Can Investor Risk Perception Be Explained by Cumulative Prospect Theory?

Master's Thesis

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August 2017

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ABSTRACT. Behavioral insights from (Cumulative) Prospect Theory (CPT) as an innovative theory of decision-making revolutionized financial risk research. Despite its theoretical appeal, the empirical relevance of CPT with regard to perceived risk remains yet unclear, partially because it requires complex implementation. While arguing that the theory fits an accurate description of investor risk perception, we empirically test this claim in an experimental investment setting, which overcomes the inherent implementation complexities of CPT by achieving gain-loss separability and subject reference point homogeneity. OLS and ordered logistic regression results as well as subsequent robustness checks show that the CPT value of an investment can significantly predict investment behavior and individual risk perception. Comparing these results with those of including standard deviation and lower partial moments measures, we discover that only the total probability of loss is comparably significant. Albeit these findings are in favor of recent behavioral insights in the academic field of finance, an additional analysis shows that revised parameters of the CPT function – in contrast to standard ones – can yield a substantially improved representation of decision-making under risky choice.

Keywords: risk perception, investment risk, Behavioral Finance, Prospect Theory

JEL Classifications: D81, G11, G41

Contents

1 Introduction

Risk – a complex theoretical phenomenon that has shaped a strand of academic literature in numerous fields around psychology – has been investigated thoroughly in an attempt to operationalize the concept (Thaler, 2005). In finance, risk can be considered as the potential of an investment prospect to suffer loss events. Currently the single most commonly used indication of risk-as-is in quantitative finance is that of dispersion around the expected outcome (mean), measured by the standard deviation of returns. Its first popular application in financial decision-making can be traced back to Markowitz's Portfolio Theory (1959). In this framework, a scenario is evaluated solely on the basis of its expected return and standard deviation, which was later proved to be insufficient with regard to several behavioral inconsistencies (see for instance Ellsberg, 1961). As a response, two decades later, a successful step back from explaining what *is* risk towards describing how individuals actually *perceive* risk is taken by Kahneman and Tversky (1979), who developed Prospect Theory (PT). This theory builds upon human cognitive features, admitting to the fact that individuals need not always act in line with the previously widely accepted *homo economicus* view. In contrast to the standard deviation, it accounts for behavioral deviations from rational decision-making, such as the individuals' particular aversion towards losses and the non-linear processing of probabilities, while evaluating gains and losses relative to a reference point. Its revised version, Cumulative Prospect Theory (CPT) also allows for rank-dependent outcomes. Despite its theoretical appeal, however, the CPT framework in particular lacks consistent empirical support. On the one hand, studies supporting CPT underline the relevance of loss aversion (Abdellaoui et al., 2007), and the suitability of the theory to predict such as decision-making in gambling tasks (Glöckner & Betsch, 2008) as well as organizational risk-return relationships (Fiegenbaum, 1990). On the other hand, Wu and Markle (2008) for instance state that Prospect Theory studies are incapable of achieving gain-loss separability, whereas Stott (2006) questions the parameterization of the CPT function. Yet other studies present mixed results, including for instance List (2003) who finds that inexperienced subjects act more in line with PT, whereas experienced market actors exhibit behavior predicted by neoclassical theory. The debate around CPT, as a model predicting financial decision-making and as approaching the actual perception of investment risks, remains yet unsettled. In this thesis, we aim to contribute to resolving this debate by investigating the following central research question:

Can investment behavior and investor risk perception be explained by Cumulative Prospect Theory?

Thus, this study aims to provide more clarity about the role of CPT in predicting risk as it is perceived, as well as its role in explaining investment behavior, by implementing a unique empirical approach. Firstly, from a theoretical perspective, we identify the factors that make Cumulative Prospect Theory particularly suitable for describing investment behavior. Then, in an experimental investment setting, subjects are to evaluate different prospects with equal return characteristics but different risk features. Anzoni and Zeisberger (2016), who confront subjects with 10 systematically different return histograms, analyze whether their investment behavior is in line with traditional measures of risk and lower partial moments measures. In this thesis, we do not only consider each distribution's implied CPT value as the most suitable predictor of perceived risk and the propensity to invest, but also account for some of these traditional risk factors, in order to compare them with the role of CPT. Moreover, participants are not confronted with 5 out of 10 but instead 10 out of 30 distributions at random, aiming to represent a broader scale of risk factor values and a wide range of CPT values. Along with applying this unique methodology, we are to our knowledge the first to provide a direct comparison between the explanatory role of risk factors and CPT with regard to perceived investment risk.

Regression results based on individual and aggregated data show that the prospect value implied by CPT is able to predict both investment behavior and investor risk perception significantly. As expected, the CPT value is found to be positively associated with investment propensity and negatively related to risk perception. The hypothesized effects are robust across individual as well as aggregated data and resist two robustness checks that control for multicollinearity and sample heterogeneity. Out of the risk factors, only one variable – the total probability of loss – is able to perform comparably well across all models. The results imply that individuals do evaluate investments in a way that is suggested by CPT, next to paying explicit attention to the probability of an investment's loss potential. Notwithstanding, standard deviation is able to explain only investment propensity, whereby this effect becomes insignificant when controlling for multicollinearity. Although the CPT findings seem appealing, when inspecting the results more closely, a revision of CPT parameters can achieve substantially improved correlations between CPT value and investment propensity/perceived risk. The new parameters imply more extreme risk attitudes in each domain when compared to standard CPT parameters, and that loss probabilities are weighted in a more linear manner compared to gain probabilities. On an academic level, the results imply a clear questioning of standard deviation as the most appropriate risk measure as well as a challenging of Cumulative Prospect Theory parameterization. On a practical level, these results ask for improved risk communication with particular emphasis on loss scenarios.

The thesis is organized as follows: Section 2 embeds Prospect Theory in a theoretical framework that describes the intuition behind the decision-making model. In Section 3 we specify the methodology of the study by elaborating on the experimental design and procedure. The data and results from the experiment are shown in Section 4. The discussion in Section 5 puts the results into context with other studies and sheds light on the relevance of Prospect Theory parameters as proposed by Kahneman and Tversky (1979). At last, a concluding section summarizes the findings and describes suggestions for future research as well as limitations of this study.

2 Theoretical Background

2.1 Traditional Risk Conceptualization

An early attempt to evaluate the risk of financial assets on a quantitative basis was provided by Markowitz (1959). His mean-variance framework illustrated the relationship between an asset's return and its variance. Because a higher variation of returns implies a higher likelihood of lower (negative) returns, investors must be compensated with higher expected return for running more risk of potential loss events. Thus, variance and in particular the standard deviation of asset returns have become the most prominent mathematical measures of risk. In this way, risk in an investment context has been considered an objective construct. In an attempt to describe solely what *is* the risk inherent in financial assets, research in the 1960s has predominantly focused on only the total variation of returns (Olsen, 1997).

The mean-variance model has encountered its application within the broader framework of Expected Utility Theory (EUT) developed by von Neumann and Morgenstern (1947). A concave utility function depicts the evaluation of return outcomes and absolute resulting wealth levels in each scenario and then takes into account the objective likelihood of each return occurring. Typical utility functions comprise the utility of earning returns and the disutility of bearing investment risk, while more detailed models take into account a certain degree of overall investor risk aversion.

Even though this simple and logically intuitive framework seems appealing, several empirical violations of EUT convulsed the model's very foundation. Ellsberg (1961) for instance illustrated a famous expected utility paradox when facing unknown risks and finds that individuals prefer known risk rather than ambiguity, an insight that is not captured by standard EUT. Besides, the Allais paradox shows that persons overweigh certain outcomes, and thereby proves an inconsistency of EUT with regard to its independence axiom (Allais, 1990). Numerous other studies indicate violations of EUT, among which for example Harbaugh et al. (2002), who state that individuals exhibit different risk attitudes towards gains and losses.

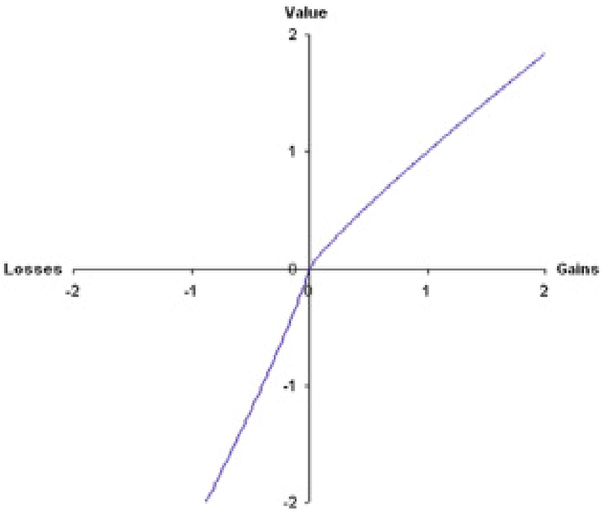
The inconsistency of individual risk preference across different situations and domains proved that EUT lacks empirical support. As a response, Kahneman and Tversky (1979) published their seminal paper on Prospect Theory (PT), which has contributed to a more elaborate and context-specific account of decision-making under risk. The theory moves away from solely describing risk by being more oriented towards how individuals actually perceive risks.

2.2 Prospect Theory

During the so-called evaluation phase, a decision-maker assesses a prospect by taking into account value and likelihood of each outcome occurring. Unlike Expected Utility Theory, Prospect Theory neither values gain and loss outcomes evenly, nor linearly. Investors for instance are observed to suffer more disutility from losses than they gain utility from equally-sized profits (Odean, 1998). However, once having incurred a loss, investors seem to be risk-seeking in an effort to regain money, eventually break even and hence avoid the discomfort of suffering a loss. On the other hand, investors in the gain domain are more likely to realize their profits early to avoid the potential of losing them. This leads to non-linear value functions, with different curvatures in the gain and loss domain (Kahneman & Tversky, 1979). Figure 1 below illustrates that the value function for negative outcomes is steeper than for positive outcomes, following the intuition behind investor loss aversion. The origin in the graph represents the reference point, which refers to the concept of reference dependence. Individuals namely do not evaluate prospects in terms of absolute resulting levels of wealth, but rather changes in it. This explains the observation that gains or losses of equal size are valued differently for people with different levels of wealth (Barberis, Huang & Santos, 2001).

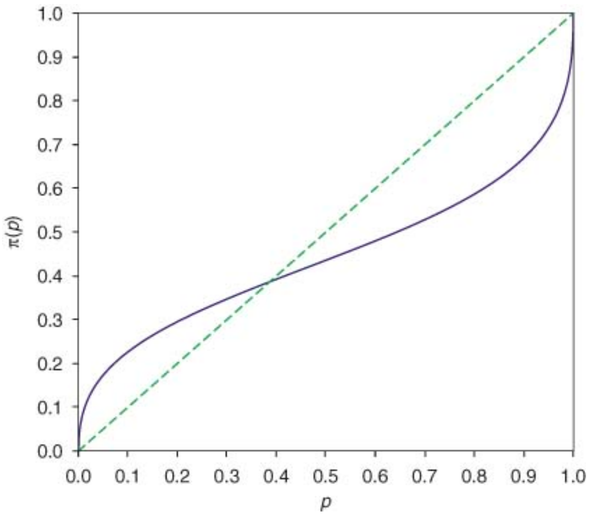
As indicated, Prospect Theory also holds that probabilities are not weighted linearly, but instead different weights are assigned to different probability sizes. Kahneman and Tversky (1979) observed that small probabilities are frequently overweighed, whereas large probabilities are underweighted, following an inverse S-shaped curve as illustrated in Figure 2. In contrast with standard probabilities used in EUT, probability weighting accounts more accurately for how risks are actually perceived by investors.

Figure 1: Value Function[1]



Courtesy of Tuyon and Ahmad (2016)

Figure 2: Probability Weighting Function[2]



Courtesy of Burns, Chiu and Wu (2010)

The equations for the value and probability weighting function are as follows:

$$V(x) = \begin{cases} x^{\alpha} & ,if\ x > 0 \\ -\lambda * (-x)^{\beta} & ,if\ x < 0 \end{cases} \tag{1}$$

$$\pi(p) = \frac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{\frac{1}{\gamma}}} \tag{2}$$

Equation (1), the value function, shows how alpha and beta represent the different curvature of the gain and loss domain and thus capture the different risk attitudes. A lambda larger than 1 magnifies losses and thus embodies the typical loss aversion feature. Gamma in Equation (2) determines the curvature of the probability weighting function for probabilities

[1] Source: http://www.sciencedirect.com/science/article/pii/S2214845015300703#fig3
[2] Source: https://www.researchgate.net/figure/228818558_fig1_Figure-1-A-typical-prospect-theory-probability-weighting-function-pp-which-is

corresponding to gains, whereas a different parameter delta is substituted for loss probabilities.

Despite its initial appeal, the original Prospect Theory Framework was criticized for not satisfying stochastic dominance (Camerer & Ho, 1994). That is why Tversky and Kahneman (1992) extended their work to Cumulative Prospect Theory (CPT), which transforms weighted probabilities to cumulative weights by ranking the prospect outcomes from the most to the least extreme in each domain. This allows for a larger amount of outcomes to be taken into consideration. With regard to its empirical relevance, Fennema and Wakker (1997) find that CPT is more suited at explaining diminishing sensitivity towards gains/losses when being further in the respective domain.

In contrast to traditional conceptualizations of risk, Prospect Theory thus provides a theoretical contribution towards individual perception of investment risks. The framework hints at risk characteristics of financial assets that go beyond the simple dispersion of returns. With its intuitive loss aversion characteristic and functional correspondence to individual risk preferences in different domains, we predict that a hypothetical investment value based on CPT calculation is representative for an individual's propensity to invest. On this basis, we formulate the following hypothesis:

Hypothesis 1: Investment propensity is positively related to the CPT value of an investment.

In line with this argument is Prospect Theory's accurate description of how risks are perceived. Risks, i.e. the potential of financial value depletion, are namely punished strongly in the CPT calculation by scaling up loss scenarios. Together with the individual perception of probabilities in a non-linear manner, this idea gives an accurate description of how humans perceive risks.

Hypothesis 2: Perception of investment risk is negatively related to the CPT value of an investment.

Several studies praise the impact of Cumulative Prospect Theory on academic progress in the fields of psychology and finance, as it has largely contributed to an improved theoretical as well as empirical understanding of how investors perceive risks and make decisions in the marketplace. Indeed, Barberis (2013) has pointed out that Prospect Theory is well-suited at explaining risky choice in an asset-market context, even though there have been many inherent complexities in applying Prospect Theory on a practical level. Difficulties have predominantly occurred with for instance stating what are exactly gains and losses, whether subjects integrate or separate these when making decisions, or where each individual's reference point is located (Stott, 2006). Such challenges entail an experimental setup that ensures the independence of prospects while providing an equal return benchmark. The unique design of our experiment allows for overcoming these challenges in an efficient yet simple manner, which is explained in the next section.

3 Experimental Design

In order to investigate whether investment propensity and risk perception can be explained by Prospect Theory, we implement an experimental setting in which subjects are instructed to determine the riskiness of a hypothetical investment, next to indicating how much (percentage-wise) they would invest in the opportunity. Complementary to research by Anzoni and Zeisberger (2016), who examine the effect of selected risk factors on investment behavior in 10 different investment scenarios, we aim to extend this approach to a wider variety of scenarios, in particular to a total of 30 different contexts. These investment scenarios are depicted by hypothetical return distributions in a histogram that shows the frequency of 100 theoretical investment return outcomes. The difference between these presented distributions is determined by several risk factors as well as their value according to CPT, while the expected return of each investment prospect remains constant at 8%, a suitable rate that reflects the average return on the S&P 500 stock index in the period 2002 – 2016.[3] This lets the investment decision be based on solely the individuals' perceived risk of investment returns (Veld & Veld-Merkoulova, 2008). In particular, controlling for different risk factors and CPT value across distributions enables us to examine which influences particularly drive investor decision-making. Therefore, before creating the return distributions, it is first necessary to identify empirically relevant risk factors.

3.1 Risk Factors

Next to the standard deviation as a traditional objective risk measure, the factors to be considered for the distributions and subsequent analysis are ones of perceived risk. Including these risk measures allows for a direct comparison between those and CPT's predictive power. The empirical literature distinguishes risk as the potential of suffering loss events

[3] Data from http://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/histretSP.html

when faced with a decision problem. Putting this into context with financial investment scenarios, Brachinger and Weber (1997) identified several risk measures that consider particularly the possibility to incur losses, so-called lower partial moments measures, among which the total probability of loss (referred to as loss probability), as well as the possibility to achieve lower-than-expected outcomes, which refers to the lower semi-variance. The former simply refers to the summed probabilities corresponding to all negative returns. Semi-variance on the other hand is a measure of downside variance, in particular the total variance for prospects with a below 0 or below-average return. In line with Konno et al. (2002), this study considers semi-variance as the variance of returns below the average, thus below the expected return of 8%. Wang et al. (2011) similarly confirm that potential downside deviations from a certain benchmark – e.g. expected return – cause uncertainty and subsequently aversion towards the risk of an asset. Other studies such as Emmer et al. (2015) describe how the most extreme outcomes, even when highly unlikely, can have a substantial impact on individual decision-making. Accordingly, the minimum and maximum return of each distribution are considered as risk factors as well, whereby the (increase in) maximum return is a factor that essentially reduces perceived risk, with the opposite impact being expected from the smallest return. However, the minimum return itself does not suffice with regard to explaining risky choice. It does for example not distinguish the negative effect of a clustering of returns slightly below the minimum (Sachse et al., 2012). Hence, the 95% Value at Risk (VaR) measure is added. This measure looks at the return that lies above the 5th percentile of the return distribution, meaning that only 5% of all returns lie below this threshold. To control for the effects of distribution shape, skewness and kurtosis of each distribution are added.

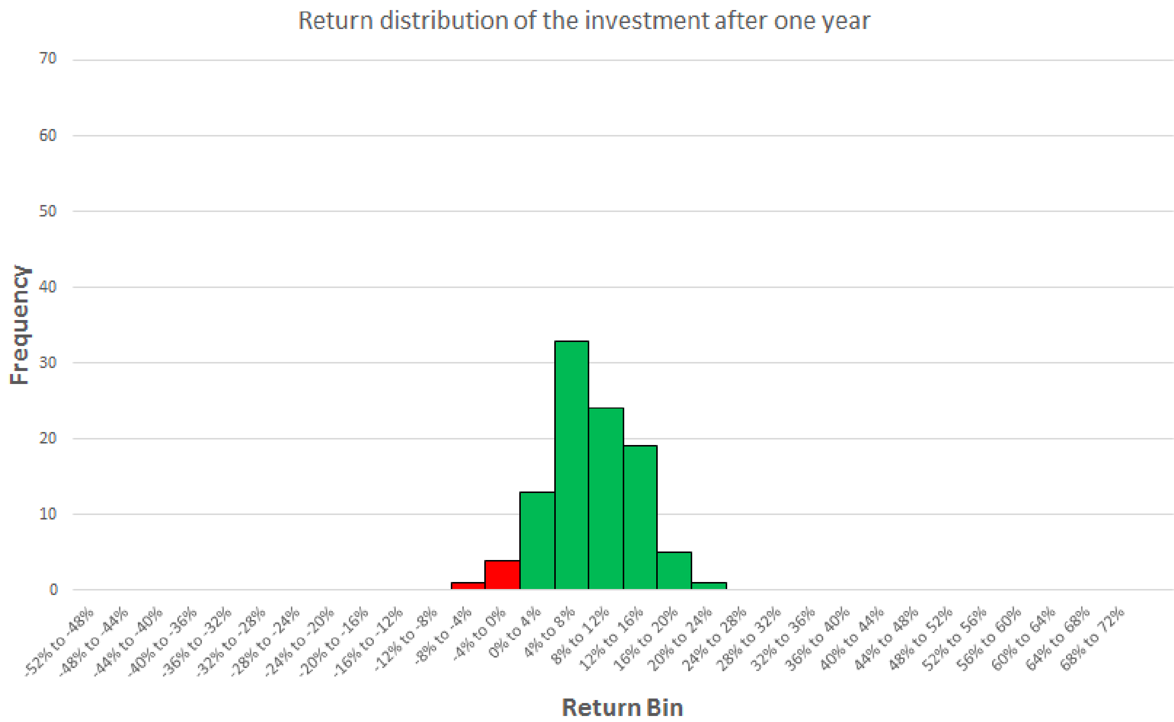
The last factor, the Cumulative Prospect Theory (CPT) value, comprises many of the features from the risk factors explained above, which is also why it is necessary to separate a statistical analysis of risk factors from an analysis of CPT value. The loss aversion characteristic of Prospect Theory for example corresponds to a likewise emphasis of semi-variance and loss probability on loss scenarios. To calculate the CPT value, the returns of each distribution are first ranked from the most to the least extreme outcome, each for the positive and the negative return domain. Then, we calculate the decision weights for all return scenarios, which are then multiplied with the parameterized return values. The calculated CPT values are created on the basis of the standard parameters as suggested by Tversky and Kahneman (1992).[4]

[4] Tversky & Kahneman's CPT parameters: $\alpha = 0.88$ $\beta = 0.88$ $\gamma = 0.61$ $\delta = 0.69$ and $\lambda = 2.25$

3.2 Return Distributions

Based on the risk factors above, return histograms are created for several different investment prospects. Figure 3 below shows an example of such a distribution. The x-axis of the histogram represents the possible return, ranging from -52% to +72%. The returns are grouped in intervals, which allows for a better visualization of a wide range of possible outcomes. Each bar in the histogram hence illustrates how likely a certain return interval is realized. Figure 3 depicting the return distribution for Investment 1 of the survey for instance shows that the most likely realized return on the investment lies with 34% probability between 4% and 8%. The illustration form is accurate, as the positions and heights of the bars likely influence how risky an investor perceives the investment to be. To enhance the readability of return interval frequencies, the bars are colored in a way that green bars represent positive return outcomes, whereas red ones illustrate loss outcome frequencies (Kliger & Gilad, 2012).

Figure 3: Investment 1 Return Distribution



To achieve a certain variation concerning the risk factors, a total of 30 distributions is created. Each distribution is unique in its risk characteristics, while retaining expected return at 8%. Thereby, particular emphasis is put on keeping the correlation of risk factors as low as possible, since some of these tend to strongly move in the same direction. The characteristics of the 30 distributions can be found in Table 1 on the next page. Note that each distribution differs substantially from others. While we see for example gradual increases in standard deviation from investment 1 to 30, we also recognize non-proportional changes in other factors. Particularly, Investment 1 for instance with a standard deviation of 5% is normally distributed (implying no skewness or kurtosis), whereas Investment 2 with only slightly higher dispersion shows the lowest skewness of -3.5 and the highest kurtosis of 13.1. On this basis, changes in subject risk perception can be related to the distinct unique characteristics of each distribution. Table A1 in Appendix A shows all 100 return outcomes for all 30 distributions that the histograms are based on. For an overview of all 30 histograms, Figure A1 in the appendix illustrates a less detailed version of all return diagrams.

Table 2 below comprises the correlations of risk factors across return distributions. Although several correlations are high, all of them are below the critical absolute threshold of 0.85, with the exception of the correlation between standard deviation and semi-variance. Since these two measures are naturally related to each other, it is barely possible to disentangle their relationship. Nevertheless, a way to solve this issue is addressed in the robustness section (see Section 4.3.1).

Table 2: Correlations among Risk Factors

	Stand. Deviation	95%-VaR	Loss Prob.	Semi-Variance	Skewness	Kurtosis	Max. Return	Min. Return
Stand. Dev.	1.000							
95%-VaR	-0.733	1.000						
Loss Prob.	0.7547	-0.4809	1.000					
Semi-Var.	0.9095	-0.8122	0.6514	1.000				
Skewness	0.2251	0.2672	0.1222	-0.0914	1.000			
Kurtosis	-0.6241	0.4071	-0.6222	-0.5627	-0.369	1.000		
Max. Return	0.6389	-0.2291	0.5113	0.36	0.7314	-0.415	1.000	
Min. Return	-0.5688	0.8206	-0.4975	-0.6801	0.4846	0.2641	-0.1145	1.000

Table 1: Characteristics of Return Distributions

	Expected Return	Standard Deviation	95% VaR	Loss Probability	Skewness	Kurtosis	Semi-Variance	Maximum Return	Minimum Return	CPT Value
1	8%	5%	0%	5%	0,0	0,0	0,14%	21%	-7%	0,08019
2	8%	8%	-14%	12%	-3,5	13,1	0,64%	13%	-39%	0,00922
3	8%	8%	-2%	25%	-0,5	-0,1	0,36%	24%	-13%	0,05393
4	8%	11%	-20%	10%	0,6	6,4	0,25%	65%	-20%	0,05814
5	8%	11%	-1%	19%	1,1	1,5	0,38%	43%	-13%	0,08277
6	8%	14%	-15%	27%	-0,9	0,9	1,28%	31%	-42%	-0,01249
7	8%	16%	-37%	8%	-0,7	1,8	1,54%	44%	-37%	0,00418
8	8%	18%	0%	0%	2,4	5,0	0,47%	72%	0%	0,14556
9	8%	19%	-52%	18%	-2,3	4,1	3,14%	21%	-52%	-0,08891
10	8%	19%	-20%	28%	-0,1	2,7	1,75%	67%	-51%	-0,00389
11	8%	21%	-35%	23%	-1,4	1,3	3,30%	32%	-52%	-0,08356
12	8%	21%	-22%	27%	-1,0	1,4	2,78%	54%	-52%	-0,05826
13	8%	24%	-49%	31%	-1,4	0,5	4,40%	30%	-52%	-0,03864
14	8%	24%	-28%	32%	0,8	0,4	2,10%	70%	-32%	0,00431
15	8%	24%	-32%	35%	0	0	2,83%	72%	-45%	-0,03881
16	8%	25%	-40%	30%	-0,4	-0,1	3,61%	68%	-51%	-0,07420
17	8%	27%	-34%	9%	1,5	1,9	1,71%	72%	-40%	0,04830
18	8%	28%	-52%	19%	-1,6	0,7	6,35%	28%	-52%	-0,14260
19	8%	29%	-51%	29%	-0,8	-0,2	5,40%	58%	-52%	-0,10781
20	8%	29%	-30%	48%	0,8	-0,5	3,05%	72%	-30%	-0,02767
21	8%	30%	-48%	45%	0,3	-0,5	3,79%	72%	-48%	-0,06017
22	8%	34%	-52%	29%	-1,0	-0,8	8,29%	39%	-52%	-0,17168
23	8%	34%	-31%	47%	0,4	-0,9	4,80%	72%	-48%	-0,08591
24	8%	35%	-50%	42%	-0,2	-1,2	6,56%	67%	-52%	-0,13503
25	8%	36%	-39%	50%	0,1	-1,2	6,18%	70%	-52%	-0,12314
26	8%	38%	-52%	41%	-0,2	-1,2	7,97%	71%	-52%	-0,14859
27	8%	38%	-35%	32%	0,6	-1,0	5,24%	72%	-35%	-0,06382
28	8%	39%	-39%	67%	0,6	-1,2	5,40%	72%	-44%	-0,10830
29	8%	43%	-50%	42%	0,0	-1,5	9,37%	72%	-52%	-0,18334
30	8%	46%	-42%	49%	0,3	-1,6	8,93%	72%	-42%	-0,15499

3.3 Procedure of the Experiment

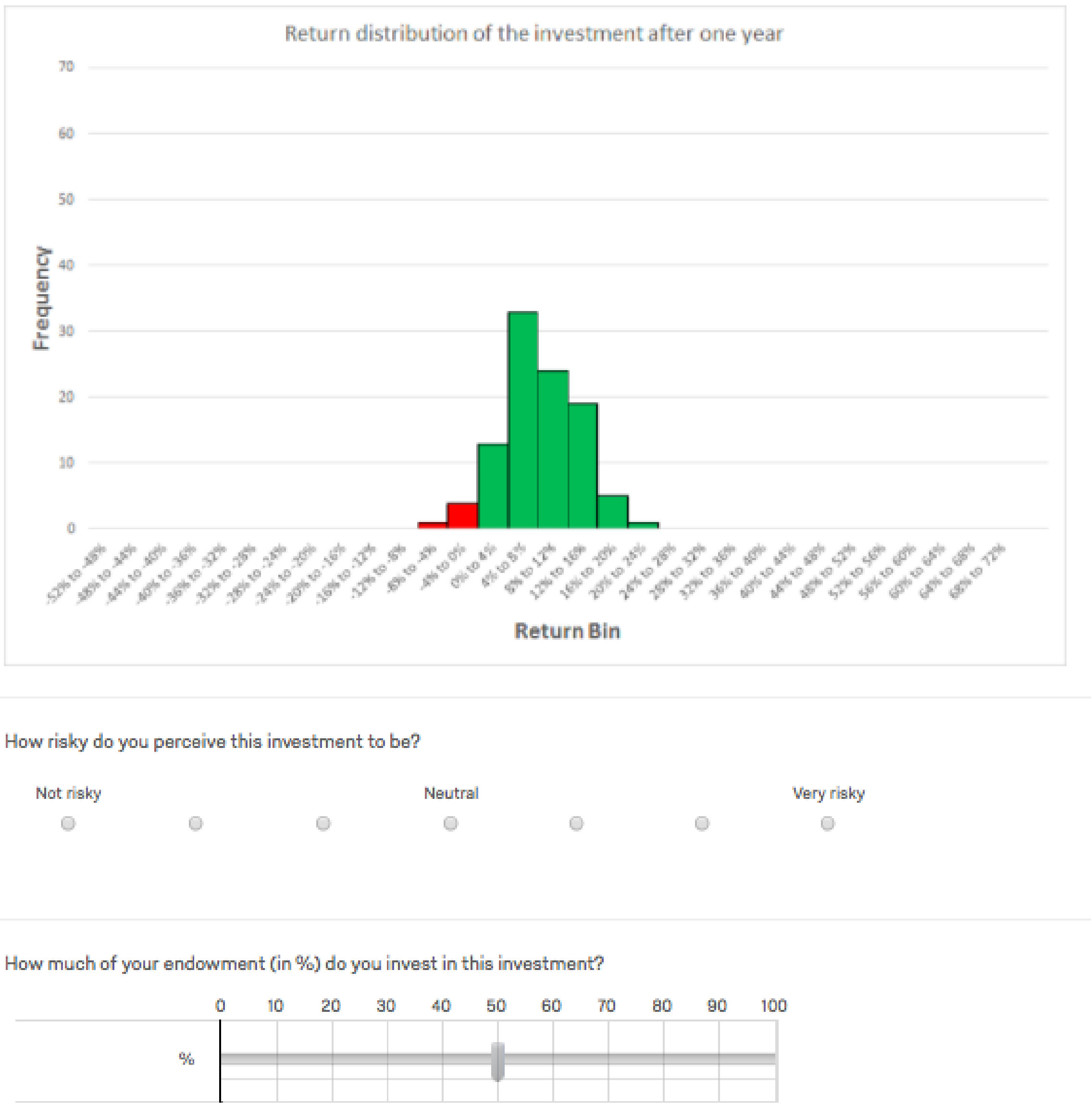
After implementing the return distributions in an online survey constructed with Qualtrics, the survey is distributed via the online platform Amazon MTurk. Upon participation in the online survey, subjects are informed that they should decide how much percent of their endowment to invest in 10 different and independent hypothetical investment opportunities based on their return outcome distributions. Only 10 out of the original 30 distributions are presented to each participant, as a larger number of investment decisions could lead to subjects getting bored in the course of the survey and subsequently produce biased results. These 10 distributions are selected at random, in order to ensure that ordering of the chart presentations does not play a role (Ryan & Morgan, 2007). Overall, the focus was set on providing precise explanations in a yet concise manner - to avoid a perceived information overload - while making the task as clear as possible. To ensure that subjects indeed understand the task clearly, a specific example is provided that explains the axes as well as the contextual meaning of the bars. Below this example, a comprehension question must be answered, which allows the participant to advance to the investment decisions only after it is answered correctly. A screenshot of this example along with the corresponding comprehension questions can be found in Figure A2 of Appendix A.

Figure 4 below shows a typical investment decision. Based on the presented return distribution at top, subjects are first asked how risky they perceive the investment to be on a 7-item Likert scale, ranging from "Not risky" to "Very risky". Afterwards, they indicate how much of an endowment of $10 they would invest in the opportunity, a question that symbolizes the propensity of investment. Responses on these two questions serve as dependent variables in the upcoming statistical analysis. As an incentive to provide a high level of effort, participants are informed at the beginning of the survey that they have the chance of earning a monetary reward additional to their regular MTurk compensation. This reward is linked to the subjects' performance regarding their investment decisions, which is aimed at increasing the validity of the experimental results (Cobanoglu & Cobanoglu, 2003).

After going through these 10 independent investment decisions, subjects are asked to answer general questions, providing information on age, sex, academic background and investment experience, and personal risk preference. Moreover, according to Lusardi (2012), individual numeracy, referring to the ability to process numerical facts, and financial literacy, the ability to understand and apply knowledge in finance, are important factors for savvy financial decision-making, which is why control questions that test the numerical and financial knowledge of participants are added. With data on all of these factors, it is possible to control for the effects of each in the later statistical analysis. All control questions are shown as a screenshot in Figure A3 of Appendix A.

Lastly, and most remarkably, note how the experiment is constructed in a way that the challenges of formal CPT testing are overcome (see Section 2.2). By visualizing the difference between negative return intervals (in red) and positive ones (in green) clearly, it is simple to distinguish gains and losses. Moreover, by stating explicitly that the investment tasks are to be treated independently of each other, participants do not integrate different prospects, while knowing that expected return - the reference rate – remains constant at 8%. The design of the experiment thus ensures gain-loss separability as well as a homogeneous reference rate across all participants.

Figure 4: Screenshot of Investment 1 Decision



4 Data Analysis

A total of 111 subjects participated in the online survey, each having had to make 10 investment decisions. However, not all observations are considered for the statistical analysis. To enhance the validity of the dataset, we check whether participants took the survey task seriously. Invalid responses if large in size can namely bias the statistical results by creating outliers (Schmidt, 1997). In this case, any respondent that did not answer both of the two control questions about expected return and initial endowment correctly, is expected to not have taken the task seriously and subsequently is filtered out. This procedure reduces the number of subjects to 94.

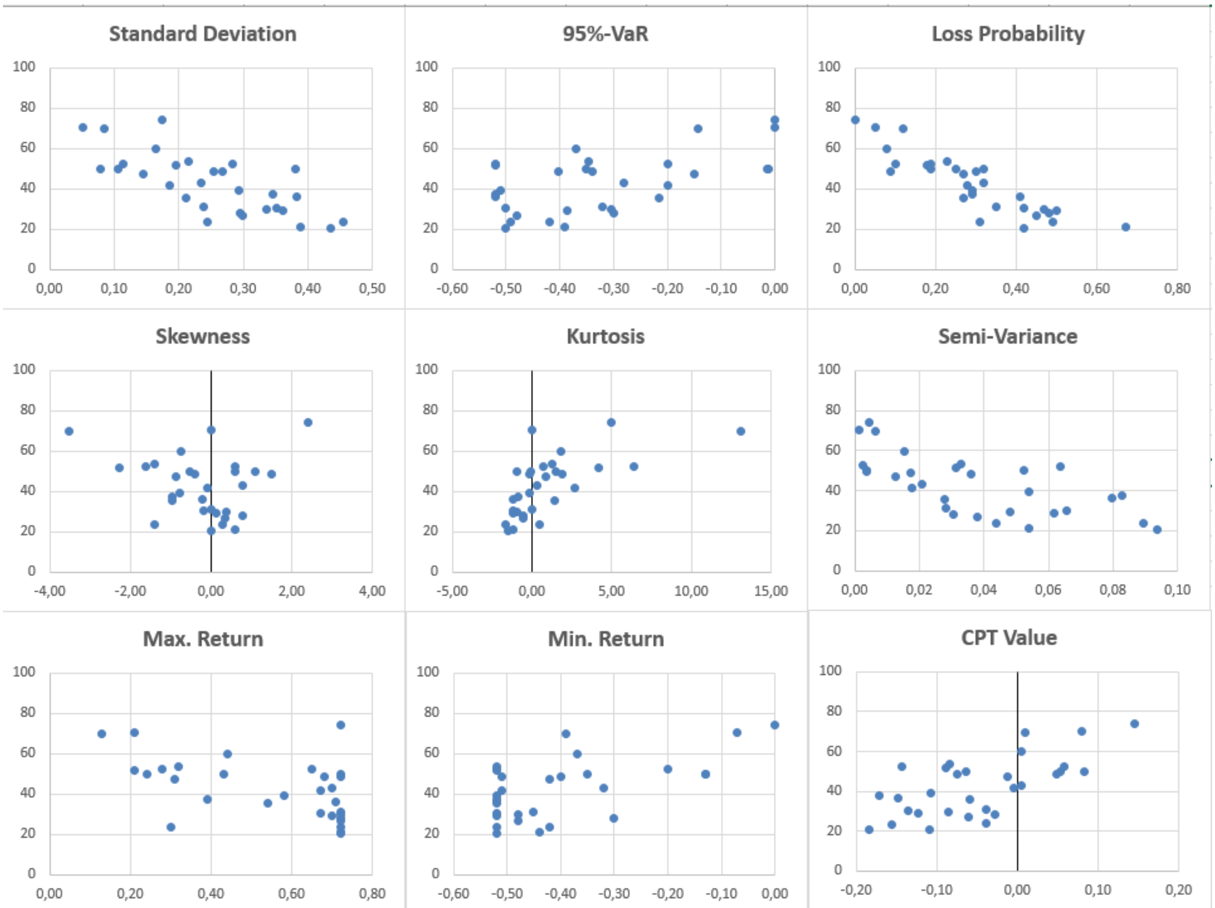
To analyze the data, the statistical software package STATA is used. In the following, the effects of risk factors, CPT and control variables on each investment propensity and risk perception are presented by means of regression analyses. Risk factors and CPT are regressed separately, as the CPT value is meant to substitute the conventional factors of (perceived) risk. This translates into four different models, measuring the effects of risk factors (1) and CPT (2) on investment propensity, next to the influence of risk factors (3) and CPT (4) on risk perception. Estimating the effects of prospect value and factors of perceived risk separately also allows for a direct comparison between the models and their explanatory power in particular. To control for heterogeneity across different individuals in observed and unobserved effects, each model is estimated once with individual and once with aggregated data. The individual dataset treats every investment decision of every participant as one observation, leading to a total of 94 x 10 = 940 observations. On the other hand, the aggregate set of data is constructed by using the average of investment propensity and risk perception scores of individuals per distribution and subsequently handles every distribution as one observation, resulting in 30 observations.

4.1 Results for Investment Propensity

Scatterplots in Figure 5 visualize the relationships between risk factors/CPT value and investment propensity as averaged over the sample individual observations. As expected, the CPT Value diagram indicates a positive association with investment propensity, whereas risk factors such as standard deviation, semi-variance and loss probability correlate negatively with investment behavior. The remaining relationships seem to be less evident. A closer look at the impact of each factor on the propensity to invest by means of regression analysis allows us to quantify the effects and assess their relevance in terms of coefficient significance.

Since investment percentage is an interval variable (ranging from 0 to 100), the standard OLS regression procedure can be applied to estimate the coefficients. To control for individual unobserved effects, however, it is necessary to use the subjects-fixed effects model for only the individual dataset (Winer et al., 1971). This regression model essentially implements a dummy for each participant, which allows the intercept to differ for each individual and allows for controlling individual unobserved effects within and outside of the model.

Figure 5: Average Investment Propensity Scatterplots



4.1.1 Risk Factors Results

The findings in Table 3 provide mixed support for single risk factors. Loss probability, skewness and semi-variance of returns all have an expected negative impact on investment propensity. This result is in line with Unser (2000), who emphasizes lower partial moments as essential factors describing perceived risk, next to identifying that individual risk perception is influenced by distribution shapes. Value-at-risk as well as kurtosis seem to have no significant impact on the propensity to invest. What strikes however is the sign and significance of the standard deviation and minimum return coefficients. With significance at the 1% level for minimum return and at 5% for standard deviation, these factors appear to contribute towards investment propensity when increasing in size. When looking at the aggregate level results, however, these effects seem to vanish. The only factor that remains strongly significant is loss probability, maintaining the expected negative influence. Hence, participants paid explicit attention to the frequency of losses when evaluating an investment prospect. This supports evidence of Kaufmann et al. (2013), who identify the importance of individual loss probability consideration in an experimental setting, and is in line with the major findings of Anzoni and Zeisberger (2016).

Table 3: OLS Subjects-FE Regression Results Risk Factors on Investment Propensity

	Individual Level	Aggregate Level
Standard Deviation	83.952**	72.744
	(32.927)	(59.195)
95%-VaR	2.567	9.668
	(9.448)	(17.384)
Loss Probability	-91.952***	-94.369***
	(9.097)	(16.557)
Skewness	-6.998***	-4.212
	(2.517)	(4.560)
Kurtosis	-0.325	-1.672*
	(0.455)	(0.831)
Maximum Return	13.241	5.556
	(10.148)	(18.458)
Minimum Return	38.568***	26.385
	(12.035)	(22.062)
Semi-Variance	-260.474**	-243.744
	(105.039)	(189.665)
Age	0.816***	
	(0.239)	
Sex	14.950***	
	(5.183)	
Academic Background	14.074***	
	(2.438)	
Investment Experience	3.200	
	(2.290)	
Willingness to take risks	1.980**	
	(0.872)	
Adjusted R^2	0.696	0.794

Note: p-values are indicated with stars (< 0.1; ** < 0.05; *** < 0.01); standard errors are in parentheses*

Surprisingly, the Adjusted R^2 is higher in the aggregate data, even though the control variables are disregarded (as these are measured on the individual level). A reason for this could be that despite being significant, the control variables do not add much to the explanatory power of the model, since the model already takes into individual differences.

4.1.2 CPT Results

Table 4 illustrates the results of the CPT regression analysis with regard to investment propensity. The coefficient of CPT Value emerges as high and strongly significant at 1%, meaning that Hypothesis 1 can be corroborated. Remarkably, the estimate remains constant in both size and significance when comparing the individual level result with the aggregate one. In the individual data sample, the adjusted R^2 of the CPT regression lies with 0.61 very close to the corresponding 0.69 of the individual-level analysis containing all the conventional risk factors. However, in contrast to the risk factor regressions, we recognize a drop in R^2 when comparing individual with aggregate results. It should be noted however that an adjusted R^2 of 0.46 for only one variable is still relatively high. Hence, the strong and significant relationship between Cumulative Prospect Theory and propensity of investment is non-negligible. This evidence suggests that individuals do evaluate prospects according to CPT. In particular, this means that the principles of CPT, i.e. loss aversion, reference dependence, and domain-specific risk attitudes guide individual investment decisions.

Table 4: OLS Subjects-FE Regression Results CPT Value on Investment Propensity

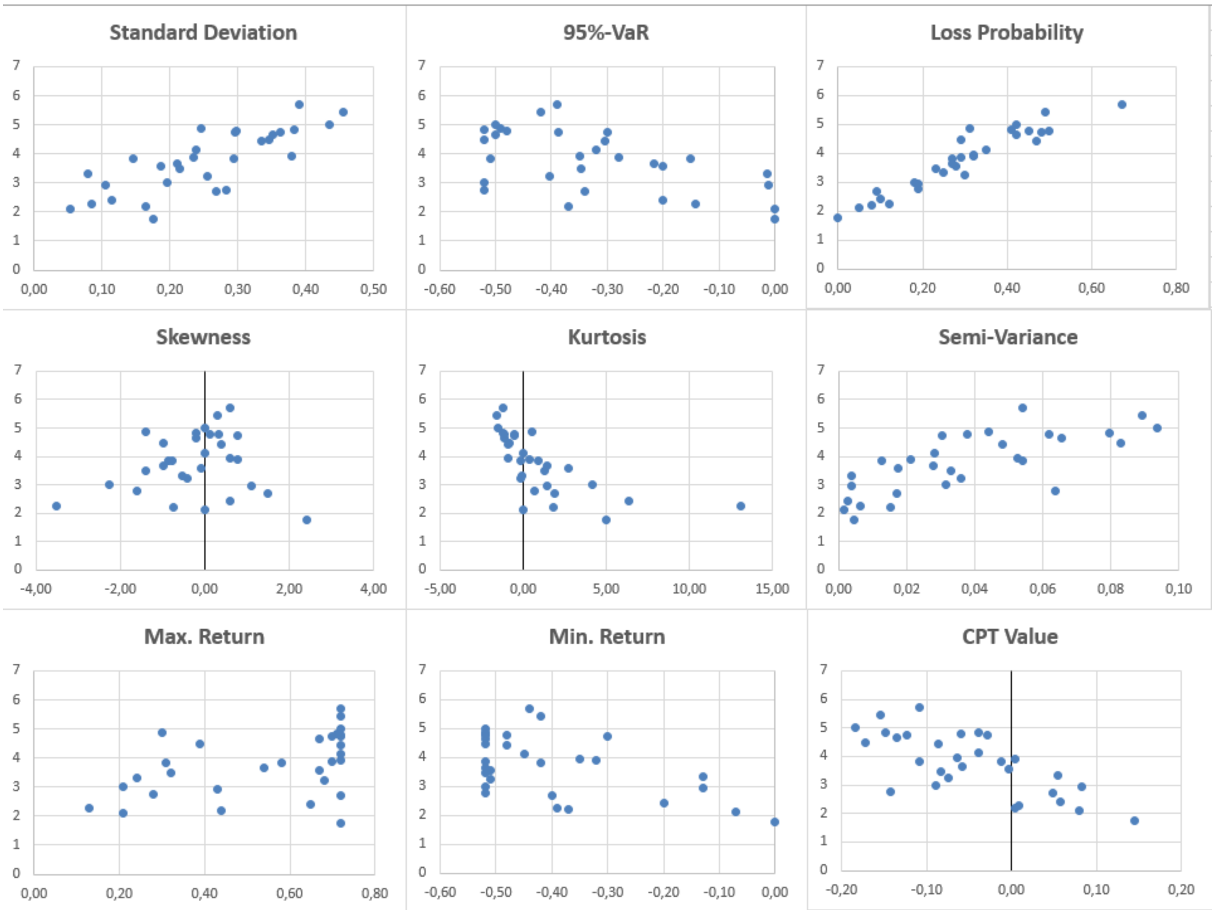
	Individual Level	Aggregate Level
CPT Value	118.574***	118.097***
	(9.272)	(23.281)
Age	0.636**	
	(0.269)	
Sex	14.433**	
	(5.858)	
Academic Background	15.426***	
	(2.754)	
Investment Experience	3.516	
	(2.592)	
Willingness to take risks	2.557**	
	(0.985)	
Adjusted R^2	0.610	0.460

Note: p-values are indicated with stars (< 0.1; ** < 0.05; *** < 0.01); standard errors are in parentheses*

4.2 Results for Risk Perception

The effect of risk factors and CPT value on the average of individual risk perception is depicted in Figure 6 below. The plotted relationships illustrate that loss probability, semi-variance and to a lesser extent standard deviation are associated positively with risk perception. On the other hand, CPT value and 95%-VaR again show the opposite effect. Though these scatterplots can be considered a rough indication of the relationships, they should be interpreted with caution. Perceived Risk is namely a categorical variable that is based on a 7-item Likert scale. As this ordinal measure can barely be assumed to have equal distances between each category, a simple linear regression would be insufficient due to not fulfilling the interval requirement of the dependent variable. Therefore, an ordered logistic regression is applied for measuring the impacts on perceived risk ratings (Winship & Mare, 1984). This implies that the coefficients of the regression output are to be interpreted as log odds.

Figure 6: Average Risk Perception Scatterplots



4.2.1 Risk Factors Results

The impact of each variable can be more clearly interpreted as the odds ratio by taking e to the power of the corresponding coefficient. For loss probability, a factor that is highly significant for both individual and aggregate observations, this means that the odds of this factor contributing to higher perceived risk are $e^{12.007} = 163898{,}07$. Since this odds ratio is far above 1, the coefficient can be interpreted as having a highly positive influence on perceived risk.

Table 5: Ordered Logistic Regression Results Risk Factors on Perceived Risk

	Individual Level	Aggregate Level
Standard Deviation	-2.947	3.195
	(3.100)	(16.648)
95%-VaR	-1.020	0.639
	(0.887)	(5.556)
Loss Probability	12.007***	52.129***
	(0.940)	(1.226)
Skewness	0.331	1.817
	(0.236)	(1.477)
Kurtosis	-0.011	0.800***
	(0.043)	(0.300)
Maximum Return	-1.724*	-14.648**
	(0.958)	(6.340)
Minimum Return	-1.616	-4.012
	(1.116)	(6.112)
Semi-Variance	16.825*	76.002
	(9.887)	(60.818)
Age	-0.101**	
	(0.043)	
Sex	-0.528	
	(2.918)	
Academic Background	-0.153	
	(0.849)	
Investment Experience	-0.947	
	(0.575)	
Willingness to take risks	0.244	
	(0.773)	
Pseudo R^2	0.254	0.365

Note: p-values are indicated with stars (< 0.1; ** < 0.05; *** < 0.01); standard errors are in parentheses*

The same is the case for semi-variance in the individual sample, which shows the expected positive influence on perceived risk. An odds ratio below 1 on the other hand would indicate a negative effect of the predictor on risk perception (Bland, 2000). Maximum return for example in both cases is significant and when transformed depicts an odds ratio lower than 1, meaning that it significantly decreases the odds of higher perceived risk. This is plausible, as the possibility to achieve a return that lies far above the average promotes the perception of lower relative potential losses, which is also why people participate in lotteries (Weber & Milliman, 1997). The standard deviation coefficient depicts an insignificant effect on risk perception. Hence, the logistic regression results provide strong evidence against the appropriateness of standard deviation as describing risk perceptions.

4.2.2 CPT Results

Again, the results of the analysis including the CPT value show the expected sign and significance. The effect on individual risk perception can be described as decreasing the odds of perceiving risk with an odds ratio of $e^{-14,662} \approx 0$. This result confirms Hypothesis 2, as the results imply that a higher CPT value translates to lower perceived risk, and vice versa. The coefficient in the aggregate data is even smaller, implying that the negative impact of CPT value here is even stronger. On a practical level, this shows that a prospect value approximated by Cumulative Prospect Theory does not only explain investment propensity, but is also able to account for the risk perception of individuals when faced with different investment prospects. The strong evidence also supports the more recent broader Prospect Theory framework by Kahneman (2002), stating that automated, sub-conscious processes driven by (myopic) loss aversion characterize individual decision-making.

One aspect that strikes, however, is that the Pseudo R^2 in the CPT model is substantially lower compared to the outcome of the risk factor logistic regression. This provides indication that the conventional factors of perceived risk all together provide higher explanatory power with regard to investor risk perception. Despite this observation, this alternative version of R^2 should be interpreted with caution, as it is only an approximation of the actual adjusted R^2. The explanatory power of the ordered logistic models is therefore also not comparable with the results of the standard OLS regressions from above (Hoetker, 2007). The detailed regression results are shown in Table 6.

Table 6: Ordered Logistic Regression Results CPT Value on Perceived Risk

	Individual Level	Aggregate Level
CPT Value	-14.662***	-22.810***
	(0.876)	(5.245)
Age	-0.064	
	(0.401)	
Sex	0.716	
	(2.706)	
Academic Background	-0.626	
	(0.805)	
Investment Experience	-0.430	
	(0.548)	
Willingness to take risks	0.406	
	(0.717)	
Pseudo R^2	0.149	0.110

Note: p-values are indicated with stars (< 0.1; ** < 0.05; *** < 0.01); standard errors are in parentheses*

4.3 Robustness Checks

An analysis of experimental data often bears potential issues of external validity of the results, i.e. representativeness, as well as general concerns about the accuracy of the experimental and subsequently statistical results (Mullinix et al., 2015). In the following, two robustness checks are applied in order to see whether the results are maintained across different procedures and across sub-samples. Firstly, the individual-level OLS regression model is checked regarding issues of multicollinearity. Secondly, it is checked whether two sub-samples including differences in the financial literacy of participants produce distant results with regard to individual perceived risk.

4.3.1 Multicollinearity

When generating VIF statistics of the OLS regression results on investment propensity, it appears that the VIFs of standard deviation, semi-variance and skewness are substantially above 10, the critical threshold for very high multicollinearity among predictor variables. With these inflation factors, the results may be biased with regard to inflated coefficients and explanatory power (O'brian, 2007). Table 7 shows the VIF statistics of all independent variables in the OLS individual-level regression.

Table 7: VIF statistics for individual data OLS Subjects-FE Regression

Variable	VIF	1/VIF
Standard Deviation	30.62	0.033
Skewness	20.3	0.049
Semi-Variance	19.51	0.051
Age	17.92	0.056
Inv. Experience	17.14	0.058
Sex	16.25	0.062
Willingness to take risks	11.1	0.09
Academic Background	10.34	0.097
Maximum Return	10.23	0.098
Minimum Return	7.8	0.128
95%-VaR	6.01	0.166
Loss Probability	4.75	0.21
Kurtosis	4.52	0.221

As a result, the *skewness* variable is discarded. Standard deviation and semi-variance are combined into one composite measure that effectively mimics the variance of these two variables. This procedure is based on Principal Components Analysis (PCA). By using PCA on the basis of the correlation matrix (see Table 2), a new factor, i.e. the principal component of standard deviation and semi-variance, is implemented. It is a composite measure of dispersion, which represents the two risk factors while keeping the correlation with other risk variables as low as possible and reduces all VIFs below 5. Combining standard deviation and semi-variance instead of simply deleting them effectively permits retaining a measure that is strongly associated with the variance of returns (Smith, 2002). With the newly generated principal component, the OLS regression on individual and aggregate data is run again. To reduce further model multicollinearity, the control variables are left out of the analysis.

The results of the subjects-fixed effects OLS regression including the principal component are shown in Table 8. The findings of both loss probability and kurtosis remain robust across both levels. However, the principal component representing a linear combination of standard deviation and semi-variance of returns is not significant. This could provide indication that the coefficient estimates of these two factors were largely inflated in the original regression. The explanatory power of the robustness check lies - with deviations of only 0.02 - very close to the original model.

Table 8: OLS Subjects-FE Regression on Investment Propensity with Principal Component

	Individual Level	Aggregate Level
Principal Component	**0.205**	**-0.269**
	(1.122)	**(2.062)**
95%-VaR	**-3.358**	**5.055**
	(9.272)	**(16.933)**
Loss Probability	**-75.199*** **	**-82.101*** **
	(7.293)	**(13.268)**
Kurtosis	**0.615** **	**-1.087***
	(0.310)	**(0.563)**
Maximum Return	**-4.050**	**-0.808**
	(4.240)	**(7.626)**
Minimum Return	**18.029** **	**15.925**
	(8.437)	**(15.391)**
Adjusted R^2	**0.694**	**0.796**

Note: p-values are indicated with stars (< 0.1; ** < 0.05; *** < 0.01); standard errors are in parentheses*

4.3.2 Financial Literacy

As explained above, Lusardi (2012) states that financial literacy can affect how individuals perceive risk. To check whether there are significant differences across more and less financially literate participants, the sample is split into two parts. Subjects who answered both survey questions on financial literacy correctly, are considered as one sub-sample, whereas participants that answered one or both of the questions wrong are assigned to the other sample. The splitting results in sub-samples with 564 (for the more financially literate) and 371 (for the less financially literate) observations.

Table 9 depicts the results. For each sub-sample, we conduct ordered logistic regressions for both risk factors and the CPT value factor. Remarkably, both loss probability and CPT value remain robust along with keeping their previous sign and size. The previous corroboration of Hypothesis 2 is thus retained. However, it is interesting that both effects are lower for the financially less literate participants. Those have put more attention towards the shape and the right end of the distribution when evaluating hypothetical investments. This becomes clear when looking at the significant factors maximum return and kurtosis.

Table 9: Ordered Logistic Regression on Risk Perception using two sub-samples

	Higher Financial Literacy	Lower Financial Literacy
Principal Component	0.155	0.127
	(0.139)	(0.163)
95%-VaR	-0.828	-0.230
	(1.152)	(1.363)
Loss Probability	13.447***	8.591***
	(1.105)	(1.171)
Kurtosis	-0.039	-0.121**
	(0.042)	(0.050)
Maximum Return	-0.780	-1.553**
	(0.543)	(0.677)
Minimum Return	-0.285	-1.092
	(1.046)	(1.244)
CPT	-14.525***	-13.691***
	(1.162)	(1.393)
Observations	564	371

Note: p-values are indicated with stars (< 0.1; ** < 0.05; *** < 0.01); standard errors are in parentheses*

5 Discussion

Daxhammer et al. (2012) point out that the variance of returns as a risk measure alone does not suffice at explaining price swings in asset markets. Assuming that returns are distributed normally – a premise for the appropriate use of standard deviation only – remains an inaccurate depiction of asset markets. Instead, we nowadays observe for instance fat tails as well as the occurrence of so-called black swan events, i.e. events that are perceived as extremely unlikely and unanticipated such as the subprime mortgage crisis. This has led to the emergence of new prominent risk measures such as VaR or loss probability. These measures of lower partial moments fit well within the loss aversion characteristic of the Prospect Theory framework first proposed by Kahneman and Tversky (1979). While having a sound theoretical foundation, these considerations seem to have achieved only mixed support yet (Barberis, 2013).

In light of this study, experimental evidence from an online survey indicates that indeed measures of lower partial moments provide accurate statistical explanations for the percentage of endowment invested in a prospect as well as the risk perceived by subjects. Loss probability, being constantly significant across all models and robustness checks proves to have a negative impact on the propensity to invest while promoting perceived risk, whereas semi-variance and minimum return as other downside risk measures follow the same intuition but do not appear to be robust. Distribution shape, in particular kurtosis, has persistent effects on both investment propensity and risk perception in the aggregate sample. Leptokurtic distributions in this regard discourage investment. Interestingly, in the sample with financially less literate subjects, the opposite is shown with significance at 5%. This can be considered suggestive evidence for non-professional investors being reluctant to fat tails. What can be regarded as even more interesting, however, is the pale role of standard deviation. The traditional risk measure is significant in only one model, the OLS subjects-FE individual-level regression, which is biased by large VIFs. When subsequently reducing multicollinearity in this regression by constructing a composite measure of return dispersion, the Principal Component of dispersion turns insignificant. These findings are in strong support against risk being solely composed of return dispersion, i.e. variance/standard deviation.

Instead, the investment's prospect value implied by Cumulative Prospect Theory does prove to perform much better at explaining investment propensity and perceived risk, both on an individual and aggregate data level. High sizes of the coefficients as well as persistent significance at 1% across all models and robustness checks support this claim. This not only provides an empirical ground for loss aversion, but also proves that rank-dependency in outcome-weighting plays a role. According to Schmidt and Zank (2008), rank dependency is integral to determining risk aversion in the CPT framework. Particularly, CPT emphasizes the distance of the most extreme outcome from the reference point – which, in the context of this study, can be considered as either 0 or 8%. Thereby, Olsen (1997) identifies the distance of negative outcomes to the reference point as having a substantially larger impact on risk perception than the most extreme scenarios in the gain domain. In general, he states that considering variance instead of lower partial moments, i.e. including the upper side of the return distribution, does not add much towards explaining attributed risk ratings.

Compared to standard deviation that was long identified as being the single most adequate predictor of (perceived) risk, CPT hence supersedes standard deviation strongly in terms of size and significance. As explained in Section 3, these results are based on the standard parameters developed by Kahneman and Tversky (1979), which were identified in a laboratory setting with only 25 MBA students. When comparing the correlation of calculated CPT values based on standard parameters with average scores on investment propensity or risk perception, the linear relationships showing correlations of 0.62 and -0.66 appear to be only moderately strong. It therefore seems questionable that the standard CPT parameters are applicable to a broader population that goes beyond these MBA students. Thus, we check whether a re-parameterization of CPT inputs can achieve higher (absolute) correlations between CPT value and investment propensity/perceived risk ratings. When discarding the assumption of taking the parameters by Kahneman and Tversky as given, we find that with the adjusted parameters depicted in Table 10 below, correlations of respectively 0.901 and -0.948 are attained, a substantial improvement compared to the original correlations. The updated correlations are obtained based on a semi-automatic, robust procedure in Microsoft Excel, which allows α and β to fluctuate between 0 and 1.5, γ and δ between 0.28 and 1, and λ between 0 and 10. The calculations were made for both our data - based on 30 return distributions - and the data by Anzoni and Zeisberger (2016), which rely on 10 distributions. The parameter results are shown in bold for our data and in italics for the Anzoni and Zeisberger data.

Table 10: Adjusted CPT Parameters for Correlation Optimization

	Investment Propensity		**Perceived Risk**	
$\boldsymbol{\alpha}$	**0.18**	*(0.03)*	**0.49**	*(0.02)*
$\boldsymbol{\beta}$	**0.04**	*(0.19)*	**0.11**	*(0.07)*
$\boldsymbol{\gamma}$	**0.28**	*(0.45)*	**0.28**	*(0.63)*
$\boldsymbol{\delta}$	**0.70**	*(0.42)*	**0.91**	*(0.86)*
$\boldsymbol{\lambda}$	**10**	*(0.61)*	**0.72**	*(3.40)*
Correlation	**0.901**	*(0.989)*	**-0.948**	*(-0.993)*

Regarding investment propensity, low values for alpha and beta indicate very strong risk aversion in the gain domain and an extremely high risk preference in the loss domain. For risk perception, a similar intuition applies, with the difference of less extreme risk aversion in the gain domain. The overweighting of small and underweighting of large probabilities seems to be mostly the case for gain probabilities, illustrated by a low gamma for both investment propensity and perceived risk. Note that deltas are higher and thus depict less non-linear probability weighting. On a theoretical basis, a lambda of 0.72 for risk perception modeling seems unrealistic, since it means that the disutility from losses is discounted rather than magnified, thus implying that individuals put significantly more emphasis on gains relative to losses (Nilsson et al., 2011). In contrast, when considering investment propensity, subjects display very high loss aversion with a lambda of 10. When comparing these parameters with the parameter estimates that yield the strongest correlations for the Anzoni and Zeisberger (2016) results, similarly lower alpha and beta parameters indicate that risk aversion in the gain domain and risk seeking in the loss domain is much more pronounced than in the standard version of Prospect Theory. Moreover, for both datasets, non-linear probability weighting occurs for gain probabilities rather than loss probabilities. This is also the case for Kahneman and Tversky parameters, but there gamma (0.61) and delta (0.69) exhibit a much smaller difference. The most remarkable difference between the two parameter re-estimations lies with lambda, which implies opposite risk attitudes for each respective measure of investment propensity and risk perception. Despite these large differences, the impact of lambda on the correlation estimates is almost negligibly small, as a sensitivity analysis with regard to changes in lambda suggests. For investment propensity correlation with CPT value in our data, for instance, a doubling of lambda does not change the correlation by a single percentage, whereas the same procedure for the Anzoni and Zeisberger parameters retains correlation close to 90% - even though a change of lambda from 0.61 to 1.22 leads towards loss magnification instead of discounting. It should be noted however that these correlations estimates assume a linear relationship between CPT value and investment propensity/perceived risk. This is a bold assumption regarding perceived risk in our data, as it presumes equal intervals between all risk ratings 1 to 7. For the Anzoni and Zeisberger (2016) data, this issue concerns even both measures, as both investment propensity and risk perception are measured on a Likert scale in their study.

Overall, we observe that even though CPT is well-suited towards explaining individual investment behavior and risk perception, its parameterization can be questioned and revised. Other research has similarly suggested revised parameters for the CPT function. Krcal et al. (2016) for instance also discover lower values for both lambda and alpha, with the lambda value being below 1 as well. Stott (2006) provides a range of value function curvatures found in several empirical studies, ranging from alphas of 0.19 to 0.89. The results hence vary much across different experimental settings, and it still remains ambiguous whether the current functional specification of CPT is accurate. As Neilson and Stowe (2002) conclude, "we are not yet ready to generalize laboratory work on relatively narrow stimuli to the wide range of stimuli embodied by applied work, at least not with the functional forms investigated so far" (p. 44).

6 Conclusion

A wide extent of academic literature has been devoted to identifying the characteristics of financial investments that drive individual risky choice. Many studies praise the importance of standard deviation of an asset as reducing investment propensity, or more recently consider lower partial moments measures. For individuals that are faced with an investment prospect in form of a return histogram, this study discovers refuting evidence regarding the role of standard deviation in financial decision-making. On the other hand, we support the empirical claim of some of the lower partial moments measures, particularly for the cumulative probability of incurring a loss. Most remarkably – to return to the central research question of this thesis – we show that investment propensity and risk perception can be forecasted by the CPT value of an underlying return distribution, for both the individual-level and aggregated data. These findings are robust across sub-samples and against multicollinearity.

In this way, the study has contributed towards resolving the dispute around cumulative prospect theory and its fit to financial applications. The thesis also contributes to current research by showing that parameter adjustment in order to optimize the explanatory power of CPT leads us to question whether the parameters fitted by Tversky and Kahneman (1992) are universally applicable – which is consistent with other empirical research (see e.g. Stott, 2006 for an overview).

For further research in this area, this implies that our adjusted parameters – alpha, beta, gamma, delta and lambda – can be tested across different experimental settings. In general, empirical studies could also consider the role of CPT further by allowing for flexible parameters across individuals. In this regard, it would be interesting to examine whether individuals exhibit different CPT parameters and which factors influence this parameterization. In addition to its academic implications, this paper also finds application for the practical financial field. To adequately present risks in a way that is the most decision-useful for investors, financial asset information should be communicated primarily with regard to its potential (particularly most extreme) losses, with an emphasis on the likelihood of these occurring (Raftery, 2016).

The study comprises limitations in terms of generalizability. A total of 111 subjects were confronted with a specific decision context, and thus the responses and subsequent statistical results should be interpreted with caution. Moreover, we do not propose a revised model of cumulative prospect theory, which is theoretically sound and simultaneously provides an improved parameter fit. Finding such a model remains one of the major tasks of future research.

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Appendix A: Figures & Tables

Table A1: Overview of return distributions, sorted from lowest to highest outcome

All returns from the 30 different return distributions are depicted below. They are sorted in an ascending order.

Scenario	Distribution									
	1	2	3	4	5	6	7	8	9	10
1	-7%	-39%	-13%	-20%	-13%	-42%	-37%	0%	-52%	-51%
2	-4%	-26%	-11%	-20%	-9%	-36%	-37%	0%	-52%	-45%
3	-2%	-20%	-11%	-20%	-7%	-27%	-37%	0%	-52%	-43%
4	-2%	-18%	-11%	-20%	-7%	-17%	-37%	0%	-52%	-34%
5	-1%	-18%	-11%	-20%	-4%	-16%	-37%	0%	-52%	-24%
6	0%	-14%	-1%	-20%	-1%	-15%	-37%	0%	-52%	-20%
7	1%	-1%	-1%	-6%	-1%	-14%	-24%	0%	-52%	-18%
8	1%	-1%	-1%	-3%	-1%	-14%	-19%	0%	-38%	-14%
9	1%	-1%	-1%	-3%	-1%	-13%	0%	0%	-18%	-13%
10	1%	-1%	-1%	-1%	-1%	-10%	0%	0%	-16%	-12%
11	2%	-1%	-1%	0%	-1%	-9%	0%	0%	-13%	-9%
12	2%	-1%	-1%	0%	-1%	-9%	0%	0%	-12%	-7%
13	2%	8%	-1%	0%	-1%	-8%	0%	0%	-12%	-6%
14	2%	8%	-1%	0%	-1%	-8%	0%	0%	-11%	-5%
15	2%	9%	-1%	1%	-1%	-8%	0%	0%	-11%	-4%
16	3%	9%	-1%	1%	-1%	-8%	0%	0%	-9%	-4%
17	3%	9%	-1%	1%	-1%	-8%	0%	0%	-8%	-3%
18	3%	9%	-1%	1%	-1%	-6%	1%	0%	-8%	-3%
19	4%	9%	-1%	3%	-1%	-6%	1%	0%	0%	-3%
20	4%	9%	-1%	3%	0%	-5%	1%	0%	8%	-3%
21	4%	9%	-1%	3%	0%	-5%	1%	0%	8%	-2%
22	4%	9%	-1%	3%	0%	-4%	1%	0%	10%	-2%
23	4%	9%	-1%	3%	0%	-3%	1%	0%	10%	-2%
24	4%	9%	-1%	3%	0%	-3%	1%	0%	10%	-2%
25	4%	9%	-1%	3%	0%	-1%	1%	0%	11%	-2%
26	4%	9%	3%	3%	0%	-1%	2%	0%	11%	-2%
27	4%	9%	3%	3%	0%	-1%	2%	0%	12%	-1%
28	4%	9%	4%	3%	0%	0%	2%	0%	12%	-1%
29	4%	9%	4%	4%	0%	1%	2%	0%	12%	0%
30	5%	9%	5%	5%	0%	1%	2%	0%	12%	0%
31	5%	9%	5%	5%	0%	1%	2%	0%	12%	1%
32	5%	10%	5%	5%	0%	2%	2%	0%	12%	2%
33	5%	10%	5%	5%	1%	3%	3%	0%	12%	2%
34	6%	10%	6%	5%	1%	3%	3%	0%	13%	2%
35	6%	10%	6%	5%	2%	4%	3%	0%	14%	2%
36	6%	10%	6%	5%	3%	5%	3%	0%	15%	3%
37	6%	10%	6%	5%	3%	5%	3%	0%	15%	3%
38	6%	10%	6%	6%	3%	5%	3%	0%	15%	3%
39	6%	10%	7%	7%	3%	6%	3%	0%	15%	5%
40	6%	10%	7%	7%	4%	7%	3%	0%	15%	5%
41	6%	10%	7%	8%	4%	7%	3%	0%	15%	5%
42	6%	10%	8%	8%	4%	8%	3%	0%	15%	5%
43	7%	10%	8%	8%	4%	8%	4%	0%	15%	6%
44	7%	10%	8%	8%	4%	8%	4%	0%	15%	6%
45	7%	10%	8%	8%	4%	8%	4%	0%	15%	6%

46	7%	10%	9%	8%	5%	8%	5%	0%	15%	7%
47	7%	10%	9%	8%	5%	10%	5%	0%	15%	7%
48	7%	10%	9%	8%	5%	10%	5%	0%	15%	7%
49	7%	10%	9%	8%	5%	11%	5%	0%	15%	7%
50	7%	10%	9%	8%	6%	11%	6%	0%	16%	8%
51	7%	10%	9%	8%	7%	12%	6%	0%	17%	8%
52	8%	10%	9%	8%	7%	12%	6%	0%	17%	9%
53	8%	10%	9%	8%	7%	12%	8%	0%	17%	9%
54	8%	10%	9%	9%	7%	12%	8%	0%	17%	10%
55	9%	10%	10%	9%	7%	12%	8%	0%	17%	10%
56	9%	10%	10%	9%	8%	13%	8%	0%	17%	10%
57	9%	10%	10%	9%	8%	14%	8%	0%	18%	11%
58	9%	10%	10%	9%	8%	14%	9%	0%	18%	11%
59	9%	10%	10%	9%	8%	14%	9%	0%	18%	12%
60	9%	10%	10%	9%	10%	14%	11%	0%	18%	12%
61	9%	10%	10%	9%	10%	14%	11%	0%	18%	12%
62	9%	10%	10%	9%	10%	15%	12%	0%	18%	12%
63	9%	10%	11%	9%	10%	15%	12%	0%	18%	12%
64	10%	10%	11%	9%	11%	15%	12%	1%	18%	12%
65	10%	10%	12%	10%	11%	15%	12%	1%	18%	12%
66	10%	10%	12%	10%	11%	15%	13%	1%	18%	14%
67	10%	10%	12%	10%	11%	16%	13%	2%	18%	14%
68	10%	10%	12%	10%	11%	16%	13%	2%	18%	16%
69	11%	10%	12%	11%	12%	16%	14%	4%	18%	16%
70	11%	10%	13%	13%	12%	16%	15%	4%	18%	16%
71	11%	10%	13%	13%	12%	17%	15%	4%	18%	17%
72	11%	10%	13%	13%	12%	17%	16%	5%	18%	18%
73	11%	11%	13%	14%	12%	17%	16%	5%	18%	18%
74	11%	11%	14%	14%	13%	18%	16%	5%	18%	18%
75	11%	11%	14%	14%	13%	19%	16%	5%	18%	18%
76	12%	11%	15%	14%	13%	19%	17%	5%	18%	18%
77	12%	12%	15%	14%	13%	19%	17%	5%	18%	18%
78	12%	12%	15%	14%	14%	20%	18%	5%	18%	19%
79	12%	12%	15%	14%	15%	20%	18%	5%	18%	19%
80	13%	12%	15%	15%	15%	20%	18%	5%	18%	19%
81	13%	12%	16%	15%	15%	21%	19%	5%	18%	19%
82	13%	12%	16%	15%	16%	21%	19%	12%	18%	19%
83	13%	12%	16%	16%	16%	21%	19%	13%	18%	21%
84	13%	12%	16%	16%	17%	22%	21%	20%	18%	21%
85	13%	12%	16%	17%	17%	22%	22%	20%	19%	23%
86	13%	12%	16%	17%	18%	23%	24%	21%	19%	23%
87	14%	12%	17%	17%	18%	24%	25%	24%	19%	23%
88	14%	12%	17%	18%	19%	24%	26%	30%	19%	24%
89	14%	12%	17%	19%	20%	25%	26%	35%	19%	25%
90	15%	12%	18%	20%	21%	25%	27%	35%	19%	27%
91	15%	12%	18%	21%	24%	25%	29%	35%	19%	27%
92	15%	12%	18%	21%	24%	25%	34%	42%	19%	27%
93	15%	12%	18%	22%	25%	25%	34%	45%	19%	29%
94	15%	13%	18%	23%	27%	26%	34%	45%	19%	32%
95	16%	13%	19%	23%	28%	27%	35%	46%	19%	35%
96	16%	13%	19%	23%	33%	28%	36%	55%	19%	35%
97	17%	13%	20%	25%	34%	30%	39%	60%	19%	41%
98	19%	13%	20%	26%	36%	30%	39%	72%	19%	59%
99	19%	13%	20%	34%	41%	30%	39%	72%	19%	63%
100	21%	13%	24%	65%	43%	31%	44%	72%	21%	67%

Scenario	Distribution									
	11	12	13	14	15	16	17	18	19	20
1	-52%	-52%	-50%	-32%	-45%	-51%	-40%	-52%	-52%	-30%
2	-52%	-52%	-44%	-31%	-44%	-50%	-40%	-52%	-52%	-30%
3	-52%	-52%	-26%	-28%	-39%	-50%	-36%	-52%	-52%	-30%
4	-52%	-52%	-22%	-28%	-36%	-49%	-36%	-52%	-52%	-30%
5	-47%	-52%	-21%	-28%	-33%	-47%	-35%	-52%	-51%	-30%
6	-34%	-20%	-21%	-28%	-32%	-40%	-34%	-52%	-51%	-30%
7	-31%	-20%	-20%	-22%	-31%	-40%	-1%	-52%	-50%	-28%
8	-30%	-20%	-18%	-19%	-30%	-38%	-1%	-52%	-50%	-25%
9	-30%	-20%	-18%	-19%	-30%	-35%	-1%	-52%	-49%	-25%
10	-30%	-20%	-18%	-19%	-24%	-27%	0%	-52%	-49%	-24%
11	-30%	-19%	-18%	-18%	-21%	-22%	0%	-52%	-48%	-24%
12	-30%	-16%	-17%	-17%	-21%	-22%	0%	-52%	-48%	-24%
13	-30%	-16%	-17%	-17%	-18%	-20%	0%	-52%	-47%	-24%
14	-10%	-13%	-17%	-17%	-18%	-20%	0%	-50%	-46%	-23%
15	-10%	-13%	-15%	-16%	-17%	-18%	0%	-50%	-43%	-22%
16	-10%	-13%	-15%	-16%	-17%	-17%	0%	-50%	-21%	-21%
17	-10%	-12%	-15%	-15%	-16%	-16%	0%	-50%	-16%	-19%
18	-10%	-11%	-14%	-14%	-16%	-16%	0%	-50%	-16%	-19%
19	-10%	-10%	-14%	-14%	-15%	-16%	0%	-13%	-14%	-18%
20	-10%	-10%	-14%	-12%	-14%	-15%	0%	10%	-13%	-18%
21	-10%	-7%	-14%	-11%	-14%	-13%	0%	10%	-12%	-18%
22	-10%	-7%	-12%	-10%	-12%	-13%	0%	12%	-10%	-17%
23	-10%	-5%	-11%	-9%	-10%	-12%	0%	13%	-8%	-15%
24	8%	-5%	-10%	-8%	-8%	-10%	0%	14%	-6%	-13%
25	8%	-3%	-10%	-7%	-7%	-9%	0%	14%	-4%	-13%
26	8%	-1%	-10%	-5%	-6%	-9%	0%	19%	-4%	-13%
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29	8%	0%	-9%	-2%	-3%	-5%	0%	20%	-1%	-11%
30	8%	1%	-9%	-2%	-3%	-5%	0%	20%	0%	-11%
31	8%	1%	-9%	-1%	-3%	4%	0%	20%	0%	-10%
32	8%	2%	-9%	-1%	-2%	4%	0%	20%	2%	-9%
33	8%	3%	-8%	0%	-1%	4%	0%	20%	2%	-8%
34	8%	3%	-8%	0%	-1%	4%	0%	20%	4%	-8%
35	8%	4%	-8%	0%	-1%	4%	0%	20%	4%	-8%
36	9%	4%	-8%	0%	0%	4%	0%	20%	4%	-7%
37	9%	5%	-8%	0%	0%	4%	0%	20%	6%	-6%
38	9%	6%	-7%	0%	1%	5%	0%	20%	6%	-6%
39	12%	6%	-7%	0%	1%	5%	0%	20%	6%	-6%
40	12%	6%	-7%	0%	1%	5%	0%	20%	8%	-6%
41	12%	6%	-7%	0%	4%	5%	0%	20%	8%	-6%
42	12%	7%	-6%	0%	5%	5%	0%	20%	10%	-5%
43	12%	7%	-5%	0%	5%	6%	0%	20%	10%	-5%
44	12%	9%	-5%	0%	5%	6%	0%	21%	10%	-4%
45	12%	9%	-4%	1%	6%	6%	0%	21%	11%	-4%
46	12%	10%	-2%	1%	6%	7%	0%	21%	11%	-2%
47	12%	11%	-2%	1%	7%	7%	0%	21%	12%	-2%
48	12%	11%	-2%	1%	8%	7%	0%	21%	12%	-1%
49	17%	12%	-2%	1%	8%	8%	0%	21%	12%	0%
50	17%	13%	-2%	1%	8%	8%	0%	21%	14%	0%
51	17%	13%	-1%	1%	9%	9%	0%	21%	14%	0%
52	17%	13%	-1%	1%	9%	10%	0%	21%	15%	0%
53	17%	14%	3%	2%	10%	10%	0%	21%	16%	0%

54	17%	14%	5%	3%	10%	10%	0%	21%	16%	0%
55	17%	14%	6%	3%	10%	11%	0%	21%	16%	0%
56	17%	14%	8%	4%	12%	11%	0%	21%	17%	1%
57	17%	14%	9%	4%	14%	11%	0%	21%	17%	1%
58	17%	14%	13%	8%	14%	12%	0%	21%	17%	1%
59	17%	15%	15%	8%	14%	12%	0%	21%	18%	1%
60	17%	15%	16%	8%	15%	12%	0%	21%	19%	1%
61	17%	16%	16%	11%	15%	13%	0%	21%	19%	1%
62	17%	16%	16%	11%	15%	14%	0%	21%	19%	4%
63	17%	16%	17%	12%	17%	15%	0%	21%	20%	4%
64	17%	16%	17%	12%	18%	16%	0%	21%	20%	6%
65	17%	16%	17%	13%	18%	18%	0%	21%	21%	8%
66	18%	17%	18%	14%	18%	18%	0%	21%	21%	8%
67	19%	17%	19%	15%	18%	18%	0%	21%	21%	8%
68	19%	18%	19%	16%	19%	19%	0%	21%	22%	8%
69	19%	19%	22%	17%	19%	20%	0%	21%	22%	9%
70	20%	20%	23%	17%	20%	21%	0%	21%	22%	9%
71	20%	20%	23%	18%	20%	23%	0%	21%	24%	28%
72	20%	21%	24%	19%	20%	24%	0%	21%	25%	31%
73	20%	21%	24%	20%	22%	27%	0%	21%	27%	33%
74	20%	21%	25%	21%	24%	28%	0%	21%	27%	33%
75	21%	21%	26%	21%	24%	29%	0%	21%	28%	34%
76	21%	21%	27%	21%	25%	31%	0%	21%	30%	35%
77	22%	23%	28%	22%	25%	31%	0%	21%	30%	36%
78	23%	23%	28%	24%	26%	32%	5%	21%	30%	39%
79	23%	24%	28%	25%	26%	32%	5%	21%	32%	39%
80	23%	24%	29%	25%	28%	32%	5%	21%	32%	40%
81	24%	25%	30%	26%	28%	32%	5%	21%	32%	40%
82	24%	26%	30%	26%	29%	33%	5%	24%	34%	41%
83	25%	26%	32%	26%	30%	33%	8%	25%	34%	41%
84	27%	26%	32%	27%	30%	33%	8%	25%	36%	42%
85	27%	27%	35%	30%	31%	33%	8%	25%	36%	42%
86	27%	28%	35%	31%	31%	34%	20%	25%	37%	43%
87	28%	29%	39%	33%	32%	35%	42%	25%	37%	44%
88	28%	30%	39%	33%	32%	36%	72%	25%	38%	46%
89	30%	30%	40%	36%	34%	37%	72%	25%	40%	48%
90	31%	30%	43%	42%	36%	37%	72%	25%	40%	49%
91	31%	31%	43%	43%	37%	38%	72%	25%	41%	59%
92	31%	31%	48%	48%	38%	39%	72%	25%	42%	59%
93	31%	31%	50%	53%	40%	41%	72%	25%	46%	60%
94	31%	33%	50%	53%	41%	43%	72%	25%	46%	61%
95	31%	33%	50%	58%	42%	44%	72%	26%	46%	72%
96	31%	34%	52%	61%	52%	46%	72%	26%	47%	72%
97	31%	34%	54%	64%	53%	47%	72%	27%	50%	72%
98	32%	34%	55%	68%	58%	47%	72%	27%	51%	72%
99	32%	50%	66%	69%	67%	50%	72%	28%	53%	72%
100	32%	54%	67%	70%	70%	68%	72%	28%	58%	72%

Scenario	Distribution									
	21	22	23	24	25	26	27	28	29	30
1	-48%	-52%	-48%	-52%	-52%	-52%	-35%	-44%	-52%	-42%
2	-48%	-52%	-47%	-52%	-52%	-52%	-35%	-43%	-52%	-42%
3	-48%	-52%	-46%	-52%	-52%	-52%	-35%	-42%	-52%	-42%
4	-48%	-52%	-45%	-52%	-52%	-52%	-35%	-41%	-52%	-42%
5	-48%	-52%	-40%	-52%	-52%	-52%	-35%	-40%	-52%	-42%
6	-48%	-52%	-30%	-50%	-38%	-52%	-35%	-39%	-50%	-42%
7	-18%	-52%	-30%	-50%	-38%	-51%	-35%	-34%	-50%	-42%
8	-18%	-52%	-30%	-49%	-38%	-51%	-34%	-32%	-50%	-42%
9	-16%	-52%	-30%	-49%	-38%	-51%	-34%	-31%	-50%	-42%
10	-16%	-52%	-30%	-48%	-38%	-50%	-34%	-31%	-50%	-42%
11	-16%	-52%	-30%	-47%	-38%	-50%	-34%	-30%	-50%	-41%
12	-16%	-52%	-30%	-45%	-36%	-50%	-34%	-29%	-50%	-41%
13	-16%	-52%	-27%	-38%	-35%	-49%	-34%	-28%	-50%	-41%
14	-15%	-52%	-27%	-35%	-35%	-49%	-34%	-28%	-50%	-41%
15	-15%	-52%	-27%	-34%	-35%	-48%	-34%	-27%	-50%	-41%
16	-15%	-52%	-27%	-33%	-35%	-48%	-34%	-27%	-50%	-41%
17	-15%	-52%	-27%	-33%	-35%	-48%	-34%	-26%	-50%	-41%
18	-15%	-52%	-27%	-31%	-35%	-46%	-34%	-26%	-50%	-41%
19	-15%	-50%	-27%	-30%	-35%	-42%	-29%	-25%	-50%	-41%
20	-15%	-47%	-24%	-30%	-35%	-38%	-29%	-25%	-50%	-41%
21	-15%	-47%	-24%	-29%	-30%	-36%	-29%	-25%	-50%	-40%
22	-15%	-38%	-24%	-28%	-30%	-29%	-29%	-25%	-48%	-40%
23	-14%	-37%	-24%	-27%	-30%	-28%	-27%	-25%	-48%	-39%
24	-14%	-30%	-24%	-26%	-30%	-27%	-27%	-24%	-47%	-39%
25	-14%	-29%	-24%	-26%	-24%	-24%	-27%	-24%	-43%	-39%
26	-14%	-20%	-24%	-22%	-22%	-24%	-27%	-24%	-40%	-39%
27	-14%	-18%	-18%	-19%	-21%	-21%	-27%	-23%	-37%	-36%
28	-14%	-12%	-17%	-19%	-19%	-21%	-25%	-22%	-35%	-36%
29	-14%	-1%	-16%	-17%	-18%	-19%	-25%	-21%	-33%	-36%
30	-14%	19%	-15%	-15%	-16%	-19%	-25%	-20%	-30%	-34%
31	-14%	19%	-14%	-14%	-16%	-17%	-25%	-19%	-30%	-34%
32	-14%	19%	-14%	-11%	-14%	-16%	-24%	-18%	-30%	-32%
33	-14%	19%	-14%	-10%	-11%	-13%	0%	-18%	-29%	-31%
34	-14%	19%	-13%	-9%	-10%	-12%	0%	-17%	-27%	-29%
35	-13%	20%	-13%	-9%	-10%	-10%	0%	-13%	-26%	-28%
36	-13%	20%	-11%	-7%	-10%	-9%	0%	-13%	-23%	-27%
37	-12%	20%	-11%	-7%	-6%	-8%	0%	-12%	-17%	-26%
38	-12%	20%	-10%	-6%	-5%	-7%	0%	-12%	-17%	-25%
39	-10%	20%	-9%	-4%	-5%	-5%	0%	-12%	-16%	-25%
40	-10%	20%	-9%	-4%	-5%	-3%	0%	-11%	-15%	-24%
41	-7%	21%	-8%	-1%	-5%	-3%	0%	-11%	10%	-22%
42	-7%	21%	-7%	-1%	-5%	4%	0%	-11%	11%	-22%
43	-6%	21%	-6%	0%	-5%	5%	0%	-11%	12%	-21%
44	-4%	22%	-6%	4%	-4%	12%	0%	-11%	13%	-20%
45	-2%	23%	-4%	5%	-4%	12%	0%	-11%	18%	-18%
46	0%	23%	-1%	5%	-3%	14%	0%	-10%	18%	-18%
47	0%	23%	-1%	5%	-3%	15%	0%	-10%	18%	-17%
48	0%	23%	2%	7%	-3%	16%	0%	-9%	18%	-17%
49	0%	23%	2%	9%	-2%	16%	0%	-9%	18%	-16%
50	1%	24%	3%	10%	-2%	19%	0%	-9%	18%	8%
51	1%	24%	4%	11%	8%	19%	0%	-9%	18%	8%
52	2%	24%	4%	12%	9%	19%	0%	-8%	18%	8%
53	3%	24%	5%	12%	10%	19%	0%	-8%	18%	8%

54	4%	25%	5%	13%	10%	20%	0%	-8%	18%	8%
55	4%	25%	5%	13%	11%	20%	0%	-7%	18%	8%
56	5%	25%	6%	17%	11%	21%	0%	-6%	21%	8%
57	8%	26%	6%	20%	13%	21%	0%	-6%	22%	8%
58	8%	26%	12%	20%	17%	22%	0%	-5%	22%	8%
59	10%	26%	14%	22%	17%	22%	0%	-5%	23%	8%
60	11%	26%	15%	22%	19%	24%	0%	-5%	24%	8%
61	12%	26%	16%	25%	20%	24%	0%	-5%	28%	8%
62	14%	27%	17%	26%	20%	24%	0%	-3%	33%	8%
63	18%	27%	18%	27%	21%	25%	0%	-3%	34%	24%
64	18%	28%	18%	29%	25%	26%	0%	-2%	36%	36%
65	19%	28%	20%	30%	26%	26%	0%	-2%	37%	42%
66	20%	29%	22%	30%	27%	28%	0%	-1%	37%	47%
67	23%	29%	25%	31%	28%	29%	0%	-1%	37%	48%
68	23%	29%	25%	33%	29%	30%	0%	34%	40%	48%
69	23%	29%	27%	33%	29%	31%	0%	36%	40%	49%
70	25%	30%	27%	36%	29%	32%	33%	37%	42%	50%
71	28%	30%	27%	37%	29%	33%	33%	40%	43%	51%
72	28%	31%	29%	38%	31%	34%	34%	42%	45%	51%
73	28%	31%	29%	38%	34%	35%	35%	43%	46%	52%
74	28%	31%	32%	39%	36%	36%	37%	47%	48%	53%
75	29%	31%	34%	39%	37%	37%	39%	49%	48%	54%
76	30%	33%	36%	39%	38%	40%	39%	52%	48%	65%
77	31%	34%	36%	41%	40%	40%	40%	55%	50%	65%
78	31%	34%	37%	41%	42%	40%	42%	56%	50%	65%
79	34%	35%	38%	41%	43%	40%	44%	58%	52%	65%
80	36%	35%	38%	42%	48%	44%	47%	62%	53%	65%
81	36%	35%	38%	43%	48%	44%	48%	63%	56%	65%
82	37%	35%	40%	44%	52%	46%	50%	64%	58%	65%
83	38%	37%	43%	44%	52%	47%	72%	65%	58%	71%
84	43%	37%	47%	45%	52%	47%	72%	67%	58%	71%
85	43%	37%	50%	47%	53%	50%	72%	67%	58%	71%
86	45%	38%	52%	47%	54%	51%	72%	68%	59%	71%
87	47%	38%	54%	47%	54%	52%	72%	68%	59%	71%
88	48%	38%	56%	48%	56%	53%	72%	68%	60%	71%
89	50%	38%	58%	48%	57%	57%	72%	69%	60%	71%
90	52%	38%	60%	50%	58%	57%	72%	69%	60%	71%
91	53%	38%	65%	50%	59%	59%	72%	70%	62%	71%
92	57%	39%	66%	52%	63%	60%	72%	70%	62%	71%
93	59%	39%	67%	53%	64%	61%	72%	71%	62%	71%
94	62%	39%	67%	55%	64%	62%	72%	71%	62%	72%
95	62%	39%	68%	56%	65%	63%	72%	71%	62%	72%
96	62%	39%	68%	57%	68%	65%	72%	72%	62%	72%
97	62%	39%	70%	63%	68%	65%	72%	72%	65%	72%
98	72%	39%	71%	64%	69%	65%	72%	72%	66%	72%
99	72%	39%	72%	66%	70%	71%	72%	72%	67%	72%
100	72%	39%	72%	67%	70%	71%	72%	72%	67%	72%

Figure A1: All Investment Return Histograms

Investment 1 is in the upper left corner, and the distribution follow a descending order from left to right and top to bottom. Investment 30 with the highest standard deviation is thus in the lower right corner of the figure. These 30 different return histograms all exhibit the same expected return but different risk and CPT characteristics. The axes and labelling are the same across all distributions, which are presented randomly to participants of the experiment in an investment task that is shown more precisely in Figure 4 (see Section 3.3).

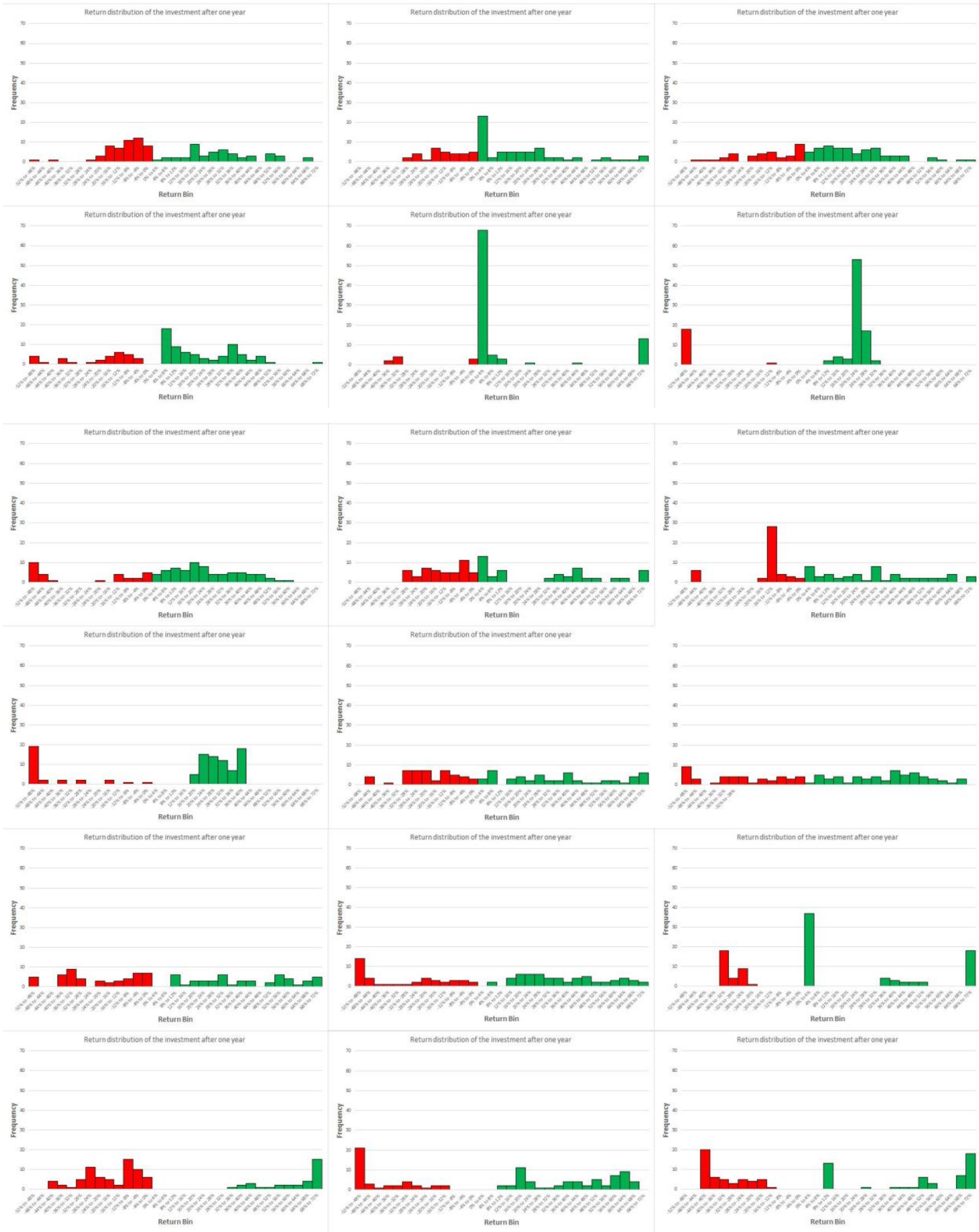
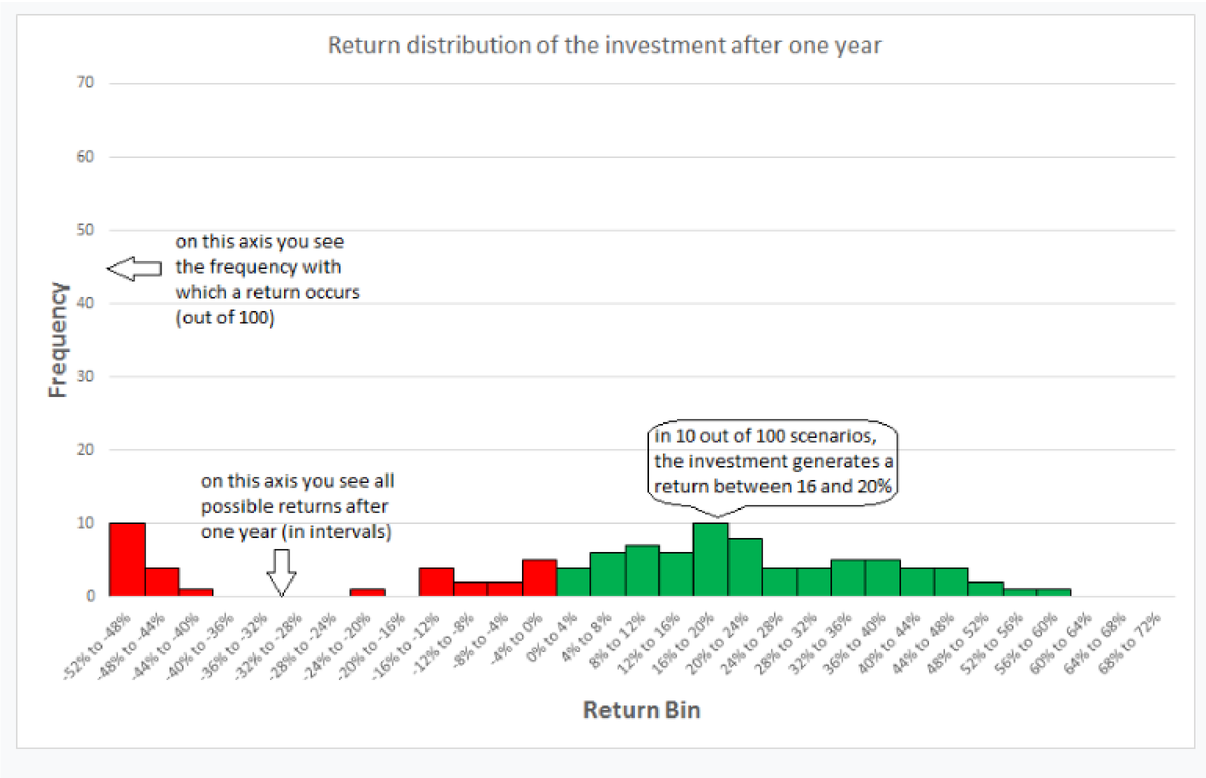

Return distribution of the investment after one year
Frequency
Return Bin

Figure A2: Investment Task Example

This figure shows the example that has been presented to experimental subjects to make sure that they understand the investment task adequately. Participants were only able to advance further in the survey until they have answered the 2 comprehension questions correctly.



Comprehension question: How many times out of 100 does this investment generate a return between -48% and -52%?

- 5
- 7
- 10
- 12

Comprehension question: How many times out of 100 does this investment generate a return of at least +48%?

- 4
- 14
- 25
- 33

Figure A3: Screenshot of Control Questions

Participants who did not answer the first two simple control questions and the last question were filtered out because they either did not take the survey seriously, or did not fully understand the investment task. The preceding questions are asked to get general information for the control variables to be used in the individual analysis. The last question on page 43 and the first on page 44 were used to classify subjects as less or more financially literate for the second robustness check (see Section 4.3.2).

What was the average (expected) return of each investment opportunity shown to you (as presented to you in the instructions at the beginning)?

- 0%
- 5%
- 8%
- 10%

How much (real) money were you given to invest in this study (as presented to you in the instructions at the beginning)?

- $0
- $0.60
- $1
- $10

What is your age?

What is your sex?

- Male
- Female

What is the highest level of school you have completed or the highest degree you have received?

- Less than high school diploma
- High school graduate
- Bachelor's degree
- Master's degree
- Doctoral degree

How do you rate your own **investment experience**, compared to the average population?

Much lower	Slightly lower	About the same	Slightly higher	Much higher
○	○	○	○	○

How do you rate your own **statistical knowledge**, compared to the average population?

Much lower	Slightly lower	About the same	Slightly higher	Much higher
○	○	○	○	○

On a scale from 1 - 10, how willing are you to take financial risks?

	very risk averse	2	3	4	5	6	7	8	9	not risk averse at all
Own willingness to take financial risks	○	○	○	○	○	○	○	○	○	○

A coin is flipped 6 times. Each time heads turns up, you earn $1, otherwise you earn $0. Assume that the costs are $0. What is your expected gain?

- ○ $0.50
- ○ $2.00
- ○ $3.00
- ○ $6.00

Two investments have the following characteristics:

Investment A: Expected return of 6% and return standard deviation of 14%
Investment B: Expected return of 8% and return standard deviation of 10%

Which of the two assets should an investor chose?

- ○ Asset A
- ○ Asset B
- ○ A and B are equally attractive
- ○ Do not know

Generally, are stock investments considered a less or a more risky investment compared to bonds?

- Less risky
- More risky
- Same riskiness
- Do not know

How well did you understand what to do and how to answer in this study?

- Did not understand it at all
- I had quite some difficulties.
- Understood somehow
- Understood well
- Everything was very clear

Appendix B: STATA Do-File

```
set more off, permanently
destring, replace dpcomma

*variable labels
lab var riskp "Risk Perception"
lab var invpct "Investment Percentage"
lab var sd "Standard Deviation"
lab var lossp "Loss Probability"
lab var skew "Skewness"
lab var kurt "Kurtosis"
lab var semiv "Semivariance"
lab var max "Maximum Return"
lab var min "Minimum Return"
lab var cpt "CPT Value"
lab var distr "Distribution Number"
*only for individual data:
lab var id "Subject ID"
lab var age "Age"
lab var sex "Sex"
lab var acad "Academic Background"
lab var invexp "Investment Experience"
lab var statknow "Statistical Knowledge"
lab var willrisks "Risk Willingness"


***INDIVIDUAL***

use IndData.dta, clear

descr
```

```
*recoding control questions and checking for response validity
recode wasexpret (3 = 1) (1 2 4 = 0)
recode wasendow (4 = 1) (1 2 3 = 0)
drop if wasexpret == 0
drop if wasendow == 0

drop if comp == 1

save AdjIndAll.dta, replace

*data screening
descr
sum, detail
*eyeballing relationships
twoway scatter invpct cpt
twoway scatter riskp cpt
corr sd var lossp semiv skew kurt max min
corr sd var lossp semiv skew kurt max min age sex acad invexp willrisks
corr cpt age sex acad invexp willrisks
twoway scatter min var, mlab(distr) mlabposition(1)


*Regressions: subjects-fixed effects regressions Invpct on Ind sample

*I
use AdjIndAll.dta, clear
xi: reg invpct sd var lossp skew kurt semiv max min age sex acad invexp willrisks i.id
estat vif
*VIF too high
*II
xi: reg invpct cpt age sex acad invexp willrisks i.id

*Regressions: ordered logit regressions Riskp on Ind sample
*III
xi: ologit riskp sd var lossp skew kurt semiv max min age sex acad invexp willrisks i.id
xi: ologit riskp pc1 var lossp kurt max min i.id
*IV
xi: ologit riskp cpt age sex acad invexp willrisks i.id


***AGGREGATE***
use AggData.dta, clear

*preparing/inspecting data
corr sd var lossp skew kurt max min
pca sd semiv skew
predict pc1, score
xi: reg invpct pc1 var lossp kurt max min i.id
estat vif
corr pc1 var lossp kurt max min
```

```
*Regressions
*I
reg invpct sd var lossp semiv skew kurt max min
*II
reg invpct cpt
*III
ologit riskp sd var lossp semiv skew kurt max min
*IV
ologit riskp cpt

*Robustness Check 1: Principal Component Analysis of Risk Factors
use AdjIndAll.dta, clear
pca sd semiv
predict pc1, score
xi: reg invpct pc1 var lossp kurt max min i.id
estat vif

*Robustness Check 2: Splitting the Sample according to financial literacy
use AdjIndData.dta, clear
recode coin (3 = 1) (1 2 4 = 0)
recode finlit (2 = 1) (1 3 4 = 0)
recode finlit2 (2 = 1) (1 3 4 = 0)
drop if finlit == 0 | finlit2 == 0
pca sd semiv
predict pc1, score
save AdjIndDataFin.dta, replace

use AdjIndData.dta, clear
recode coin (3 = 1) (1 2 4 = 0)
recode finlit (2 = 1) (1 3 4 = 0)
recode finlit2 (2 = 1) (1 3 4 = 0)
keep if finlit == 0 | finlit2 == 0
pca sd semiv
predict pc1, score
save AdjIndDataNoFin.dta, replace

xi: ologit riskp pc1 var lossp kurt max min i.id
xi: ologit riskp cpt i.id
```