.22	173.82	0.79
PhD or higher (education level)	274.22	235.07	0.25
Part-time employed (employment status)	-60.79	79.08	0.44
Self-employed (employment status)	124.71	95.02	0.19
Unemployed (seeking employment) (employment status)	-10.92	97.74	0.91
Retired (employment status)	107.78	112.41	0.34
Unemployed (not seeking employment) (employment status)	46.68	102.96	0.65
Other (employment status)	-66.14	188.32	0.73
Belgium (Country of residence)	-140.16	202.63	0.49
France (Country of residence)	NA	NA	NA
Other (country of residence)	49.14	120.21	0.68
Limited experience (Investing experience)	-32.03	54.67	0.56
Moderate experience (investing experience)	2.03	65.48	0.98
Extensive experience (investing experience)	-115.22	86.92	0.19
Professional experience (investing experience)	-79.47	176.49	0.65
Basic understanding (self-reported financial knowledge)	-9.96	62.15	0.87
Moderate understanding (self-reported financial knowledge)	-110.91	64.83	0.09
Advanced understanding (self-reported financial knowledge)	44.77	76.34	0.56
Expert knowledge (self-reported financial knowledge)	NA	NA	NA
Wrong 1 (Tested Financial Knowledge)	34.79	41.77	0.41
Wrong 2 (Tested Financial Knowledge)	60.07	47.97	0.21
R2	0.41		
Adjusted R2	0.16		

Table 5: Regression analysis output table

Table 5 presents the results of an OLS regression analysis, in which risk-taking behavior, measured as the average amount allocated to the high-risk stock across the eight investment questions, serves as the dependent variable. The treatment group serves as the independent variable. In addition, ten control variables were included to account for potential baseline differences between the treatment groups. These are: self-reported risk preference, age, gender, student status, highest completed education level, employment status, country of residence, investing experience, self-reported financial knowledge and tested financial knowledge.

The regression coefficient for the price-framed treatment group is 48.45, suggesting that participants exposed to price-framing, allocate \$48.45 more to the high-risk stock per investment question on average, than those exposed to return-framing. However, this effect is not statistically significant. The p-level of 0.15, as shown in table 5, exceeds the significance threshold of 0.05. Despite the lack of significance, the positive direction of the coefficient is consistent with earlier statistical results, again pointing towards a potential framing effect whereby people exposed to price-framing may engage in greater risk-taking behavior.

A noteworthy finding is the strong and statistically significant effect of self-reported risk preference. The coefficient is 18.43, with a p-value of 0.02, indicating that for each one-point increase in self-reported risk preference, participants allocated \$18.43 more to the high-risk stock on average across the eight investment questions. This suggests a positive correlation between individuals' self-reported risk preference and their actual risk-taking behavior.

The regression output states missing values (NAs) for two categories within the control variables. This is due to the fact that these categories contained only one observation. To address the issue of missing values caused by categories with only a single observation, several variations of the regression model were tested in which certain categories within the control variables were merged. These variations ranged from minimal adjustments, merging only the categories responsible for the missing values, to more extensive restructuring of the categorical variables. Importantly, this study did not limit the analysis to only those categories responsible for the missing values, this study also explored broader restructuring by merging additional categories beyond those affected by missing values. However, in all cases, the R^2 and the adjusted R^2 of the model decreased compared to the original model (shown in Table 5). This suggests that merging reduced the model's ability to explain variation in the risk-taking behavior variable. Therefore, no categories were merged in any further analysis.

Finally, the explanatory power of the model is modest, with an R^2 of 0.41 and an adjusted R^2 of 0.16. These values suggest that while some variance in risk-taking behavior is captured by the model, a large part remains unexplained. The relatively low adjusted R^2 compared to the R^2 may be due to the large number (10) of control variables included in the regression model, relative to the sample size (110), which may have resulted in overfitting.

To mitigate potential overfitting and to evaluate the robustness of the framing effect, additional regression analyses are conducted using alternative sets of control variables. Prior to introducing models with selected control variables, a baseline regression is conducted including only the treatment group as independent variable and risk-taking behavior as dependent variable. This model provides the unadjusted estimate of the framing effect on risk-taking behavior. Comparing this model to those that incorporate control variables, allows for an assessment of whether the observed treatment effect is potentially driven by confounding factors.

Term	Estimate	Std. Error
Treatment group (Price-Framed)	55.06*	31.36
Constant	386.06***	22.38
R2	0.03	
Adjusted R2	0.02	

Table 6: Regression output table with no control variables

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

Table 6 presents the regression output of the baseline model, which excludes all control variable. Notably, the treatment coefficient increases to 55.06 and is weakly significant (p -value < 0.10). The baseline regression model also indicates the potential existence of a framing effect, pointing in the same direction as the earlier analyses. Specifically, participants exposed to price framing tend to exhibit higher levels of risk-taking behavior. However, the explanatory power of the baseline model is very limited, with an R^2 of 0.03 and an adjusted R^2 of 0.02, indicating that the majority of the variance in risk-taking behavior remains unexplained. The difference between the baseline model and the full model presented in table 5, which includes all ten control variables, suggests that omitted variable bias may be present when relevant control variables are excluded. These findings highlight the importance of including relevant control variables in the regression analyses to ensure the validity of the framing effect.

To determine which control variables should be included in the regression model to mitigate potential overfitting, to evaluate the robustness of the framing effect and to reduce the risk of potential omitted variable bias, two factors were considered: 1) the degree to which each control variable is unevenly distributed across the treatment groups and 2) its potential influence on the dependent variable, risk-taking behavior.

As demonstrated in earlier analysis (Table 2), all control variables are distributed relatively evenly across the treatment groups, indicating that the random assignment of the participants to the two treatment groups was largely effective. In addition, this study investigates which control variables have the strongest association with risk-taking behavior. To determine the extent to which each control variable is associated with the dependent variable, an overall F-test was conducted using the Anova function in Rstudio. This test indicates the extent to which each control variable, taken as a whole, contributes to explaining variation in risk-taking behavior.

Variable	P-value
Risk preference	0.021
Age	0.044
Gender	0.007
Student status	0.613
Education level	0.637
Employment status	0.691
Country of residence	0.663
Investing experience	0.72
Self-reported financial knowledge	0.013
Tested Financial knowledge	0.295

Table 7: F-test output

As shown in table 7, the control variables gender, self-reported financial knowledge, risk preference and age exhibit the lowest p-values, all below the 0.05 significance threshold. This indicates a statistically significant association with the dependent variable. Among the ten control variables, these four appear to have the strongest overall relationship with the dependent variable (risk-taking behavior). The remaining six control variables yield p-values that are well above the 0.05 threshold, indicating that they are not strongly associated with the variation in the dependent variable.

Overall, the control variables appear to be relatively evenly distributed across the treatment groups, while four of them show a statistically significant association with the dependent variable.

Based on these findings, two additional regression analyses were conducted using different subsets of control variables. The first subset includes the four variables most strongly associated with the dependent variable (Gender, Self-reported Financial Knowledge, risk preference and age). The second subset builds on this by adding the two control variables that exhibited the greatest distributional imbalance across the two treatment groups (Student status and employment status, as shown in Table 2).

term	estimate	std.error	p.value
(Intercept)	322.76	57.92	0
Treatment group (Price-Framed)	41.49	29.08	0.16
Gender (Female)	66.83	35.88	0.07
Basic understanding (Self-reported financial knowledge)	-51.25	43.06	0.24
Moderate understanding (Self-reported financial knowledge)	-134.91	46.01	0
Advanced understanding (Self-reported financial knowledge)	-23.79	50.64	0.64
Expert knowledge (Self-reported financial Knowledge)	-120.02	153.76	0.44
Risk Preference	18.26	6.81	0.01
26 - 35 years old (Age)	-14.83	44.86	0.74
36 - 45 years old (Age)	45.17	69.57	0.52
46 - 55 years old (Age)	14.17	42.01	0.74
56 - 65 years old (Age)	4.71	67.51	0.94
66 years and older (Age)	148.99	54.18	0.01
R2	0.31		
Adjusted R2	0.22		

Table 8: Regression output (first subset of control variables)

term	estimate	std.error	p.value
(Intercept)	326.44	79.57	0
Treatment group (Price-Framed)	50	30.2	0.1
Gender (Female)	74.22	36.35	0.04
Basic understanding (Self-reported financial knowledge)	-53.37	44.35	0.23
Moderate understanding (Self-reported financial knowledge)	-144.32	46.82	0
Advanced understanding (Self-reported financial knowledge)	-28.14	52.07	0.59
Expert knowledge (Self-reported financial Knowledge)	-134.3	160.96	0.41
Risk Preference	18.95	6.95	0.01
26 - 35 years old (Age)	-21.75	58.49	0.71
36 - 45 years old (Age)	15.41	85.08	0.86
46 - 55 years old (Age)	-3.23	57.97	0.96
56 - 65 years old (Age)	20.85	86.6	0.81
66 years and older (Age)	31.14	102.87	0.76
Student (yes)	6	71.12	0.93
Part-time employed (employment status)	-41.91	67.05	0.53
Self-employed (employment status)	98.89	75.3	0.19
Unemployed (seeking employment) (employment status)	11.87	84.03	0.89
Retired (employment status)	120.86	100.99	0.23
Unemployed (not seeking employment) (employment status)	67.88	89.42	0.45
Other (employment status)	-76.05	168.5	0.65
R2	0.36		
Adjusted R2	0.22		

Table 9: Regression output (second subset of control variables)

The regression analyses using different subsets of control variables are represented in tables 8 and 9. When comparing these results to the model with all ten control variables (table 5) and the baseline regression model without any control variables (table 6), a consistent pattern emerges. Across all specifications, the coefficient of the treatment variable (price-framed group) remains positive, ranging from 41.49 to 55.06, potentially indicating a robust framing effect. In all regression models, individuals exposed to price framing tend to exhibit higher levels of risk-taking behavior.

However, in the regression models including control variables, whether all of a selected subset, the framing effect is not statistically significant. Furthermore, the treatment coefficient (price-framed) is systematically lower in these models compared to the baseline regression model, suggesting the presence of omitted variable bias when relevant control variables are excluded. Importantly, the two regression models with control subsets, both show an increase in the adjusted

R^2 to 0.22, compared to 0.16 in the model with all the control variables and 0.02 in the model with no control variables. This indicates an improvement in explanatory power, while mitigating the risk of overfitting. These findings underscore the value of selecting relevant control variables that enhance the robustness of the results, reduce omitted variable bias and improve the model efficiency.

As shown in the regression models that include control variables, both the model with all the control variables and the two models with different subsets of control variables, that the variable risk preference consistently emerges as highly statistically significant, with p-values around or below the 0.01 threshold. This consistent significance suggests that risk preference plays a substantial role in explaining the variation in risk-taking behavior (dependent variable). Therefore, it is relevant to explore whether the effect of framing is moderated by the participant's level of risk preference. To test this, an additional regression analysis is conducted in which an interaction term between the treatment group and risk preference is included. This model builds on the earlier specification with the subset of six control variables, now extended with the interaction term.

term	estimate	std.error	p.value
(Intercept)	353,46	82,23	0
Treatment group (Price-Framed)	-38,09	76,81	0,62
Risk Preference	11,31	9,25	0,22
Gender (Female)	78,96	36,44	0,03
26 - 35 years old (Age)	-15,79	58,5	0,79
36 - 45 years old (Age)	1,82	85,52	0,98
46 - 55 years old (Age)	-0,24	57,84	1
56 - 65 years old (Age)	22,05	86,34	0,8
66 years and older (Age)	32,12	102,56	0,75
Basic understanding (Self-reported financial knowledge)	-36,57	46,22	0,43
Moderate understanding (Self-reported financial knowledge)	-134,72	47,31	0,01
Advanced understanding (Self-reported financial knowledge)	-17,64	52,59	0,74
Expert knowledge (Self-reported financial Knowledge)	-101,75	162,58	0,53
Student (yes)	-1,7	71,17	0,98
Part-time employed (employment status)	-33,12	67,21	0,62
Self-employed (employment status)	92,49	75,24	0,22
Unemployed (seeking employment) (employment status)	34,6	85,73	0,69
Retired (employment status)	121,08	100,68	0,23
Unemployed (not seeking employment) (employment status)	73,49	89,26	0,41
Other (employment status)	-59,56	168,5	0,72
Treatment group (Price-Framed):Risk Preference (interaction term)	17,15	13,75	0,22
R2	0.37		
Adjusted R2	0.23		

Table 10: Regression model with interaction term (risk preference)

The regression model including the interaction term between the treatment group and risk preference (shown in table 10), shows that the treatment group (price-framed) coefficient becomes negative (-38.09), which reflects the estimated effect for respondents with a level of risk preference of zero. However, as only two respondents fall into this category and the result is not statistically significant (p-value of 0.62), this finding has limited interpretive value. The interaction term itself is positive, but not significant, indicating no clear evidence that the framing effect depends on the participant's level of risk preference. Overall, the results indicate that the framing effect is not meaningfully moderated by risk preference.

5.2.3 Random effects Panel data regression

In the previous analysis, the dependent variable (Risk-taking behavior) was defined as the average amount allocated to the high-risk stock across all eight investment questions. While this provides a useful summary measure of risk-taking behavior, it does not account for the variation in the individual questions. Since each participant made eight separate investment decisions, additional insights can be gained by analyzing these decisions at the individual level. Therefore, this study conducted a Random Effects Panel Data Regression to more precisely estimate the framing effect across all investment questions, rather than relying solely on average behavior per participant. The analysis is based on 880 observations (8 questions x 110 participants) and includes six control variables (Employment status, Student status, age, gender, financial knowledge 1 (self-reported financial knowledge) and risk preference). The results of the Random Effects Panel Data Regression are presented in table 11.

Term	Estimate	std.error	p-value
(Intercept)	326.44	79.57	0.00
Treatment group (Price-Framed)	50.00	30.20	0.10
Part-time employed (employment status)	-41.91	67.06	0.53
Self-employed (employment status)	98.89	75.3	0.19
Unemployed (seeking employment) (employment status)	11.87	84.03	0.89
Retired (employment status)	120.86	100.99	0.23
Unemployed (not seeking employment) (employment status)	67.88	89.42	0.45
Other (employment status)	-76.05	168.5	0.65
Student (yes)	6.00	71.12	0.93
26 - 35 years old (Age)	-21.75	58.49	0.71
36 - 45 years old (Age)	15.41	85.08	0.86
46 - 55 years old (Age)	-3.23	57.97	0.96
56 - 65 years old (Age)	20.85	86.6	0.81
66 years and older (Age)	31.14	102.87	0.76
Risk Preference	18.95	6.95	0.0077
Basic understanding (Self-reported financial knowledge)	-53.37	44.35	0.23
Moderate understanding (Self-reported financial knowledge)	-144.32	46.82	0.0027
Advanced understanding (Self-reported financial knowledge)	-28.14	52.07	0.59
Expert knowledge (Self-reported financial Knowledge)	-134.3	160.96	0.41
Gender (Female)	74.22	36.35	0.04

Table 11: Random effects Panel data regression output with 6 control variables

As shown in Table 11, the coefficient for the treatment group (Price-Framed) is positive, with a value of 50.00. This suggests a potential framing effect, that aligns with previous analyses, whereby

participants in the price-framed treatment group, allocated on average, 50 dollars more to the high-risk stock per investment question compared to those in the return-framed treatment group. However, this effect is not statistically significant at the 0.05 threshold, as the p-value is 0.10. The control variable risk preference, on the other hand, remains highly significant (p-value = 0.0077). Overall, the results of the Random Effects Panel Data Regression are consistent with earlier analyses in this study, where the potential framing effect points towards increased risk-taking behavior in the price-framed treatment group, however, this effect is not statistically significant. Risk preference still emerges as a robust predictor of risk-taking behavior.

5.2.4 Multivariate multiple linear regression

To gain deeper insights into the framing effect (price vs return) on risk-taking behavior, this study goes beyond aggregated measures across all investment questions (the average risk-taking). Instead, it examines whether the impact of price versus return framing varies across individual investment questions. Since each participant answered eight separate investment questions, the framing effect may differ by question. To investigate this, a multivariate multiple linear regression is conducted in which the amounts allocated to the high-risk stock for each question serve as the dependent variables. This approach models all eight outcomes simultaneously, accounting for the fact that responses come from the same participant, which enhances the robustness and efficiency of the analysis. The main independent variable is the treatment group and the second subset of control variables (age, gender, employment status, student status, risk preference and financial knowledge) is included to address potential confounding factors.

By using this method, the study can determine whether the framing effect is consistent across all eight investment questions or varies between them. This approach provides a more nuanced and reliable answer to the research question than analyses solely based on average risk-taking, while also improving statistical power and controlling for within-participant correlations.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
(Intercept)	452.02 (125.8)***	144.52 (121.51)	351.62 (146.27)**	402.55 (140.53)***	372.6 (153.16)**	311.39 (150.77)**	350.32 (135.93)**	226.49 (117.01)*
Treatment group (Price-Framed)	62.46 (47.75)	65.86 (46.12)	0.95 (55.52)	20.63 (53.34)	38.86 (58.13)	110.7 (57.23)*	70.58 (51.59)	29.99 (44.41)
Employment status: Part-time	-167.82 (106.01)	16.66 (102.39)	-40.56 (123.25)	-95.23 (118.41)	30.83 (129.06)	-90 (127.04)	-4.99 (114.54)	15.82 (98.6)
Employment status: Self-employed	20.53 (119.04)	227.6 (114.98)*	-2.57 (138.41)	118.43 (132.97)	17 (144.93)	-114.28 (142.67)	119.68 (128.63)	404.77 (110.72)**
Employment status: Unemployed (seeking employment)	-130.91 (132.85)	143.58 (128.32)	-96.91 (154.46)	87.68 (148.39)	36.62 (161.74)	-137.26 (159.21)	88.82 (143.54)	103.33 (123.56)
Employment status: Retired	-16.36 (159.66)	209.44 (154.22)	88.28 (185.64)	166.74 (178.35)	122.87 (194.38)	-79.18 (191.35)	178.58 (172.51)	296.5 (148.5)**
Employment status: Unemployed (Not seeking employment)	-92.47 (141.37)	151.14 (136.55)	56.76 (164.37)	79.73 (157.91)	86.3 (172.11)	-136.51 (169.43)	130.24 (152.75)	267.83 (131.49)**
Employment status: Other	-265.06 (266.4)	-71.66 (257.31)	-70.18 (309.74)	-228.66 (297.57)	-33.89 (324.33)	117.25 (319.27)	-30.36 (287.84)	-25.83 (247.77)
Student (yes)	71.11 (112.45)	-20.45 (108.61)	104.01 (130.74)	-43.49 (125.61)	-71.09 (136.9)	194.9 (134.77)	-83.95 (121.5)	-103.05 (104.59)
Age (26 - 35 years old)	49.2 (92.47)	-28.59 (89.31)	21.74 (107.51)	-83.73 (103.29)	-94.31 (112.58)	43.9 (110.82)	-98.86 (99.91)	16.67 (86)
Age (36 - 45 years old)	-17.31 (134.52)	-4.72 (129.93)	34.82 (156.4)	-11.32 (150.26)	-36.31 (163.77)	1.07 (161.21)	56.58 (145.34)	100.47 (125.11)
Age (46 - 55 years old)	-50.04 (91.65)	172.84 (88.52)*	-12.55 (106.56)	-162.24 (102.38)	-107.34 (111.58)	147.7 (109.84)	25.37 (99.03)	-39.6 (85.24)
Age (56 - 65 years old)	210.2 (136.91)	222.27 (132.24)*	-82.88 (159.18)	-42.45 (152.93)	-22.31 (166.68)	-50.2 (164.08)	49.22 (147.93)	-117.07 (127.34)
Age (66 years and older)	97.84 (162.64)	-41.81 (157.09)	121.14 (189.1)	26.51 (181.67)	54.18 (198.01)	131.73 (194.92)	-15.07 (175.73)	-125.44 (151.27)
Risk Preference Basis Financial Knowledge	29.77 (10.98)***	35.65 (10.61)***	8.43 (12.77)	23.19 (12.27)*	8.23 (13.37)	13.14 (13.16)	6.78 (11.87)	26.43 (10.21)**
Moderate Financial Knowledge	-222.34 (70.12)***	-1.44 (67.73)	-39.13 (81.53)	-27.4 (78.33)	-39.32 (85.37)	-54.73 (84.04)	-33.9 (75.76)	-8.68 (65.22)
Advanced Financial Knowledge	-291.96 (74.02)***	-119.21 (71.49)*	-34.33 (86.06)	-205.5 (82.68)**	-138.77 (90.12)	-90.26 (88.71)	-107.29 (79.98)	-167.24 (68.85)**
Expert Financial Knowledge	-189.82 (82.32)**	-65.63 (79.51)	49.87 (95.71)	-35.36 (91.96)	53.83 (100.22)	11.74 (98.66)	15.31 (88.95)	-65.06 (76.57)
Gender (Female)	-603.8 (254.48)**	581.67 (245.8)**	-256.85 (295.88)	-345.77 (284.26)	-289.13 (309.82)	-340.52 (304.99)	424.77 (274.96)	-244.76 (236.69)
	29.6 (57.47)	101.48 (55.51)*	71.48 (66.82)	34.99 (64.2)	53.4 (69.97)	102.04 (68.88)	59.54 (62.1)	141.26 (53.46)***

Table 12: Multivariate multiple linear regression output (with the second subset of control variables)

Note: Table 12 shows the regression coefficients and the standard errors are in the brackets. * Indicates p-value < 0.10, ** indicates p-value < 0.05 and *** indicates p-value < 0.01.

Table 12 shows that for all eight investment questions, the coefficient for the treatment group (price-framed) is positive. This indicates that participants exposed to price framing generally allocated more to the high-risk stock, which is consistent with the direction of the aggregate results found earlier in this thesis. However, this effect is not statistically significant for seven of the eight questions and is only weakly significant (p-value 0.0562) for one question (Q6). Risk preference stands out as a significant predictor in several questions, confirming that individuals who report themselves as more willing to take risks also tend to allocate more to the high-risk stock. Overall,

the findings of the multivariate multiple linear regression indicate that the potential framing effect consistently points in the direction of the price-framed group across all questions, which aligns with the previous analyses in this study. However, this effect lacks statistical significance in most cases, suggesting that there is no significant framing effect.

5.3 Reflecting on the research question

The central research question of this study is: How does the framing of investment options (price vs return) affect risk-taking behavior in investors? Based on the empirical analyses, an answer to this question can be formulated.

Across all statistical analyses conducted in this study, the effect of the framing condition on risk-taking behavior consistently points in the same direction, exposure to the price frame tends to increase risk-taking behavior compared to exposure to the return-frame. Specifically, in all regression models that include control variables, the coefficient for the treatment group indicates that participants in the price-frame treatment group allocate more to the high-risk stock than those in the return-framed treatment group. This pattern is also observed in the panel data analysis and the multivariate multiple linear regression for the individual investment questions, where the potential framing effect points towards increased risk-taking under price framing.

However, this effect is not statistically significant in any of the regression analyses that account for control variables. The only exception is a weakly significant effect found for one out of the eight investment questions in the multivariate multiple linear regression ($p < 0.10$). In the independent samples t-test and the baseline regression model without control variables, the framing effect is also weakly significant ($p < 0.10$), but loses significance once (relevant) control variables are included. In sum, the direction of the effect is remarkably consistent, but its statistical significance does not meet conventional thresholds.

Therefore, the answer to the research question is that there is no statistically significant effect of price versus return framing on risk-taking behavior in this experimental setting. While the results suggest that price framing may lead to somewhat higher risk-taking compared to return-framing, the evidence is not strong enough. Therefore, the hypothesis that price versus return framing has a significant effect on risk-taking behavior, is rejected.

6 Conclusion

This study investigates whether the framing of investment options, specifically framing in terms of prices versus returns, affects the risk-taking behavior of individual investors. The motivation behind this research stems from the substantial body of literature documenting the impact of framing effects on financial decision-making and the observation that the specific effect of price versus return framing on actual risk-taking behavior remains understudied. By addressing this gap, the study aims to provide both theoretical and practical insights into the mechanisms that influence investors' behavior.

To answer the central research question, an experiment was conducted in which participants were randomly assigned to either a price-framed or return-framed treatment group and asked to allocate hypothetical investment capital across higher- and lower risk stocks in a series of investment questions. The experiment controlled for a set of demographic factors, including (among others) risk preference, age, gender, education level and investing experience, to ensure the robustness and validity of the findings.

The results show a consistent pattern across all statistical analyses. Participants exposed to the price-framed scenarios generally allocated more to the high-risk stock than those in the return-framed treatment group. This trend was observed in the t-test, various regression models with different sets of control variables, panel data regression and multivariate multiple linear regression of individual investment questions. However, in all cases, the observed effect of framing on risk-taking behavior was not statistically significant according to the conventional threshold. Only in the simplest models, which did not control for potential confounding variables, or in one out of the eight investment questions, did a weakly significant effect emerge. Once (relevant) control variables were included, the effect consistently lost significance, suggesting that the framing effect, while directionally robust, does not exert a statistically meaningful influence on actual risk-taking behavior in this experimental context.

When these findings are placed in the context of existing literature, an interesting contrast emerges. Prior studies have demonstrated that framing effects can alter financial expectations, risk perception and even broader dynamics. For instance, Glaser et al. (2007) and Glaser et al. (2019) found that framing can influence investors' expectations. Additionally, Hanaki et al. (2023) showed that return-frames can destabilize markets. Studies such as Huber and Huber (2019) and Stössel

and Meier (2015) provided evidence that return framing tends to elevate perceived risk and potentially induce more cautious investments. Whereas price framing can lower perceived risk and potentially promote risk-taking. Together, these studies suggest that framing matters for how individuals perceive risk, form expectations and make investment decisions.

In contrast, this study does not find statistically significant evidence that price versus return framing influences (actual risk-taking) behavior. While the direction of the observed effects aligns with the notion from previous literature, that price framing may encourage greater risk-taking, the lack of statistical significance indicates that this influence is not robust, in this experimental context.

In summary, this paper concludes that there is no statistically significant framing effect (price vs return) on risk-taking behavior, in this experimental context.

7 Discussion

While this study provides insights into the effect of price versus return framing on risk-taking behavior, several limitations should be taken into account. First, although age was included as a control variable in the analyses, the sample of this study predominantly consisted of young, highly educated participants. As a result, the findings may not fully generalize to older or more diverse populations. Second, all investment questions in the experiment were hypothetical and did not involve real financial incentives, which potentially could have influenced participants' decision-making. Additionally, while a broad set of control variables was included, other unmeasured factors such as cognitive ability, numeracy or attitude towards hypothetical scenarios could still have played a role. Finally, the overall sample size was relatively modest, which may have limited the ability to detect small or subgroup-specific effects.

Given these limitations, future research could examine whether framing effects are more pronounced in different settings or among specific subgroups, such as investors with a broader range of ages. Field experiments using real financial incentives could provide more insight into the actual real-life behavior. It is also valuable to investigate whether the price versus return framing effect, interacts with other behavioral biases. Or whether more complex investment scenarios yield different results.

Overall, while this study does not find a significant behavioral effect of the price versus

return framing, it highlights the importance of further research into the conditions and populations for which framing effects may play a role in financial decision-making.

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9 Generative AI statement

Generative AI tools (e.g., ChatGPT, Copilot) were used to assist in coding, data analysis, and/or refining the language of this thesis. Appendix D of this thesis provides a detailed account of the use of Generative AI tools during the development of this thesis. By submitting this thesis I declare that I am fully responsible for the accuracy and completeness of its content.

10 Appendices

10.1 Appendix A: Qualtrics survey

Return-Framed Treatment group questions:

Dear Participant,

Thank you for taking the time to fill out this survey. My name is Jelle Philipsen and I am completing my Master's thesis at Radboud University. As part of my research, I am conducting a survey focused on investment decision-making. I would greatly appreciate your input.

Before we start, it is essential that you provide your consent to participate in this survey. The data will be handled with significant care, ensuring that all responses remain anonymous and are not shared with any third parties. The collected data will be used solely for scientific purposes. Participants cannot be identified from the data. There are no right or wrong answers.

- I have reviewed and comprehended the information provided above and I give my consent to participate in the survey.
- I do not give my consent to participate in this survey.

In this Survey, you will be asked to make choices between two similar investment options, but each with different possible outcomes. To ensure you are familiar with the format of the questions, here is an **example** in advance:

"You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 70% chance that the stock price will increase by 20% and a 30% chance that it will decrease by 20%.
- **Stock B:** There is a 50% chance that the stock price will increase by 40% and a 50% chance that it will decrease by 40%."

It is important to note that the entire investment amount of \$1000 will be distributed across the stocks. The specific distribution is at your discretion. You may choose to invest the full \$1000 in a single stock, or you may opt for a more diversified approach (e.g., \$600 in one stock and \$400 in the other). The allocation decision is entirely up to you.

When you want to invest \$600 in stock A and \$400 in stock B, the investment allocation should be as follows:



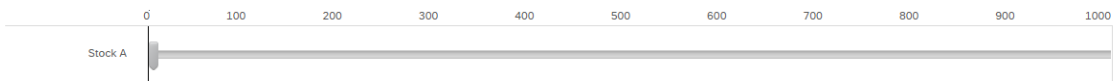
On a scale of 0 to 10, how willing are you to take risks in stock investments? (0 means no willingness to take risks in stock investments and 10 means you are very willing to take risks in stock investments)



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 60% chance that the stock price will increase by 25% and a 40% chance that it will decrease by 15%.
- **Stock B:** There is a 40% chance that the stock price will increase by 50% and a 60% chance that it will decrease by 30%.

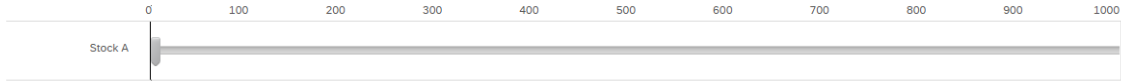
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 70% chance that the stock price will increase by 15% and a 30% chance that it will decrease by 10%.
- **Stock B:** There is a 50% chance that the stock price will increase by 40% and a 50% chance that it will decrease by 30%.

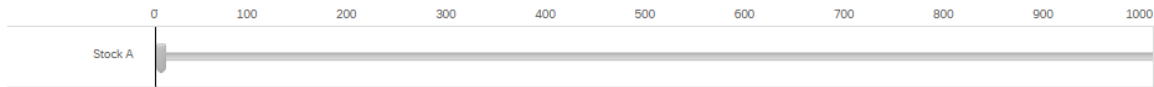
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 60% chance that the stock price will increase by 40% and a 40% chance that it will decrease by 20%.
- **Stock B:** There is a 80% chance that the stock price will increase by 12% and a 20% chance that it will decrease by 5%.

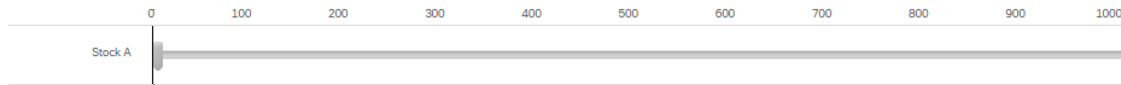
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 55% chance that the stock price will increase by 50% and a 45% chance that it will decrease by 30%.
- **Stock B:** There is a 90% chance that the stock price will increase by 15% and a 10% chance that it will decrease by 5%.

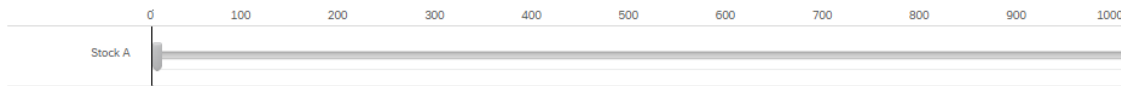
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is an 85% chance that the stock price will increase by 10% and a 15% chance that it will decrease by 5%.
- **Stock B:** There is a 30% chance that the stock price will increase by 80% and a 70% chance that it will decrease by 50%.

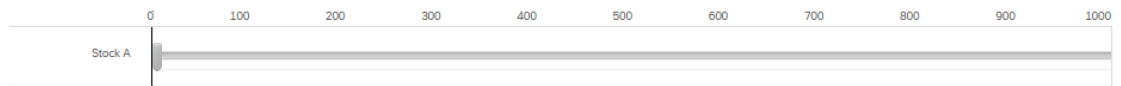
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 75% chance that the stock price will increase by 25% and a 25% chance that it will decrease by 20%.
- **Stock B:** There is an 85% chance that the stock price will increase by 15% and a 15% chance that it will decrease by 10%.

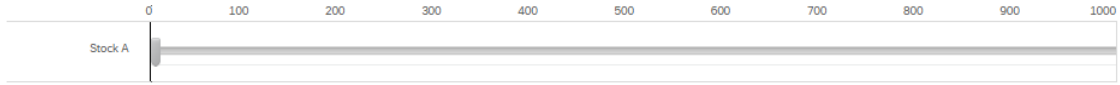
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 67% chance that the stock price will increase by 18% and a 33% chance that it will decrease by 9%.
- **Stock B:** There is a 36% chance that the stock price will increase by 60% and a 64% chance that it will decrease by 38%.

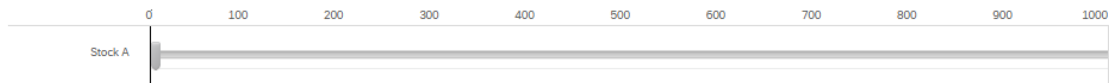
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 40% chance that the stock price will increase by 75% and a 60% chance that it will decrease by 50%.
- **Stock B:** There is a 70% chance that the stock price will increase by 20% and a 30% chance that it will decrease by 15%.

Investment allocation:



Price-Framed Treatment group questions:

Dear Participant,

Thank you for taking the time to fill out this survey. My name is Jelle Philipsen and I am completing my Master's thesis at Radboud University. As part of my research, I am conducting a survey focused on investment decision-making. I would greatly appreciate your input.

Before we start, it is essential that you provide your consent to participate in this survey. The data will be handled with significant care, ensuring that all responses remain anonymous and are not shared with any third parties. The collected data will be used solely for scientific purposes. Participants cannot be identified from the data. There are no right or wrong answers.

- I have reviewed and comprehended the information provided above and I give my consent to participate in the survey.
- I do not give my consent to participate in this survey.

In this survey, you will be asked to make choices between two similar investment options, but each with different possible outcomes. To ensure you are familiar with the format of the questions, here is an **example** in advance:

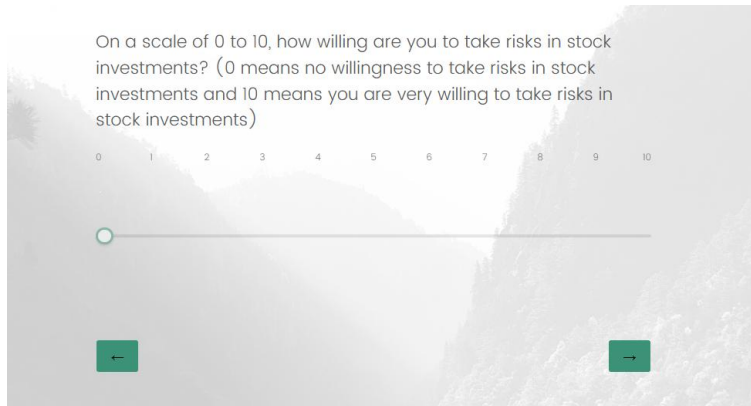
"You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 70% chance that the stock price will increase to \$120 and a 30% chance that it will decrease to \$80.
- **Stock B:** There is a 50% chance that the stock price will increase to \$140 and a 50% chance that it will decrease to \$60."

It is important to note that the entire investment amount of \$1000 will be distributed across the stocks. The specific distribution is at your discretion. You may choose to invest the full \$1000 in a single stock, or you may opt for a more diversified approach (e.g., \$600 in one stock and \$400 in the other). The allocation decision is entirely up to you.

When you want to invest \$600 in stock A and \$400 in stock B, the investment allocation should be as follows:

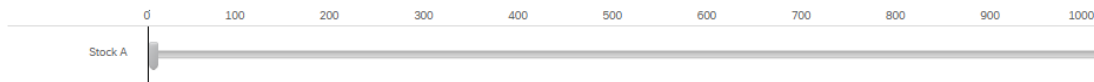




You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 60% chance that the stock price will increase to \$125 and a 40% chance that it will decrease to \$85.
- **Stock B:** There is a 40% chance that the stock price will increase to \$150 and a 60% chance that it will decrease to \$70.

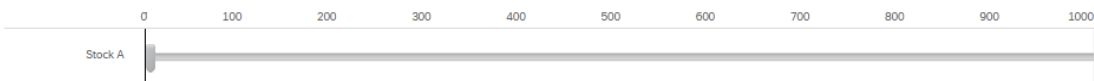
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 70% chance that the stock price will increase to \$115 and a 30% chance that it will decrease to \$90.
- **Stock B:** There is a 50% chance that the stock price will increase to \$140 and a 50% chance that it will decrease to \$70.

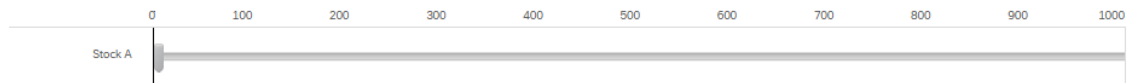
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 60% chance that the stock price will increase to \$140 and a 40% chance that it will decrease to \$80.
- **Stock B:** There is an 80% chance that the stock price will increase to \$112 and a 20% chance that it will decrease to \$95.

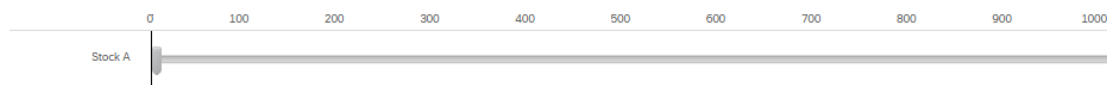
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 55% chance that the stock price will increase to \$150 and a 45% chance that it will decrease to \$70.
- **Stock B:** There is an 90% chance that the stock price will increase to \$115 and a 10% chance that it will decrease to \$95.

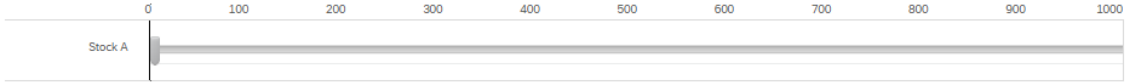
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 85% chance that the stock price will increase to \$110 and a 15% chance that it will decrease to \$95.
- **Stock B:** There is a 30% chance that the stock price will increase to \$180 and a 70% chance that it will decrease to \$50.

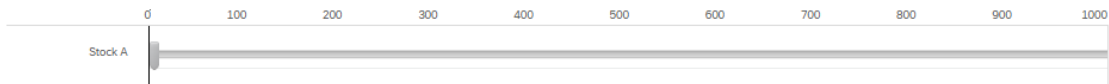
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 75% chance that the stock price will increase to \$125 and a 25% chance that it will decrease to \$80.
- **Stock B:** There is a 85% chance that the stock price will increase to \$115 and a 15% chance that it will decrease to \$90.

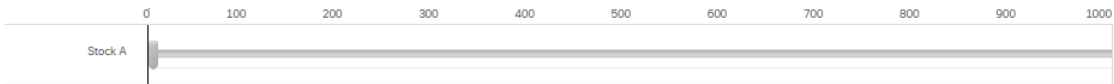
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 67% chance that the stock price will increase to \$118 and a 33% chance that it will decrease to \$91.
- **Stock B:** There is a 36% chance that the stock price will increase to \$160 and a 64% chance that it will decrease to \$62.

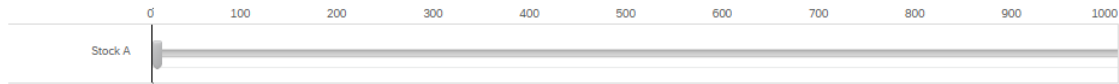
Investment allocation:



You are considering investing in the stock market. There are two similar stocks available, each with different possible outcomes (shown below). Both stocks have an initial price of \$100. You are given an investment amount of \$1000, allocate this amount between the two stocks, based on your preferences. Please use the slider for Stock A below. The remaining amount (not allocated to stock A) will be assigned to stock B.

- **Stock A:** There is a 40% chance that the stock price will increase to \$175 and a 60% chance that it will decrease to \$50.
- **Stock B:** There is a 70% chance that the stock price will increase to \$120 and a 30% chance that it will decrease to \$85.

Investment allocation:



Shared control variable questions:

Please indicate your age

- 18 - 25 years old
- 26 - 35 years old
- 36 - 45 years old
- 46 - 55 years old
- 56 - 65 years old
- 66 years and older

Please indicate your gender

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

Are you a student at the moment?

No

Yes

What is the highest level of education you have completed?

Primary School (Basisschool)

Secondary School (Middelbare school)

MBO

HBO

Bachelor's Degree (WO)

Master's Degree (WO)

PhD or higher

Other

What is your current employment status?

Full-time employed

Part-time employed

Self-employed

Unemployed but seeking employment

Retired

Unemployed (not currently looking for work)

Other

Which country do you currently reside in?

Netherlands

Belgium

Germany

France

Other

How would you describe your experience with investing?

No experience

Limited experience

Moderate experience

Extensive experience

Professional experience

How would you rate your financial knowledge?

- Very limited
- Basic understanding
- Moderate understanding
- Advanced understanding
- Expert knowledge

What does the term "beta" refer to in the context of a stock or portfolio?

- The correlation between the asset's return and the overall market's return.
- The average return of a stock over the past year.
- The overall price level of a stock compared to the economy's price level.

This is a verification question. Please select the number 7.

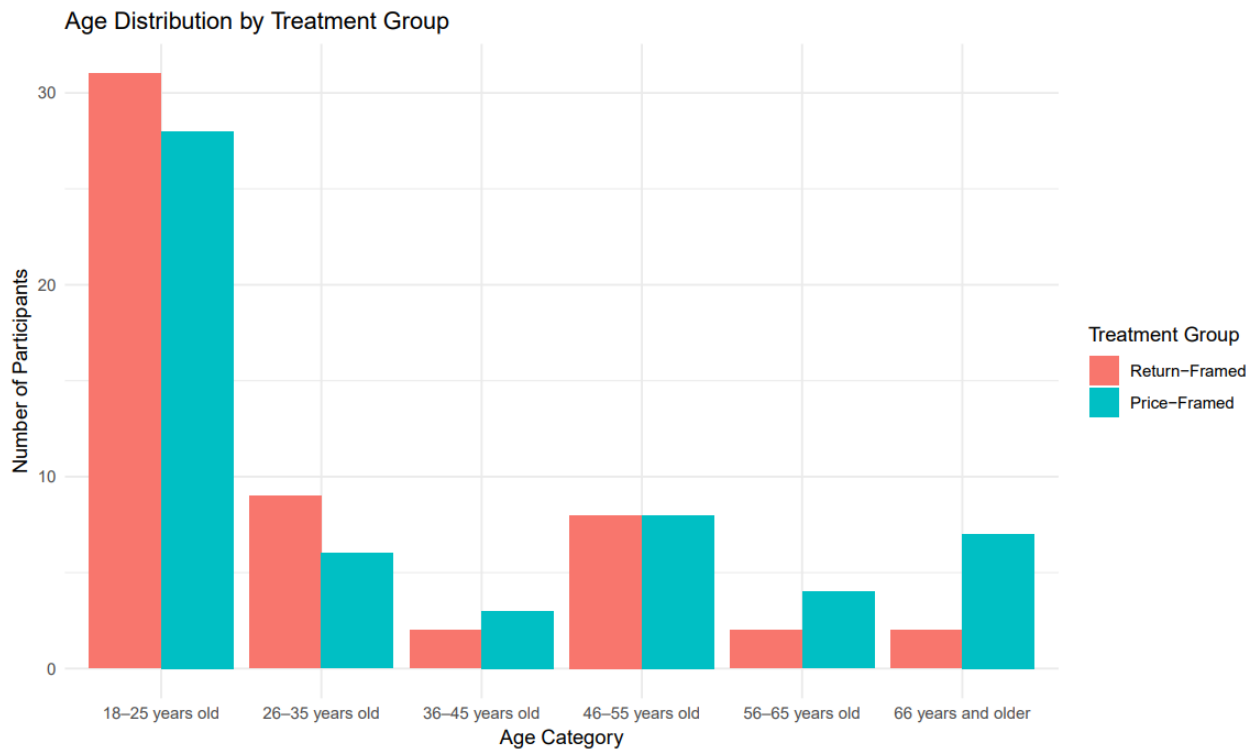
- 10
- 7
- 4
- 1

10.2 Appendix B: Defining the High-risk stock per investment question based on the variance

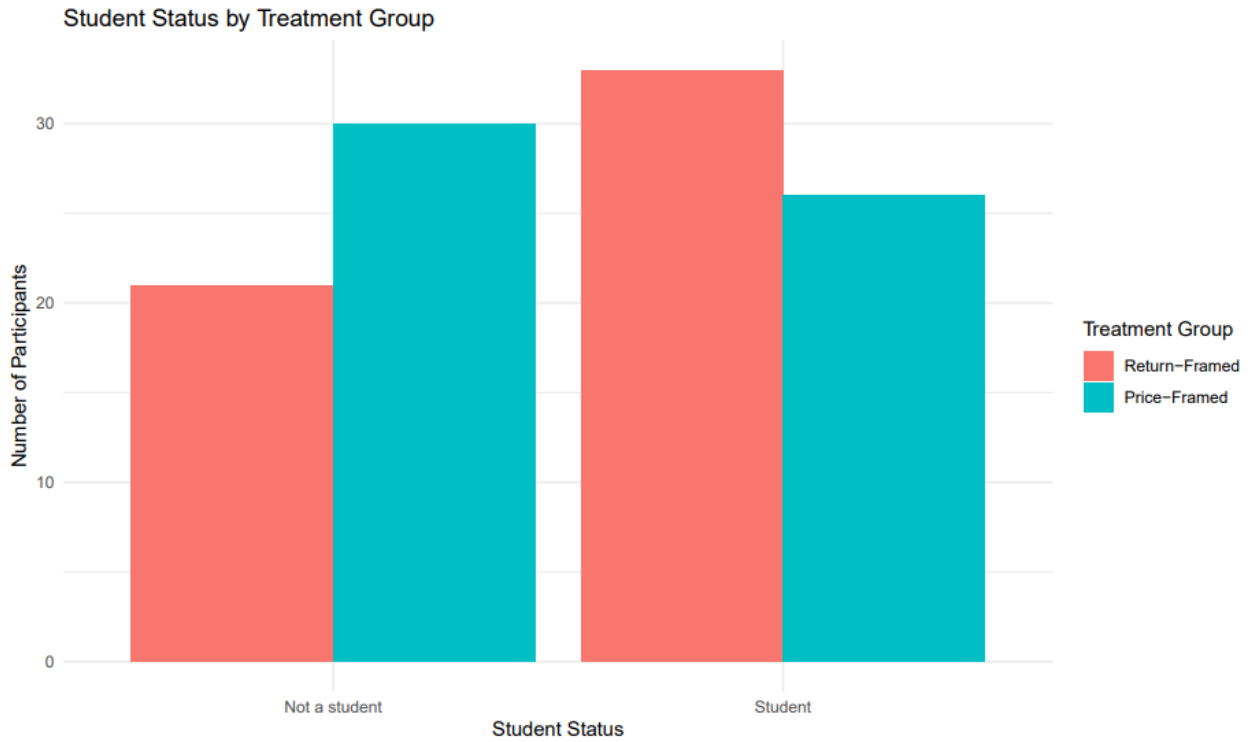
Question Number	High-Risk stock
1	B
2	B
3	A
4	A
5	B
6	A
7	B
8	A

Table 13: Defining the high-risk stock per investment question

10.3 Appendix C: Visuals of the control variables distribution



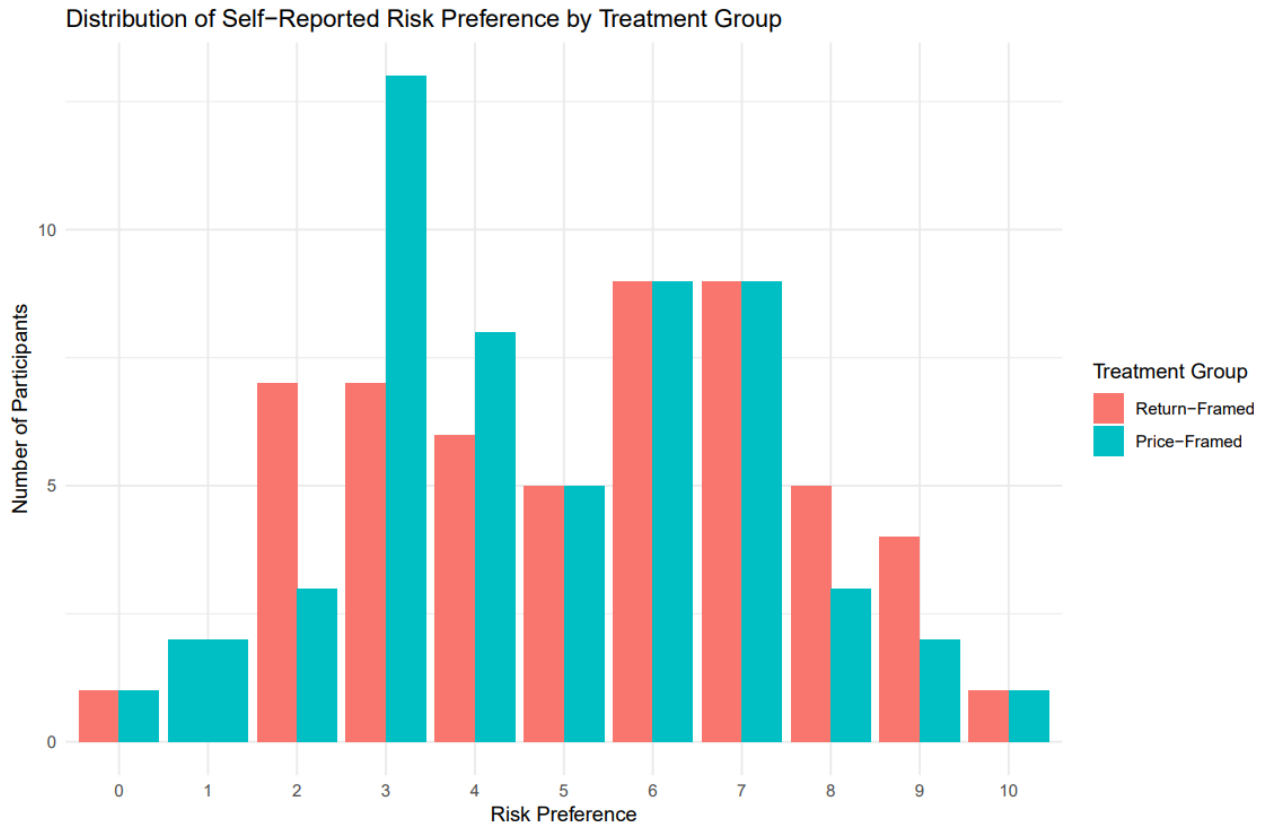
Graph 1: Age distribution by treatment group



Graph 2: Distribution of student status by treatment group



Figure 3: Distribution of six other variables by treatment group



Graph 3: Distribution of the self-reported risk preference by treatment group

10.4 Appendix D: Documentation of Generative AI usage

Statement of purpose

In the process of writing my thesis, Generative AI tools were used to support with coding in Rstudio. This helped me solve coding issues. All Rcodes were critically reviewed and adjusted when necessary.

Tools used

ChatGPT

Scope of use

Coding

Description:

Tool: ChatGPT

Purpose: Generating and improving codes in Rstudio, that were needed to analyze the data.

My role: The AI output was constantly reviewed and adjusted when necessary.

My reflection: AI helped me improved my coding skills.

Applied in the results and the appendix C sections.

Complete log of AI interaction

1: Coding assistance

Query to Chatgpt: “Give Rstudio codes to check the distributional imbalances across the treatment groups for all the control variables via a t-test for the variable risk preference and chi squared tests for the other 9 control variables. Take the treatment group as a factor. ‘’.

After several prompts, this was the output from chatgpt: ‘

```
df <- Dataset_voor_R_studio_download_van_10_juni_2320_uurr

control_vars <- c("Age", "Gender", "Student", "Education", "Employment_status",
                 "Geo_location", "Investing_experience",
                 "Financial_Knowledge1", "Financial_Knowledge2", "Risk_Preference")

df$Treatment_group <- as.factor(df$Treatment_group)
```

```

var_names <- c()
p_values <- c()
test_type <- c()

for (var in control_vars) {
  var_names <- c(var_names, var)

  if (is.numeric(df[[var]]) || is.integer(df[[var]])) {
    # T-test
    test <- t.test(df[[var]] ~ df$Treatment_group)
    p_values <- c(p_values, round(test$p.value, 4))
    test_type <- c(test_type, "t-test")
  } else {
    # Chi-squared test
    tab <- table(df[[var]], df$Treatment_group)
    test <- chisq.test(tab)
    p_values <- c(p_values, round(test$p.value, 4))
    test_type <- c(test_type, "Chi-squared")
  }
}

```

How it was used: The generated code was used for analyses of the distributional imbalances between the treatment groups across all control variables.

2: coding assistance

Query to ChatGPT: ‘‘Please give the Rstudio codes for generating, in rstudio, a boxplot of the distribution of the dependent variable, risk-taking behavior, across the treatment groups.’’

After several prompts I got the following output:

Output from chatgpt: ‘

```
Dataset_voor_R_studio_download_van_10_juni_2320_uurr$Treatment_group <- factor(
  Dataset_voor_R_studio_download_van_10_juni_2320_uurr$Treatment_group,
  levels = c(0, 1),
  labels = c("Return-Framed", "Price-Framed")
)
```

```
ggplot(Dataset_voor_R_studio_download_van_10_juni_2320_uurr,
  aes(x = Treatment_group, y = Average_Risk_Taking, fill = Treatment_group)) +
  geom_boxplot() +
  labs(
    title = "Distribution of Risk-Taking Behavior by Treatment Group",
    x = "Treatment Group",
    y = "Average Allocation to High-Risk Stock"
  ) +
  scale_fill_manual(values = c("red", "blue")) + # rood = return, blauw = price
  theme_minimal() +
  theme(legend.position = "none")
“
```

How it was used: The generated code was used to analyze the boxplot.

3: Coding assistance

Query to chatgpt: “Give me the Rstudio codes for creating a barchart in Rstudio that shows the distribution for the control variable age. With the categories of age in the x-as and the number of participants on the y-ax.”

After several prompts I got this output:

Output from chatgpt:”

```
library(ggplot2)
ggplot(df, aes(x = Age, fill = Treatment_group)) +
  geom_bar(position = "dodge") +
  labs(title = "Age Distribution by Treatment Group",
    x = "Age Category",
```

```

y = "Number of Participants",
fill = "Treatment Group") +
theme_minimal()
‘,

```

How this was used: The generated code was used as assistance to create the code for the barchart.

4: code assistance

Query to Chatgpt: ‘‘Please give me the rstudio codes for a random effects panel data regression. Use the amounts allocated to the high risk stock for all investment questions as the dependent variable, the treatment group as independent variable and the subset of 6 control variables’’

After several prompts I got this output:

Output from chatgpt:’’

```

data_copy <- Dataset_voor_R_studio_download_van_10_juni_2320_uurr

names(data_copy)[names(data_copy) == "Q3_HR_Allocation"] <- "Q2_HR_Allocation"
names(data_copy)[names(data_copy) == "Q4_HR_Allocation"] <- "Q3_HR_Allocation"
names(data_copy)[names(data_copy) == "Q5_HR_Allocation"] <- "Q4_HR_Allocation"
names(data_copy)[names(data_copy) == "Q6_HR_Allocation"] <- "Q5_HR_Allocation"
names(data_copy)[names(data_copy) == "Q7_HR_Allocation"] <- "Q6_HR_Allocation"
names(data_copy)[names(data_copy) == "Q8_HR_Allocation"] <- "Q7_HR_Allocation"
names(data_copy)[names(data_copy) == "Q10_HR_Allocation"] <- "Q8_HR_Allocation"

```

```

library(dplyr)

```

```

library(tidyr)

```

```

pdata$Employment_status <- as.factor(pdata$Employment_status)

```

```

pdata$Student      <- as.factor(pdata$Student)
pdata$Age          <- as.factor(pdata$Age)
pdata$Financial_Knowledge1 <- as.factor(pdata$Financial_Knowledge1)
pdata$Gender       <- as.factor(pdata$Gender)

library(dplyr)
library(tidyr)

data_long <- data_copy %>%
  mutate(respondent_id = row_number()) %>%
  pivot_longer(
    cols = c(
      Q1_HR_Allocation, Q2_HR_Allocation, Q3_HR_Allocation, Q4_HR_Allocation,
      Q5_HR_Allocation, Q6_HR_Allocation, Q7_HR_Allocation, Q8_HR_Allocation
    ),
    names_to = "question_label",
    values_to = "HR_allocation"
  ) %>%
  mutate(
    question_number = as.numeric(gsub("Q([0-9]+)_HR_Allocation", "\\1", question_label)),
    Treatment_group = as.factor(Treatment_group),
    Employment_status = as.factor(Employment_status),
    Student = as.factor(Student),
    Age = as.factor(Age),
    Financial_Knowledge1 = as.factor(Financial_Knowledge1),
    Gender = as.factor(Gender),
    Risk_Preference = as.numeric(Risk_Preference)
  )

```

```
)
```

```
pdata <- pdata.frame(data_long, index = c("respondent_id", "question_number"))
```

```
table(data_long$respondent_id) # moet allemaal 8 zijn
```

```
head(index(pdata))          # moet respondent_id 1, question_number 1 t/m 8 tonen
```

```
library(nlme)
```

```
model_full <- lme(
```

```
  HR_allocation ~ Treatment_group + Employment_status + Student +
```

```
  Age + Risk_Preference + Financial_Knowledge1 + Gender,
```

```
  random = ~1 | respondent_id,
```

```
  data = pdata
```

```
)
```

```
summary(model_full)
```

```
‘,’
```

How it was used: The generated code was used to finish the panel data regression codes.

5: coding assistance

Query to chatgpt: "Please give rstudio codes voor a Multivariate multiple linear regression. Where you take the individual allocated amounts to the high risk stock of the 8 individual investment questions as the dependent variables, the treatment group as independent variable and the subset of 6 control variables". "

After several prompts this was the output:

Output from chatgpt:"

```
multi_model <- lm(
```

```
  cbind(
```

```
Q1_HR_Allocation,  
Q3_HR_Allocation,  
Q4_HR_Allocation,  
Q5_HR_Allocation,  
Q6_HR_Allocation,  
Q7_HR_Allocation,  
Q8_HR_Allocation,  
Q10_HR_Allocation  
) ~ Treatment_group + Employment_status + Student + Age + Risk_Preference +  
Financial_Knowledge1 + Gender,  
data = Dataset_voor_R_studio_download_van_10_juni_2320_uurr  
)
```

```
summary(multi_model)
```

```
‘,
```

How it was used: The generated code was used to get to the output of the Multivariate Multiple linear regression in rstudio.