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Abstract
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Keywords: (un)Bounded Rationality, Satisficing, Risk, Uncertainty, Experiments

JEL Codes: D03, D81, C91

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(Sub) Optimality and (Non) Optimal Satisficing in Risky Decision Experiments

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August 24, 2016

Abstract

A risky choice experiment is based on one-dimensional choice variables and risk neutrality induced via binary lottery incentives. Each participant confronts many parameter constellations with varying optimal payoffs. We assess (sub)optimality, as well as (non)optimal satisficing, partly by eliciting aspirations in addition to choices. Treatments differ in the probability that a binary random event, which are payoff- but not optimal choice–relevant, is experimentally induced and whether participants choose portfolios directly or via satisficing, i.e., by forming aspirations and checking for satisficing before making their choice. By incentivizing aspiration formation, we can test satisficing, and in cases of satisficing, determine whether it is optimal.

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1 Introduction

The rational choice approach, which still dominates (micro)economics, should be considered with caution or even neglected in the real world because optimizing is often difficult: limited cognitive abilities, information overload and complexity will regularly lead to suboptimal decision making.[1]

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[1]See Buchanan and Kock (2001) on information overload issues.

Additionally, the notion of "rationality with errors" has been questioned.[2] Moreover most choice situations involve multiple incompatible goals that must somehow be combined to reach a decision (a so-called multi-objective optimization).[3]

Many scholars now focus on alternative models[4] and, more generally, on bounded rationality[5], such as satisficing behavior. To compare these two different strands of the literature (i.e., optimizing versus satisficing), we implement a choice class allowing for unique and set-valued optimality and partly enforce the satisficing approach via experimentally controlled and incentivized aspiration formation.

Specifically, the experimental setting relies on the following:

i individual choice making and a portfolio choice frame to strengthen the purely individual consequences of choices;

ii experimentally induced risk neutrality;

iii known and unknown probabilities of the binary random event, which are payoff- but not (optimal) choice-relevant;

iv a rich set of parameter constellations, experienced by all participants, and a slider that visualizes the payoff consequences of choices and can be used repeatedly before deciding.[6]

The latter is important since both optimality and satisficing might require learning and experience.[7] In particular, each participant confronts two random sequences of 18 different choice tasks in which one faces a (partly) piecewise quadratic success function and a binary random event. Optimality requires only two assumptions, namely, preferring more money to less and finding the (corner) maxima of the success function, most likely by using the slider as often as possible. Abstaining

[2]For an example of this literature, see Hey and Orme (1994), Hey (1995), Loomes and Sugden (1995), and Harless and Camerer (1994), among others.

[3]Merley (1997).

[4]See, among others, Savikhin (2013) on financial analysis and risk management.

[5]See, for instance, Selten et al. (2012) and Güth and Ploner (2016)

[6]Consequentialist bounded rationality assumes that choosing among alternatives by anticipating their likely implications requires causal relationships linking the choice (means) and determinants beyond one's control, such as chance events, to the relevant outcome variables (ends).

[7]Note that this kind of experimental analysis can shed light on mental modeling and – more generally – on cognitive processes, in addition to eliciting the usual choice data.

from "rationality in making mistakes," in the following analysis, optimality is assessed based on how choices deviate from the (corner) optimum and how costly this is.

To avoid criticizing without providing alternatives, we consider bounded rationality based on consequentialist choice deliberations and satisficing rather than optimizing. Instead of reacting to given and well-behaved preferences and beliefs about circumstances beyond their control, participants form goal aspirations and then successively test behavioral options to determine whether they are satisficing these aspirations before making a choice. [8]

In our setup, the realization of a binary chance event is beyond our control either "boom" (good outcome) or "doom" (bad outcome) circumstances result. In abstaining from intrapersonal payoff aggregation as in expected utility and prospect theory (by aggregating the probability-weighted choice implications of the boom and doom scenarios), one has to form goal aspirations for the boom and doom scenarios. Due to the binary lottery incentives, an obvious goal is to increase the probability of earning more rather than less. This means forming probability aspirations for two scenarios, the doom scenario wherein a risky investment would be lost and the boom scenario wherein such an investment will be rewarded. When satisficing, one chooses a portfolio whose returns in the boom case, respectively doom, satisfy the aspirations in both these scenarios. This does not rule out optimality as a border case: set-valued optimal satisficing requires that it is impossible to increase the aspiration for one scenario without a corresponding reduction for the other scenario. This set optimality does not rely on the probabilities of scenarios, which are not experimentally induced.[9] Even when probabilities are experimentally induced, these may not be used for intrapersonal payoff aggregation but for forming and adapting aspiration levels, for instance, by forming more ambitious (moderate) aspirations for more (less) likely scenarios.[10]

A portfolio choice may be either satisficing (but not set optimal) or non-satisficing. In an experiment, one can confirm a portfolio choice even when it is not satisficing. According to our interpretation, satisficing is based on a forward-looking decision-making process involving several successive

[8] From the seminal contribution of Simon (1955) to contributions in mathematics (see Kunreuther and Krantz, 2007) and psychology (Kruglanski 1996 and Kruglanski et al. 2002), as well as to the literature on the role of mental models in decision making (Gary and Wood, 2010), this approach has increasingly contaminated economics (Camerer 1991, Pearl 2003 and Gilboa and Schmeidler 2001), although not always beyond lip service.

[9] One essentially employs a multiple selves approach that does not require intrapersonal payoff aggregation.

[10] All 18 cases prevent the optimal choice from depending on the positive probabilities of the two random events.

steps for the task at hand, aspiration formation and searching for satisficing options in the action space, with possible feedback loops in light of new information. We experimentally compare participants who are forced to reason according to this structure before deciding to participants who are allowed to decide freely, that is, without having to form aspirations.

Section 2 introduces the 18 choice tasks, or cases, and derives their optimal choices or choice sets. We then discuss the hypotheses in Section 3. The treatments and other details of the experimental protocol are described in Section 4. Sections 5 presents the results on (sub)optimality as pairwise comparisons of treatments; Section 6 focuses on satisficing and its statistical analysis, while Section 7 refers to special cases in the data. Section 8 concludes.

2 The choice class

To induce risk neutrality, participants earn, in addition to their show-up fee, either €4 or €14, i.e., we implement binary lottery incentives. In doing so, we are not troubled by doubtful evidence (see Selten et al., 1999) that such incentives imply risk neutrality. When testing expected utility theory, one presupposes that this means "binary lottery incentives work". Specifically, what participants may try to maximize via their portfolio choice is the probability of receiving €14 rather than €4, where we assume:

Assumption 1 *Participants prefer more money, €14, to less, €4.*

When describing the choice class, we rely on the financial portfolio selection frame used in the instructions (see the translated instructions for the experiment in Appendix A). There is no claim that this realistically captures portfolio choice problems in the field, since the choice class is designed to imply various controls, e.g., for risk neutrality and probabilities being optimal-choice irrelevant. Nevertheless, we have intentionally framed the decision tasks as portfolio choices in order to strengthen the purely individual choice consequences, i.e., to discourage other-regarding concerns. An endowment (of a positive amount) e can be invested in a risk-free bond with a constant repayment rate c (≥ 0) or in a risky asset. The repayment rate of the risky asset is $r(i)$ with probability p, where $r(i)$ depends on the amount i invested in the risky asset, or it is 0 with probability $(1-p)$, where

$0 < p < 1$. We refer to the $(1-p)$-probability event when i is lost as doom and to the p-probability event as boom, where the return from i is $r(i) \cdot i$. We let $r(i)$ depend linearly on i via $r(i) = e - i$ for all $0 \leq i \leq e$, and $P(i)$ denotes the expected probability of earning €14 rather than €4. For the expected utility of choice i, namely, $E(i) = [1 - P(i)]\, u(€4) + P(i)u(€14))$, setting $u(€4) = 0$ and $u(€14) = 1$ based on Assumption 1 implies that $E(i) = P(i)$, i.e., the expected utility of choice i is the probability that choice i implies for earning €14.

Now the return from investing i in the risky asset and $e - i$ in the safe bond is $(e-i)c$ in case of doom and $(e-i)(c+i)$ in case of boom. Since $P(i)$ is restricted to $0 \leq P(i) \leq 1$, expected utility is given by:

$$P(i) = (1-p) \cdot \min\{1, (e-i)c\} + p \cdot \min\{1, (e-i)(c+i)\} \tag{1}$$

Across all 18 cases, one has $(e-i)c < 1$ via $ec < 1$ due to $(e-i)(c+i) \leq 1$. Thus, the 18 constrained optimization tasks require us to determine the i level(s) for which

$$P(i) = (1-p)(e-i)c + p \cdot \min\{1, (e-i)(c+i)\} \tag{2}$$

is maximal. Solving the unconstrained maximization of

$$P^{\circ}(i) = (1-p)(e-i)c + p(e-i)(c+i) \tag{3}$$

yields $i^{\circ} = \frac{pe-c}{2p}$, which exceeds, for all cases with $c > 0$, the smallest i level for which $(e-i)(c+i)$ equals 1, namely,

$$i^{*} = \frac{e-c}{2} - \frac{\sqrt{(e+c)^2 - 4}}{2} \tag{4}$$

Assumption 2 *One can determine for $c > 0$ the lowest i level i^{*} with* $\min\{1, (e-i)(c+i)\} = 1$.

To render Assumption 2 likely in the experiments, participants can consider 6 options i by moving a slider displaying $\overline{P}(i) = \min\{1, (e-i)(c+i)\}$ and $\underline{P}(i) = (e-i)c$, as well as their complementary probabilities, before making their choice. For all i levels above i^{*}, especially for i°, one can reduce i and, as $c > 0$, improve the chances of earning €14 in the doom case without reducing the chances of earning €14 with probability 1 in the boom case. Figure 2 displays five different curves: the two strictly concave curves both neglecting the constraint $\overline{P}(i) = \min\{1, (e-i)(c+i)\}$ of which the upper is the unconstrained boom payoff $(e-i)(c+i)$ and the lower is the unconstrained payoff $P^{\circ}(i)$ in equation (3). The other curves display the success probability $\overline{P}(i)$ for the boom (flat top), $\underline{P}(i)$ (linear) for the doom cases, their probability-weighted sum $P(i)$ (piecewise linear and concave), the expected utility of choice i, whose corner maximum is i^*, and the lowest i level with $\overline{P}(i) = 1$.

Proposition 1 *For $c > 0$, the optimal unique investment is given by i^* in equation (4), which does not depend on p.*

For $c = 0$, there exist no chances in the doom case to win €14 rather than €4, as $\underline{P}(i) = (e-i)c = 0$. Thus, for $c = 0$, the probability p is not optimal-choice relevant. For the $c = 0$ cases, the problem of intra-personal payoff aggregation does not arise in choice making. If $c = 0$ and $e = 2$, the unique optimal choice is $i^* = 1$ so that $\frac{i^*}{e} = 1/2$, which is often referred to as the "Golden Mean". However, when $c = 0$ and $e > 2$, all investment choices i^* in the range

$$\frac{e-c}{2} - \frac{\sqrt{e^2-4}}{2} \leq i \leq \frac{e-c}{2} + \frac{\sqrt{e^2-4}}{2} \tag{5}$$

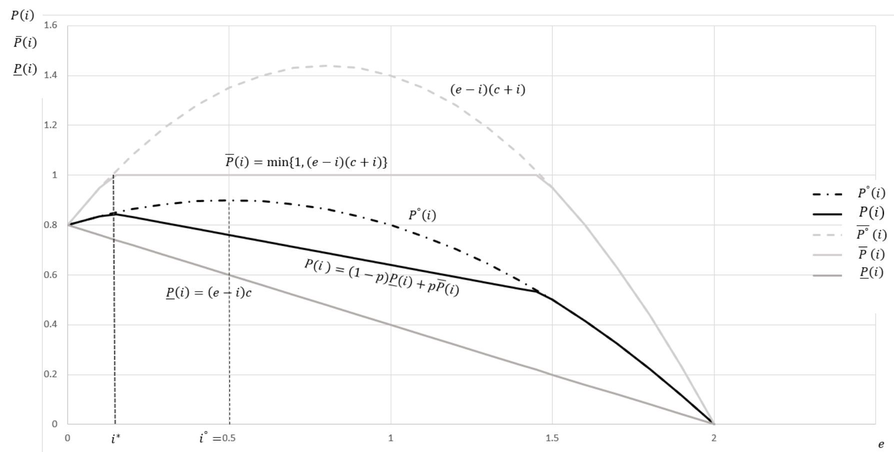
are expected utility maximizing. (Figure 2 graphically illustrates that $\overline{P}(i) = 1$ and $P(i) = p \cdot \max\{1, (e-i)i\} = p$ are flat in that range.) For $e = 2$, the flat interval degenerates to a single tangential point with $(e-i^*)i^* = 1$. Figure 2, based on two (of the three) $c = 0$ cases with $e = 2$ and $e = 4$, displays the curves $\overline{P}(i)$ for $e = 2$ with $\overline{P}(i) = 1$ just for $i^* = 1$, as well as for $e = 4$ with a wide range of optimal investments i^* in the generic interval (5).

Proposition 2 *For $c = 0$, the point and set values optimality coincide and predict a unique choice for $e = 2$ but a generic interval prediction (5) for $e > 2$.*

We extend Assumption 2 to include the following:

Assumption 3 *Participants can determine some i with $\overline{P}(i) = 1$ when $c = 0$.*

Figure 1: Illustration of payoff incentives $P(i), \overline{P}(i), \underline{P}(i)$



Notes: $p = c = 0.4$ and $e = 2$ yield a similar graph for all $p, c > 0$ and $e \geq 2$ such that $0 < i^* < i^\circ < \frac{e-c}{2} < \frac{e}{2}$.

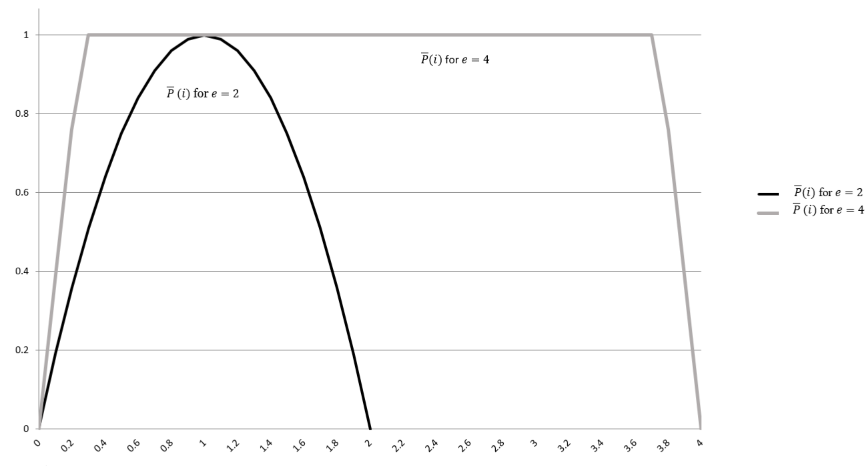
Again, given that participants can use the slider repeatedly, this does not seem unrealistic for $e > 2$ when the interval (5) is generic. However, even for $e = 2$, the unique optimal choice $i^* = 1$ may be found after some experience.

The (sets of) optimal i^* choices for all 18 parameter constellations, referred to as cases, are listed in Table 3 (the columns indicate investing decisions, i choices). When generating the parameter constellations confronted by participants, we wanted to include rather large and small probabilities p, although the numerical probability p does not affect the optimal choice i^*. The advantage of corner solutions i^* is that optimality can be achieved via the heuristic of determining the smallest (and for $c = 0$, only when $e = 2$ or some when $e > 2$) i level guaranteeing $\overline{P}(i) = 1$ by repeatedly using the slider provided by the software (see the decision screens in Figures 10 and 11 in Appendix B and their explanation in the instructions in Appendix A).

3 Hypotheses

Each participant confronts all 18 different parameter constellations (twice) in two successive random orders. We refer to the first random sequence of 18 cases as phase 1 and to the second as phase 2.

Figure 2: Illustration of payoff incentives $\overline{P}(i)$ when $c = 0$ and $e = 2$ or 4



Notes: For $e = 2$ and $e = 4$.

For (sub) optimality, one could predict symmetry [11] , as well as a decline with experience.

Hypothesis 1 *(Symmetry and Learning Hypothesis): The observed i choices are more symmetrically distributed below and above i^* the closer $q^* = \frac{i^*}{e}$ is to 1/2 with a variance of $i - i^*$ or $q - q^* = \frac{i}{q} - \frac{i^*}{q}$ being smaller in phase 2.*

We do not analyze sub-optimality via "rationality in making mistakes" meaning that mistakes (here, deviations of i from i^*) with higher losses – compared to optimality – are less likely. In our view, rationality in committing errors is questionable as it presupposes an awareness of what one loses.[12]

For the concept of satisficing, aspiration formation means specifying an aspired probability

(1) $\overline{A}$ for $\overline{P}(i) = \min\{1, (e - i)(c + i)\}$

(2) $\underline{A}(\leq \overline{A})$ for $\underline{P}(i) = (e - i)c$ when the risky investment is lost.

[11] In the spirit of Fechner's (1876) law for visual distance perception, symmetry could be questioned by concavity in perceiving numerical success for all numerical goals, irrespective whether the goals are monetary or probabilities of earning €14 rather than €4. Rather than risk aversion postulating a concave utility of money, in our context, the concavely perceived numerical goal would be the probability of earning €14, which suggests more i choices below rather than above i^*.

[12] Nevertheless, concepts relying on "rational mistakes" are often used to account for empirical, mostly experimentally observed, behavior, e.g., Quantal Response (Equilibrium) estimates (McKelvey and Palfrey, 1995), but also in game theory, e.g., in case of the "intuitive criterion" (Cho and Kreps, 1987) and "properness" (Myerson, 1978).

Since $(e-i)(c+i)$ can partly exceed 1 for generic i intervals, in these intervals, one can decrease the i level and increase $\underline{P}(i)$ for $c > 0$ without questioning $\overline{P}(i) = \min\{1, (e-i)(c+i)\} = 1$. In the terminology of satisficing, one can form a higher doom aspiration, $\underline{A}$, without having to reduce the boom aspiration, $\overline{A}$.

Across all 15 cases with $c > 0$, the optimal choice i^* is the right corner of the interval from 0 to i^* of all i choices that are set optimal in the sense that it is impossible to increase $\overline{P}(i)$ without reducing $\underline{P}(i)$, and vice versa. Using the slider generates column heights indicating the probabilities of earning €14 in the boom and doom cases, which a participant has to translate into numerical success probabilities. This might cause problems when considering i choices suggesting probability aspirations for €14 below 1 that, however, only apply to set-optimal choices i, with $i < i^*$ for $c > 0$. For i choices that guarantee earning €14 with probability 1, the translation of column heights into numerical aspirations $\overline{A} = 1$ should matter less.

If a choice i with $0 \leq i \leq e$ is guaranteeing $\overline{P}(i) \geq \overline{A}$, as well as $\underline{P}(i) \geq \underline{A}$, we say that i is satisficing $(\overline{A}, \underline{A})$. Furthermore, we speak of optimal satisficing if neither $\overline{A}$ nor $\underline{A}$ can be increased without questioning such satisficing. For $c > 0$, optimal satisficing excludes any choice i yielding $(e-i)(c+i) > 1$: if $i > i^* := \frac{e-c}{2} - \frac{\sqrt{(e+c)^2-4}}{2}$, one can increase $\underline{P}(i)$ by a lower i in the range $i^* \leq i$ without questioning that $\overline{P}(i) = 1$. Since for the 15 cases with $c > 0$ one has $e \geq 2$ and, thus, $(e+c)^2 > 4$, the term $\sqrt{(e+c)^2 - 4}$ is positive across all $c > 0$ cases: set optimality in the sense of optimal satisficing requires $0 \leq i \leq i^*$ for $c > 0$ (see Figure 1 for an illustration).

The set-optimal choices i and aspiration profiles $(\overline{A}, \underline{A})$ with $\overline{A} \geq \underline{A}$ are thus given by $0 \leq i \leq i^*$, $\overline{A} = \overline{P}(i) = 1$ and $\underline{A} = \underline{P}(i) = c(e-i)$. This set definition of optimally satisficing choices i and of optimal aspiration profiles $(\overline{A}, \underline{A})$ does not pay any attention to probability p. Rather than weighting cases (1) and (2) by probabilities and aggregating their probability-weighted success, the decision maker is concerned with two alter egos, only one of which would be rewarded for risky investment.

For the three $c = 0$ cases, the doom scenarios has $\underline{P}(i) = 0$ for all i with $0 \leq i \leq e$. Thus, one should only aspire $\underline{A} = 0$, which avoids intra-personal payoff aggregation. As a consequence, the sets of utility-maximizing and optimally satisficing choices coincide with the point prediction $i^* = \frac{(e-c)}{2}$ for $e = 2$ and the set prediction $\frac{e-c}{2} - \frac{\sqrt{(e+c)^2-4}}{2} \leq i^* \leq \frac{e-c}{2} + \frac{\sqrt{(e+c)^2-4}}{2}$ for $e > 2$.

Table 1 provides an overview of the optimality predictions based on expected utility maximization or optimal satisficing, i.e., optimal aspiration formation and choice making.

Table 1: Optimality predictions

cases		optimal investment	optimal satisficing	
			in investing	in aspiration formation
$c > 0$	$e \geq 2$	$i^* = \frac{e-c}{2} - \frac{\sqrt{(e+c)^2-4}}{2}$	$0 \leq i \leq i^*$	$\overline{A} = \min\{1, (e-i)(c+i)\}; \underline{A} = (e-i)c$
$c = 0$	$e = 2$	$i^* = 1$	$i^* = 1$	$\overline{A} = 1; \underline{A} = 0$
	$e > 2$	$\frac{e-c}{2} - \frac{\sqrt{(e+c)^2-4}}{2} \leq i^* \leq i\frac{e-c}{2} + \frac{\sqrt{(e+c)^2-4}}{2}$		$\overline{A} = 1; \underline{A} = 0$

Notes: Optimality predictions for investing and aspiration formation based on expected utility maximization (left column) and optimal satisficing (middle, and right columns).

The set of satisficing choices and aspiration profiles in the sense of $\overline{A} \leq \overline{P}(i)$ and $\underline{A} \leq \underline{P}(i)$ becomes empty when aspirations are too ambitious, whereas when aspirations are moderate, the set is rather large. In view of previous experiences (Güth et al., 2009), aspiration formation was incentivized by paying for aspirations only when satisficing them; no payment was received otherwise. Thus, a participant with an aspiration profile $(\overline{A}, \underline{A})$ and choice i earns €14

- in case (1), with probability $\overline{A}$ if $\overline{P}(i) \geq \overline{A}$ and zero probability otherwise
- in case (2), with probability $\underline{A}$ if $\underline{P}(i) \geq \underline{A}$ and zero probability otherwise

where 0 probability of earning €14 means earning €4 with probability 1.

Hypothesis 2 *(Non-Optimal Satisficing): Participants learn to satisfice, but aspiration profiles* $(\overline{A}, \underline{A})$ *are, at least initially, non-optimal, i.e., one could increase either* $\overline{A}$ *or* $\underline{A}$ *without having to decrease the other. Furthermore, many* i *choices will not be set optimal in the sense of optimally satisficing choices.*

In the experiment, participants can use the slider to revise $(\overline{A}, \underline{A})$ once. We predicted some "burning money" in the sense of small positive differences in $\overline{P}(i) - \overline{A}$ and $\underline{P}(i) - \underline{A}$, but much less for the former when $\overline{P}(i) = 1$, as it is easier to identify visually. Compared to "burning money", we predicted significantly less evidence of "committing suicide" via $\overline{A} > \overline{P}(i)$ or $\underline{A} > \underline{P}(i)$, meaning that the chance of earning 14 is lost when earning $\overline{A} \cdot \delta(\overline{P}(i) \geq \overline{A})$ or $\underline{A} \cdot \delta(\underline{P}(i) \geq \underline{A})$ in the boom and doom cases, respectively, with $\delta(\cdot)$ denoting the indicator function that takes the value 1 if its condition is satisfied and 0 otherwise.

When a probability $0 < p < 1$ is experimentally induced, a participant might use it for intrapersonal payoff aggregation or for aspiration formation and adjustment (see Sauermann and Selten, 1962). The latter could mean to be more ambitious in the more likely case (1) or (2), e.g., by increasing the respective aspiration level, $\overline{A}$ or $\underline{A}$.

Hypothesis 3 *(Probability-Use Hypothesis): Participants will react mainly qualitatively to information about the probability p when choosing or forming aspirations.*

When participants are not informed of the probability p, they are partly asked to generate a subjective probability $\hat{p} = 1/2$, e.g., $p = 1/2$ due to the principle of insufficient reason. However, $\hat{p} \neq p$ does not change i^* and does not call into question the optimality predictions in Table 3. Experiences with and without experimentally induced prior probabilities, to the best of our knowledge, have found few differences in their choice data.

Hypothesis 4 *(Homogeneity Hypothesis): The distributions of i choices are similar with and without p information.*

4 Experimental protocols

The four between subjects treatments (T1,T2, T3 and T4) rely on the 2×2 factorial design in Table 2:

- one factor is whether we experimentally induce a probability p;
- the other factor concerns whether only the choice i – the I treatments – or aspirations $(\overline{A}, \underline{A})$ and choice i are elicited – the S treatments.

For each treatment, we conducted three sessions with student participants recruited from Luiss University from different fields of study (mainly economics, law and political science) using Orsee software (Greiner, 2004). The number of participants per treatment varied from 71 to 78. Overall, we employed a total of 298 participants. The experiment was fully computerized using Z-Tree (Fischbacher, 2007). Sessions lasted approximately 90 minutes. After each session, participants answered a brief questionnaire, mainly to collect demographic information, before being privately paid in cash for a randomly selected round. No one participated in more than one session. All participants confronted the 18 parameter constellations twice in two successive phases (each with 18 rounds and in a random order) to assess experience effects. In each round, participants invest their endowment e in two assets.

Table 2: The 2×2-factorial between subjects treatments

Choice Format	**Probability Information**	
	p given	p unknown
I-treatment (direct i-choice)	T1: $i_1, i_2, i_3, i_4, i_5, i_6$ $\rightarrowtail$ final choice of i	T2: first $\hat{p}$ then. $i_1, i_2, i_3, i_4, i_5, i_6$ $\rightarrowtail$ final choice of i
S-treatment (first aspiration profiles then i-choice)	T3: first. $\overline{A}$, $\underline{A}$ then $i_1, i_2, i_3, i_4, i_5, i_6$ $\rightarrowtail$ final choice of i	T4: first $\overline{A}$, $\underline{A}$ then $i_1, i_2, i_3, i_4, i_5, i_6$ $\rightarrowtail$ final choice of i

Only in T1 and T3 is the probability p known. The choice data include the final choice of i in T1 and, additionally, in T2 the stated probability $\hat{p}$, respectively in T3 and T4 the stated aspirations $\overline{A}$, $\underline{A}$ with $1 \geq \overline{A} \geq \underline{A} \geq 0$. The choice of i affects only the probability of winning €14 or €4, which also depends on a random event. In different rounds, subjects face different parameters (characterizing the 18 cases in Table 3). Participants can test up to 6 choices of i by moving the cursor on the scrollbar (as depicted in Figure 10 in Appendix B) before confirming their choice and proceeding to the next round. The interval remains constant across cases, with the integer endowment e (see Table 3) stated at the right corner. Thus, moving the cursor changes the investment share i/e.

The 18 cases in Table 3 were constructed by neglecting that $\overline{P}(i)$ cannot exceed 1 and imposing $P^\circ(i^\circ) = (1-p)(e-i^\circ)c + p(e-i^\circ)(c+i^\circ) = (e-i^\circ)(c+pi^\circ) = 0.9$ for the unconstrained optimal choice i° across all cases. The actual optimal expected success probability, due to $\overline{P}(i) \leq 1$, varies considerably (see $P(i^*)$ in Table 3), namely, from 0.23 to 0.9. The cases are defined by the endowment e and the i°/e-investment share of the unconstrained optimal investment i°. Together, these determine the parameters p and c when imposing $P(i^\circ) = 0.9$.

The different parameter constellations:

- include the "Golden Mean" $i^* = e/2$, with $c = 0$ and $e = 2$;
- exclude $\underline{P}(i) = (e - i)c \geq 1$ via $ec < 1$;
- capture some rather small and at least some rather large probabilities p in the range $0 < p < 1$, which are payoff- but not optimal-choice relevant.

Table 3: Cases and optimal payoffs

	$P(i^*)$			p			c		
$q^\circ = i^\circ/e$	e=2	e=3	e=4	e=2	e=3	e=4	e=2	e=3	e=4
1/12	0.90	0.90	0.88	0.27	0.12	0.07	0.45	0.30	0.22
2/12	0.88	0.88	0.88	0.32	0.14	0.08	0.43	0.29	0.22
3/12	0.85	0.83	0.81	0.40	0.18	0.10	0.40	0.27	0.20
4/12	0.81	0.74	0.71	0.51	0.23	0.13	0.34	0.23	0.17
5/12	0.78	0.59	0.52	0.66	0.29	0.17	0.22	0.15	0.11
6/12	0.90	0.40	0.23	0.90	0.40	0.23	0.00	0.00	0.00

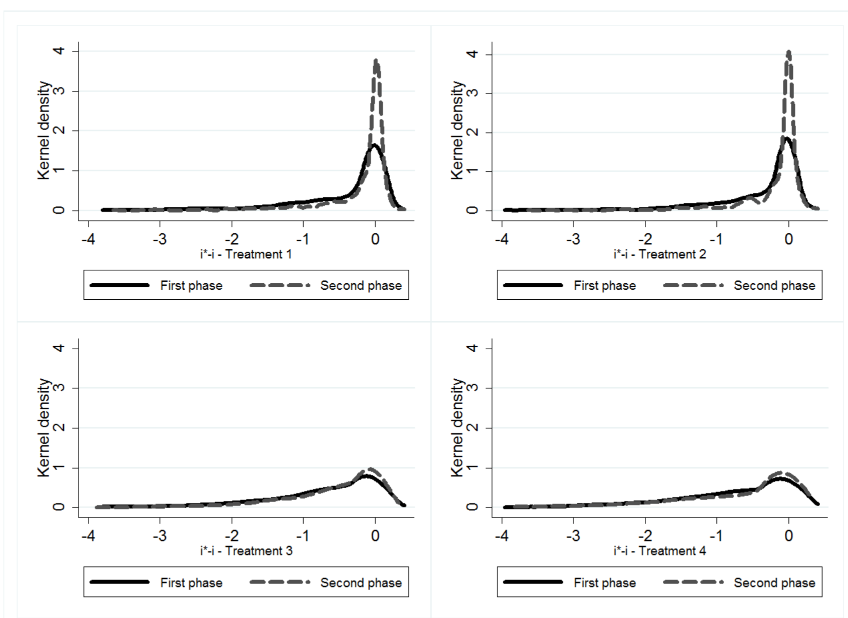
A subject earns either €14 or €4 in addition to the show-up fee of €4. Participants are paid for one random round selected by the computer at the end of the experiment. In T1 and T2, earnings depend on the investment choice and the random event, whereas in T3 and T4, earnings depend on the investment choice, the random event and the aspiration levels ($\overline{A}$, $\underline{A}$ for winning €14). An aspiration level that does not exceed the probability of winning €14 (in either boom or doom cases) determines the probability of winning €14.If the aspiration level exceeds the probability of winning €14 for the i choice (in either boom or doom), the probability of winning €14 is nil (but one receives €4 with probability 1).

For an example of the payoffs in T3 and T4, see Figure 11 in Appendix B: the boom aspiration level is 60%, lower than the probability represented by the left bar. The doom aspiration level is higher than the overall probability represented by the right bar. Since $p = 0.14$, doom results with probability 0.86. As aspiration $\underline{A}$ exceeds the level $\underline{P}(i) = (e - i)c$, i.e., the chance of earning €14 in the case of doom is nil, and the probability of earning €14 is only $0.6 \times 0.14 = 0.084$.

5 Assessing (Sub) Optimality For $c > 0$

Before our data analysis, let us comment on which observations count as independent. Since optimality, irrespective of whether it postulates expected utility maximization or optimal satisficing in investing and aspiration formation, predicts that each participant behaves optimally in all 36 choice tasks, we feel justified in considering each choice as an observation to test optimality. However, when assessing the extent of suboptimality and non-optimal satisficing, one might take into account which choices are made by the same participant and consider only the individual averages as independent. We will often employ both possibilities by reporting significance levels based on each choice and individual averages, with the latter in brackets.

Figure 3: Deviation $i^* - i$ by Phase and Treatment



Notes: Kernel density function for cases with $c > 0$.

Although repeated slider use should quickly reveal that increasing i in the interval from i^* to i° is suboptimal, someone solving the unconstrained optimization task analytically might have overlooked this. We therefore checked (sub)optimality in view of i°, although our main focus is, of course, the optimal choice i^* and the optimal interval $0 \leq i \leq i^*$. Analyzing suboptimality across all 15 cases with $c > 0$ via deviations $i^\circ - i$ across treatments T1, T2, T3, T4 and phases 1 and 2 (see Figure 12 in Appendix B) consistently reveals a positive mode, meaning that $i < i^\circ$ is more focal. This could point in the direction of optimality, i^*. In fact, (see Figure 3) the modes of the deviations $i - i^*$ from optimality are close to 0 for all treatments (the much longer tails in the range $i > i^*$ are due to $\frac{i^*}{e}$ usually being small in the unit interval).

Figure 3 reveals some significant differences in $i^* - i$ deviations aggregated across all 15 cases of either phase 1 or phase 2, as well as for all 30 i choices with $c > 0$ across treatments. Some will be discussed in more detail via pairwise comparisons of treatments. What we observe so far is a tighter distribution around i^* and stronger experience from phase 1 to 2 for T1 and T2.

Table 4: Average level i by restricted and unrestricted optimal investment intervals

		$i \leq i^*$			$i^* < i \leq i^\circ$			$i > i^\circ$		
		i	obs	%	i	obs	%	i	obs	%
T1	Phase 1	0.060	369	31.54	0.323	480	41.03	1.366	321	27.44
	Phase 2	0.058	532	45.47	0.260	450	38.46	1.195	188	16.07
T2	Phase 1	0.086	292	25.04	0.424	694	59.52	1.383	180	15.44
	Phase 2	0.076	422	36.38	0.321	622	53.62	1.128	116	10.00
T3	Phase 1	0.076	176	15.64	0.417	413	36.71	1.369	536	47.64
	Phase 2	0.068	207	18.40	0.378	431	38.31	1.295	487	43.29
T4	Phase 1	0.114	164	15.40	0.400	373	35.02	1.431	528	49.58
	Phase 2	0.107	158	14.84	0.323	452	42.44	1.527	455	42.72

Notes: Average for 15 cases where $c > 0$.

Table 5: Average level i by restricted and unrestricted optimal investment intervals and by q^* levels

		q Low				q High			
		T1	T2	T3	T4	T1	T2	T3	T4
$i \leq i^*$	i-mean	0.034	0.055	0.042	0.064	0.193	0.171	0.201	0.203
	%	37.43	27.69	15.95	11.59	45.51	50.16	24.00	38.03
$i^* < i \leq i^\circ$	i-mean	0.272	0.372	0.386	0.341	0.472	0.421	0.488	0.482
	%	41.22	60.69	38.56	39.54	30.13	29.90	30.67	33.45
$i > i^\circ$	i-mean	1.329	1.388	1.356	1.505	1.154	0.884	1.189	1.150
	%	21.35	11.61	45.94	48.86	24.36	19.94	45.33	28.52
	Obs.	2028	2015	1950	1846	312	311	300	284

Notes: Average results for the 15 cases with $c > 0$ when $q^* \leq 0.10$ is Low, and $0.10 < q^* \leq 0.5$ is High.

Table 4 displays the average i choices, as well as their frequencies and % shares for $i \leq i^*$,

$i^* < i \leq i^\circ$ and $i > i^\circ$. The share of set-optimal i choices is considerably larger in T1 and T2. Treatments T3 and T4 asking for aspirations $\overline{A}$ and $\underline{A}$ fare worse. Specifically, the share of i choices with $i > i^\circ$ is much higher in T3 and T4 than in T1 and T2. It seems that incentivized aspiration formation crowds out rather than promotes better decision making.

Regarding Hypothesis 1:

- the symmetry hypothesis is hardly in line with the low shares of i choices in the interval $i \leq i^*$
- which only increases considerably from phase 1 to phase 2 in T1 and T2.

The influence of $q^* = i^*/e$ is demonstrated in Table 5, which distinguishes between cases with $q^* \leq 0.1$ and $0.1 < q^* \leq 0.5$. For all four treatments, the share of i choices with $i \leq i^*$ is always larger when q^* exceeds 0.1, i.e., the direction of deviation from the optimal choice i^* is mainly determined by the lengths of the $q = i/e$ intervals to the left and right of i^*/e. However, these shares are considerably smaller for T3 and T4 than for T1 and T2, irrespective whether q^* is "Low"or "High".

In the payoff space, we compare the following:

- expected payoff losses

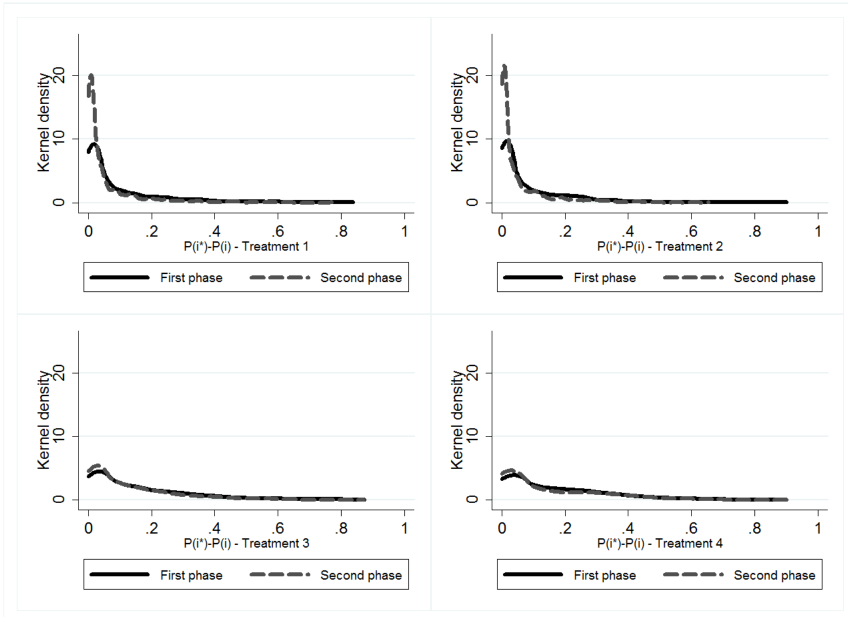
$$P(i^*) - P(i) = (1-p)(e-i^*)c + p - (1-p)(e-i)c - p \cdot \text{min}\,\{1, (e-i)(c+i)\}$$

  separately for phase 1 and 2, as well as for all 30 $c > 0$ case choices (see Figure 4) and

- separate payoff losses for boom (see Figure 13 in Appendix B) and doom (see Figure 14 in Appendix B) in order to determine whether suboptimality is due to special concerns in either boom or doom cases.

The payoff distributions are consistent with the i choice distributions, in particular, deviations are closer to zero in the payoff space for T1 and T2 and more so in phase 2 in all three dimensions, $P(i^*) - P(i)$, $\overline{P}(i^*) - \overline{P}(i)$ and $\underline{P}(i^*) - \underline{P}(i)$.

Figure 4: Distance in payoff space: $P(i^*) - P(i)$ by phase



Notes: Kernel density function, considering only cases where $c > 0$; Treatment 2 $P(i^*)$ has been computed based on objective probabilities p.

We now consider pairwise treatment comparisons based on data for 15 cases with $c > 0$. Pairwise treatment comparisons allow us to control specifically for whether p information is granted and which additional data are elicited.

(a) T1$\leftrightarrow$ T2: differ in that p is known in T1 but not in T2, which also asks for $\hat{p}$, the subjectively stated probability of a boom.

Table 6: Action and payoff space comparison - T1 vs. T2

	$i^* - i$			$P(i^*) - P(i)$			$\overline{P}(i^*) - \overline{P}(i)$			$\underline{P}(i^*) - \underline{P}(i)$		
T1 vs. T2	T1	T2	WRST(Ind.)	T1	T2	WRST	T1	T2	WRST	T1	T2	WRST
All sample	-0.305	-0.282	0.013(0.004)	0.076	0.070	0.056	0.063	0.043	0.000	0.075	0.069	0.049
Phase 1	-0.409	-0.369	0.427(0.409)	0.095	0.087	0.315	0.056	0.040	0.001	0.102	0.091	0.666
Phase 2	-0.201	-0.195	0.005(0.029)	0.057	0.054	0.063	0.071	0.045	0.000	0.049	0.046	0.015
KST(Ind.)	0.000(0.000)	0.000(0.000)		0.000	0.000		0.000	0.000		0.000	0.000	

Notes: A Wilcoxon Rank Sum Test (WRST) for two independent samples is used to compare across treatments, and a Kolmogorov-Smirnov equality of distributions test (KST) for the analysis across phases. The parentheses report the tests on individual averages. For these tests, p-values are reported. In T2, $P(i^*)$ is computed based on objective probabilities p.

Figure 5: Comparison of p and $\hat{p}$ for T2

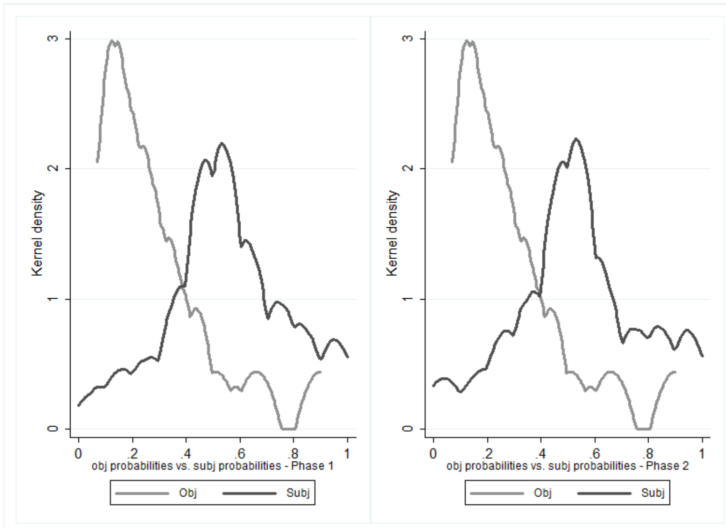


Figure 5, displaying the densities of p and $\hat{p}$ for all participants of T2 separately for both phases, reveals a dominance of wishful thinking in both phases and hardly any learning.[13] Such optimism, however, does not account for the suboptimal choices, since i^* does not depend on p or $\hat{p}$. Table 13 in Appendix B shows that excessive optimism is significant, which is insignificantly ($p > 0.05$) reduced by experience. Table 6 reveals a smaller average deviation $i^* - i$ for T1 than for T2, which seems mainly due to differences in behavior in phase 1. In the payoff dimensions $P(i)$, $\overline{P}(i)$ and $\underline{P}(i)$, the differences are minor but significantly affected by phase with only $\overline{P}(i^*) - \overline{P}(i)$ increasing from phase 1 to phase 2.

(b) T1 $\leftrightarrow$ T3: Participants in both treatments are aware of probability p and differ only in that participants in T3 also have to form aspirations, which they can revise only once.

In Table 7, we restrict the comparison to aspects for which both treatments provide data. In spite of what the overall comparisons across all treatments suggest, homogeneity of deviation from optimality in the action and payoff space, as well as across phases, is not rejected, except for the smaller payoff losses $\overline{P}(i^*) - \overline{P}(i)$ in phase 2 of T3.

[13]In each round of T2, we allow participants to modify the stated probability once: this actually occurred 3% and 2% of the times in phase 1 and 2, respectively.

Table 7: Action and payoff space comparison - T1 vs. T3

	$i^* - i$			$P(i^*) - P(i)$			$\overline{P}(i^*) - \overline{P}(i)$			$\underline{P}(i^*) - \underline{P}(i)$		
T1 vs. T3	T1	T3	WRST(Ind.)	T1	T3	WRST	T1	T3	WRST	T1	T3	WRST
All sample	-0.305	-0.650	0.000(0.000)	0.076	0.139	0.000	0.063	0.036	0.000	0.075	0.165	0.000
Phase 1	-0.409	-0.699	0.000(0.000)	0.087	0.150	0.000	0.056	0.036	0.000	0.102	0.177	0.000
Phase 2	-0.201	-0.600	0.000(0.000)	0.054	0.129	0.000	0.071	0.036	0.000	0.049	0.152	0.000
KST(ind.)	0.000(0.000)	0.001(0.000)		0.000	0.010		0.000	0.917		0.000	0.005	

Notes: A Wilcoxon Rank Sum Test (WRST) for two independent samples is used to compare across treatments, and a Kolmogorov-Smirnov equality of distributions test (KST) for the analysis across phases. The parentheses report the tests on individual averages. For these tests, p-values are reported.

(c) T2 $\leftrightarrow$ T3: Both treatments burden participants by eliciting additional choices, $\hat{p}$ in the case of T2 and $\overline{A}$, $\underline{A}$ in the case of T3, where of course, the latter seems to be more cognitively demanding.

Table 8: Action and payoff space comparison - T2 vs. T3

	$i^* - i$			$P(i^*) - P(i)$			$\overline{P}(i^*) - \overline{P}(i)$			$\underline{P}(i^*) - \underline{P}(i)$		
T2 vs. T3	T2	T3	WRST(Ind.)	T2	T3	WRST	T2	T3	WRST	T2	T3	WRST
All sample	-0.282	-0.650	0.000(0.000)	0.070	0.139	0.000	0.043	0.036	0.000	0.069	0.165	0.000
Phase 1	-0.369	-0.699	0.000(0.000)	0.087	0.150	0.000	0.040	0.036	0.000	0.091	0.177	0.000
Phase 2	-0.195	-0.600	0.000(0.000)	0.054	0.129	0.000	0.045	0.036	0.000	0.046	0.152	0.000
KST(ind.)	0.000(0.000)	0.001(0.000)		0.000	0.010		0.000	0.917		0.000	0.005	

Notes: A Wilcoxon Rank Sum Test (WRST) for two independent samples is used to compare across treatments, and a Kolmogorov-Smirnov equality of distributions test (KST) for the analysis across phases. The parentheses report the tests on individual averages. For these tests, p-values are reported. In T2, $P(i^*)$ is computed from objective probabilities p.

Again restricting the comparison to aspects for which both treatments provide data (see Table 8), one qualitative conclusion is that knowing p, only in T3, apparently does not help: average choice behavior and outcomes are closer to optimality in T2, although $\overline{P}(i^*) - \overline{P}(i)$ is smaller for T3 than for T2.

(d) T1 $\leftrightarrow$ T4 and T2 $\leftrightarrow$ T4

All statements for T2 $\leftrightarrow$ T3 apply analogously (see Tables 14 and 15 in Appendix B).

6 Comparing Satisficing across Treatments

Let us first compare how often aspirations were adjusted: in T3, aspirations were adjusted 25% (35%) of the time in phase 1 (phase 2), while in T4, aspirations were adjusted 35% (39%) of the time in phase 1 (phase 2). With experience, one engages in more frequent aspiration adaptation (Sauermann and Selten, 1962).

Table 9: Action and payoff space comparison - T3 vs. T4

	$i^* - i$			$P(i^*) - P(i)$			$\overline{P}(i^*) - \overline{P}(i)$			$\underline{P}(i^*) - \underline{P}(i)$		
T3 vs. T4	T3	T4	WRST(Ind.)	T3	T4	WRST	T3	T4	WRST	T3	T4	WRST
All sample	-0.650	-0.718	0.114(0.000)	0.139	0.152	0.197	0.036	0.030	0.015	0.165	0.175	0.275
Phase 1	-0.699	-0.749	0.348(0.003)	0.150	0.161	0.131	0.036	0.035	0.613	0.177	0.185	0.488
Phase 2	-0.600	-0.688	0.207(0.041)	0.129	0.142	0.820	0.036	0.025	0.003	0.152	0.165	0.391
KST(Ind.)	0.001(0.000)	0.000(0.000)		0.010	0.000		0.917	0.842		0.005	0.000	

Notes: A Wilcoxon Rank Sum Test (WRST) for two independent samples is used to compare across treatments, and a Kolmogorov-Smirnov equality of distributions test (KST) for the analysis across phases. The parentheses report the tests on individual averages. For these tests, p-values are reported.

Regarding deviations from i^* in the action and payoff space, Table 9 reveals a significant phase effect for $i^* - i$, $P(i^*) - P(i)$ and $\underline{P}(i^*) - \underline{P}(i)$ for both treatments and rejects homogeneity of payoff deviations $\overline{P}(i^*) - \overline{P}(i)$ across treatments for phase 2.

Table 10: Share and average level of satisficing

	T3		T4	
	Phase 1	Phase 2	Phase 1	Phase 2
% of ($\overline{P}(i) - \overline{A} \geq 0$) & ($\underline{P}(i) - \underline{A} \geq 0$)	0.77	0.81	0.80	0.83
Obs	1125	1125	1065	1065
% of ($\overline{P}(i) - \overline{A} \geq 0$)	0.97	0.98	0.97	0.98
$\phi(\overline{P}(i) - \overline{A} \mid \overline{P}(i) - \overline{A} \geq 0)$	0.307	0.304	0.295	0.245
s.d.	0.15	0.18	0.17	0.19
% of ($\underline{P}(i) - \underline{A} \geq 0$)	0.77	0.82	0.80	0.84
$\phi(\underline{P}(i) - \underline{A} \mid \underline{P}(i) - \underline{A} \geq 0)$	0.212	0.230	0.165	0.149
s.d.	0.19	0.21	0.16	0.15

Notes: Average for 15 cases where $c > 0$.

Tables 10 and 11 both rely on the finally confirmed $\overline{A}, \underline{A}$ aspiration profiles. Table 10 lists the percentage share of satisficing (top row), and below, the percentage shares of $\overline{P}(i) \geq \overline{A}$ and $\underline{P}(i) \geq \underline{A}$, together with the average differences between actual success and aspiration for boom and doom, separately for both phases and treatments. Satisficing is prevalent in approximately 80% of all individual choices and increases slightly with experience. Failures are mainly caused by not meeting the doom condition $\underline{P} \geq \underline{A}$ as predicted due to $\underline{P}(i) < 1$, rendering it more difficult to

Table 11: Share and average level when $\overline{P}(i) < 1$ and $\overline{P}(i) = 1$

	$\overline{P}(i) < 1$				$\overline{P}(i) = 1$			
	T3		T4		T3		T4	
	Ph. 1	Ph. 2	Ph. 1	Ph. 2	Ph. 1	Ph. 2	Ph. 1	Ph. 2
Obs.	216	242	198	181	909	883	867	884
% of ($\overline{P}(i) - \overline{A} \geq 0$)	0.86	0.89	0.86	0.90	1.00	1.00	1.00	1.00
$\phi(\overline{P}(i) - \overline{A} \mid \overline{P}(i) - \overline{A} \geq 0)$	0.201	0.234	0.210	0.161	0.329	0.321	0.311	0.261
s.d.	0.15	0.20	0.16	0.15	0.14	0.17	0.16	0.19

Notes: We consider the 15 cases where $c > 0$. Obs. refers to the total number of choices, where $\overline{P}(i) < 1$ and $\overline{P}(i) = 1$, and the share accounts for those consistent with condition $\overline{P}(i) - \overline{A} > 0$.

specify a numerical visual slider cue.

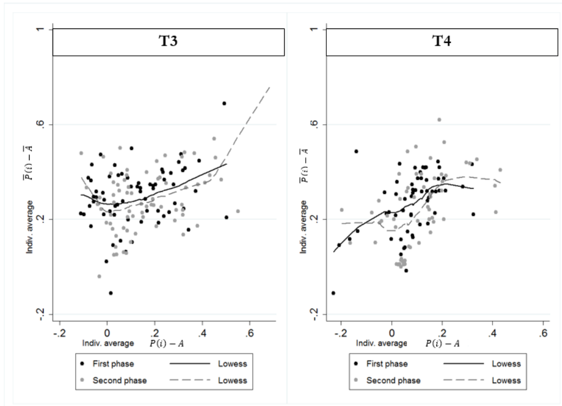
To justify that failing to satisfice is due to numerically translating column heights in numerical aspirations when they are below 1. Table 11 separates the relatively few i observations yielding $\overline{P}(i) < 1$, where the same difficulty arises. The fact that the shares of $\overline{P}(i) \geq \overline{A}$ are considerably smaller for $\overline{P}(i) < 1$ than for $\overline{P}(i) = 1$ supports our interpretation.

The average distance, $\phi(\overline{P}(i) - \overline{A} \mid \overline{P}(i) - \overline{A} \geq 0)$, in Table 11 is consistently larger for $\overline{P}(i) = 1$ than for $\overline{P}(i) < 1$: why guaranteeing $\overline{P}(i) = 1$, as predicted by optimality, but not aspiring it? An interpretation could be that one aspires to a satisficingly high probability of earning more (€14), suggesting that $\overline{P}(i) - \overline{A}$ is equally large for $\overline{P}(i) < 1$ and $\overline{P}(i) = 1$. The fact that $\overline{P}(i) - \overline{A}$ ranges from 0.161 to 0.234 for $\overline{P}(i) < 1$ and from 0.261 to 0.329 for $\overline{P}(i) = 1$ supports this explanation.

The scatter plots displaying the average individual $(\overline{P} - \overline{A}, \underline{P} - \underline{A})$ differences in T3 and T4 in Figure 6 suggest a positive correlation between these dimensions, specifically 0.27 (0.42) for phase 1 (phase 2) in T3 and 0.50 (0.44) for phase 1 (phase 2) in T4, which are all statistically significant.

Setting $\overline{A} < \overline{P}(i)$ or $\underline{A} < \underline{P}(i)$ means sacrificing the probability of earning €14 to earn only €4, which is referred to as "burning money", $\overline{BM} = \max\left\{\overline{P}(i) - \overline{A}, 0\right\}$ and $\underline{BM} = \max\left\{\underline{P}(i) - \underline{A}, 0\right\}$, which had to be expected when $\overline{P}(i) < 1$, and due to $\underline{P}(i) < 1$, always for doom. In our view, burning moderate amounts reveals a general skepticism of or timidity to exploit the investment choice i. Participants seemingly do not mind sacrificing some probability of earning more in order to compensate for slight misunderstandings or mistakes (see Güth et al., 2009, for similar results). However,

Figure 6: Scatter plots of individual average deviations $\overline{P}(i) - \overline{A}$ and $\underline{P}(i) - \underline{A}$ for T3 and T4



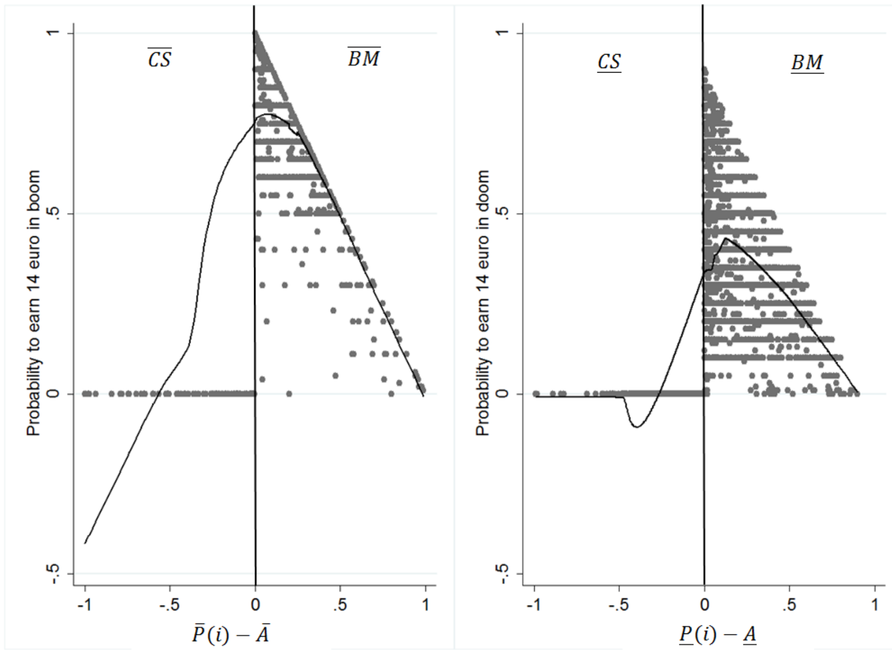
Notes: Individual average deviation for cases where $c > 0$.

as Figure 6 reveals, "burning money" may be more than a moderate sacrifice.

Whereas "burning money" does not question satisficing, "committing suicide" via $\overline{A} > \overline{P}(i)$ in case of $\overline{P}(i) < 1$, $\overline{CS}$, or $\underline{A} > \underline{P}(i)$, $\underline{CS}$ does question it. Figure 7 presents the evidence of "burning money" and "committing suicide" for all data (both phases of both treatments), as well the consequences for the chances to earn €14, where the left (right) diagram depicts boom (doom). When the aspiration exceeds what the i choice yields, the chances are nil, and when "burning money", the aspired probability is the actual chance of earning €14. Figure 7 clearly reveals the expected and striking preponderance of "burning money", which is confirmed by the kernel density plots in Figure 8 separately for boom (upper plots) and doom (lower plots) as well as for T3 (left plots) and T4 (right plots). The modes are in the BM ranges with the only remarkable reduction from phase 1 to phase 2 in case of $\overline{BM}$ in T4.

The top row of Table 16 (in Appendix B) shows that optimal aspiration formation is very unlikely ($\overline{A} = \overline{P}(i)$ is always below 5%, and $\underline{A} = \underline{P}(i)$ is granted only twice) but more frequent in T4, as if information about p crowds out better decision making. Table 16 also displays the expectedly high percentage shares of BM and low CS shares, with $\underline{CS}$ being more frequent than $\overline{CS}$. Finally, Table 17 (in Appendix B) compares BM and CS across treatments and phases by tolerating ϵ amounts of "burning money" and "committing suicide" when smaller than $\epsilon = 0.025$ (upper part of Table17)

Figure 7: Chances to earn €14 depending on aspirations



Notes: Pooled observations for phase 1, phase 2, Treatment 3 and Treatment 4. The probability of winning €14 is the probability $\overline{A}$ respectively $\underline{A}$ when "burning money", $\overline{BM}$ respectively $\underline{BM}$, and the probability is 0 for "committing suicide", $\overline{CS}$ respectively $\underline{CS}$.

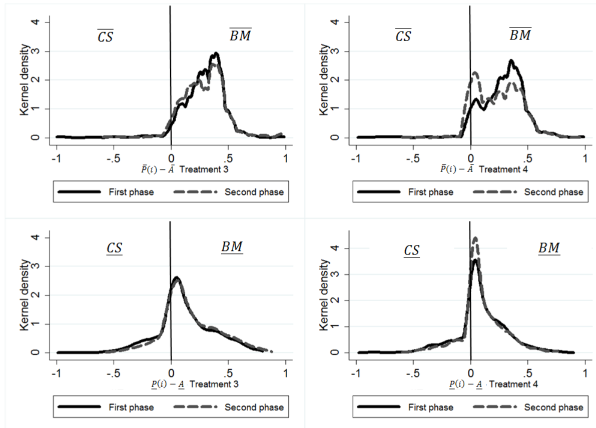
and $\epsilon = 0$ (lower part). Compared to the average amounts of "burning money" ($\phi\overline{BM}, \phi\underline{BM}$) and "committing suicide" ($\phi\overline{CS}, \phi\underline{CS}$) for $\epsilon = 0$, the corresponding averages for $\epsilon = 0.025$ are considerably larger: many deviations from optimal aspiration formation for given i choices are beyond small margins. The striking reduction from phase 1 to phase 2 is restricted to "committing suicide" (see Table 17).

7 The $c = 0$ cases

The $c = 0$ cases are important, since they allow us to compare the point and set-valued optimality predictions differently.

- for $e = 2$, even generically set-valued optimal satisficing becomes a point prediction coinciding with expected utility maximization;
- for $e > 2$, even generically unique expected utility maximization becomes set-valued, again

Figure 8: Deviations from optimal aspirations $\overline{P}(i) - \overline{A}$ for given i choices and $\underline{P}(i) - \underline{A}$ by Treatment



Notes:Kernel density function.

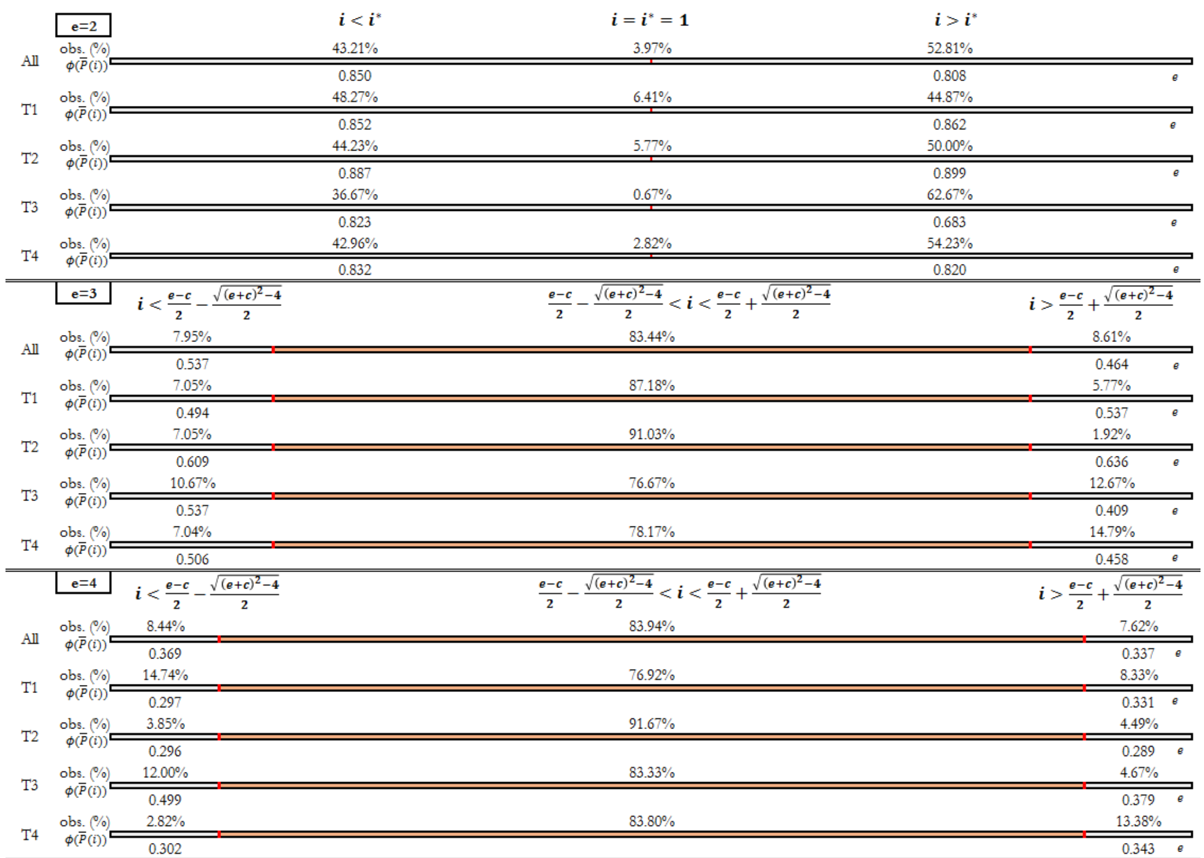
coinciding with optimal satisficing; and

- via cases with $e = 3$ and $e = 4$, one can determine how the size of the optimal set affects the degree of (non)optimal behavior.

Figure 9 and Table 12 report the choice behavior for $c = 0$. Figure 9 distinguishes between the different levels of endowment (e equal to 2, 3 and 4) and lists the percentage shares of i choices below, equal to and larger than the optimal choices. Optimality is rare when point valued ($e = 2$) but predominant when set valued ($e > 2$). Surprisingly, optimality is less strongly supported in treatment T1 when its set prediction is larger ($e = 4$ compared to $e = 3$). Only for treatments T3 and T4 does set optimality increase significantly as the set gets larger. Percentage shares below and above the optimality sets are, on average, quite similar.

Table 12 presents evidence of satisficing, which requires only $\overline{P}(i) \geq \overline{A}$ for $c = 0$ separately for treatments T3 and T4 and for i choices yielding $\overline{P}(i) = 1$ when satisficing cannot be violated and $\overline{P}(i) < 1$. In the latter case, satisficing is predominant but increasing across phases only in T3. The average amount of "burning money", $\phi(\overline{P}(i) - \overline{A})$, is larger for $\overline{P}(i) = 1$ than for $\overline{P}(i) < 1$ when satisficing, corresponding to $c > 0$ behavior. Only for T4 is "burning money" consistently reduced across phases.

Figure 9: Investment distribution and payoff averages when $c = 0$



Notes: Each bar represents the endowment interval: the share of investment choices in different endowment range is reported on top of each bar, while the average $\overline{P}(i)$ in that endowment interval is reported under the bar. In the central optimal (range) corresponding to the optimal investment level, $\overline{P}(i)$ is always equal to the maximum, that is, $\overline{P}(i) = 1$

Table 12: Share and average level of satisficing when $c = 0$

	T3		T4	
	Phase 1	Phase 2	Phase 1	Phase 2
% of $(\overline{P}(i) - \overline{A} \geq 0)$	0.84	0.88	0.89	0.88
$\phi(\overline{P}(i) - \overline{A} \mid \overline{P}(i) - \overline{A} \geq 0)$	0.279	0.290	0.267	0.228
s.d.	0.17	0.21	0.17	0.20
	$\overline{P}(i) < 1$			
% of $(\overline{P}(i) - \overline{A} \geq 0)$	0.65	0.74	0.75	0.74
$\phi(\overline{P}(i) - \overline{A} \mid \overline{P}(i) - \overline{A} \geq 0)$	0.217	0.214	0.229	0.201
s.d.	0.16	0.20	0.17	0.18
Obs.	105	105	97	99
	$\overline{P}(i) = 1$			
% of $(\overline{P}(i) - \overline{A} \geq 0)$	1.00	1.00	1.00	1.00
$\phi(\overline{P}(i) - \overline{A} \mid \overline{P}(i) - \overline{A} \geq 0)$	0.314	0.339	0.290	0.244
s.d.	0.16	0.20	0.17	0.21
Obs.	120	120	116	114

Notes: Average for 15 cases where $c > 0$.

Altogether the strongest support for optimality applies under the following conditions:

- expected utility maximization and set-optimal satisficing coincide, as $c = 0$ renders intrapersonal payoff aggregation irrelevant; and
- both concepts are set valued ($e > 2$) rather than point valued ($e = 2$). In fact, for $e > 2$, the shares of non-optimal investment choices lie between 5 and 10%; see Figure 9.

8 Conclusion

Our analysis assesses the following:

- (sub)optimality across four different between-subject treatments, T1, T2, T3 and T4; two phases with 18 i choices each, and all 36 i choices of each individual participant; and
- (non)optimal satisficing across T3 and T4, allowing the testing of satisficing and measurement of non-optimal satisficing via "burning money" and "committing suicide" separately for binary random events, boom and doom.

Due to our focus on (sub)optimality and (non)optimal satisficing, our assessments and conclusions are based on robust findings for all cases, both phases and comparable treatments. Neither optimality concept conditions its predictions on probability. What is elicited instead, namely, $\hat{p}$ in T2 and $\overline{A}$, as well as $\underline{A}$ in T3 and T4, might cognitively crowd out concentration on behaving (set)optimally but does not affect the (set)optimal choice prediction, i.

Assessing and testing (sub)optimality and (non)optimal satisficing for 18 different cases with systematically varying parameters c, e and p and varying optimal investment shares is clearly superior to concentrating on one or two cases whose conclusions could be rather case specific.

Furthermore, optimality in choosing i, as well as in aspiration formation, requires rather weak assumptions, namely, Assumption 1 and 2, respectively 3 to prefer €14 over €4, respectively to maximize payoffs via repeated use of the slider alerting participants to the payoff consequences of i choices.

Even such rather weak assumptions are systematically violated. This throughly questions accounting for empirical, i.e., experimentally observed, behavior via "rationalizing" with small noise. Neither rationality in making mistakes nor aversion concepts, of which there are several, are applicable in our setup. The systematic rejection of even weak assumptions renders any rational choice explanation an as-if explanation without any claim to be able to explain how choices are generated, i.e., without any behavioral or, specifically, psychological appeal. Nevertheless, one could learn a considerable amount from as if-explanations such as most of our findings; they suggest when and why deviations from (set)optimality occur. To provide such a rationalization is, however, quite difficult, since many instruments are ruled out by design.

In our view, taken together, the main findings and statistical results question the view that through consequentialist deliberations we aim at the best outcome. Participants do not generate their choices by anticipating their expected consequences, which presupposes that they are not only fully aware but also certain of the implications of their choice. We often seem to not trust ourselves, and we doubt whether we mentally perceive choice tasks and assess choice consequences correctly.

Our analysis is not merely destructive. Although participants are apparently not "born satisficers", learning and advising could reduce the extent of "burning money" and "committing suicide":

suboptimality and non-optimal satisficing may be avoided or reduced when alerting participants to their excessive losses and advising them on how to reduce these losses. Teaching and learning could help limit suboptimality and non-optimal satisficing.

This study should not prevent us from adopting psychological approaches (except for prospect theory and its variants) that view forward-looking consequentialist decision making as a dynamic deliberation process (see for such a process framework, albeit very far from offering an algorithm, Güth and Ploner, 2016), which denies exogenously given preferences and beliefs. A follow-up study will focus on how participants have reacted to specific parameters captured by the 18 different cases, as well as how they responded to what has been elicited in addition to the i choices. This will hopefully provide stylized facts and some orientation when theorizing about what matters, as well as how and when, in (experiments on) risky decision making.

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Appendix A

In this appendix, we report the translated version of the instructions given to participants.These instructions were given to participants in T1.

CESARE

Centro di Economia Sperimentale a Roma Est

INSTRUCTIONS FOR THE EXPERIMENT

Welcome to our experiment!

Please, read the instructions carefully.

During this experiment you will be asked to make several decisions. These decisions as well as random events will determine what you gain. You are now told how.

The experiment has two identical phases, each one composed of 18 rounds. At the beginning of each round you are endowed with an amount which you can invest in two kinds of investment: investment A and investment B. Investment A is a risk-free bond with **constant** repayment factor, **independent from the market condition**; Investment B is a risky asset whose repayment factor **changes with the market condition and the amount invested in it.**

The market can be in good or bad condition, whose probabilities are told to you in each round.

At the end of the experiment, the computer will randomly select a round and you will be paid for that round.

Once the experiment ended, you will be asked to answer a questionnaire whose information will be strictly reserved and will be used only anonymously and for research purposes.

Please, work in silence and do not disturb other participants. If you have some doubts, please, rise your hand and wait: one experimenter will come and help you as soon as she can.

ENJOY!

INVESTMENT CHOICE

Each round, you will be endowed with an amount (**e**), different in each round, that must be allocated between investment A and investment B, by moving the cursor in the bar (see screenshot). Investment A has a **constant** repayment factor (**c**), **independent from the market condition**; Investment B is a risky asset and its repayment factor **changes with market condition** (**good or bad) and the amount invested**: specifically, the investment in B is lost in bad market condition and repays only in good market condition.

Market is in good or bad condition with given probabilities **p,** respectively (**1-p**), about which you will be informed in each round.

We will illustfactor you choice task by an example which is also used to familiarize you with screenshot for stating your choice (see the figure below).

Assume, for the sake of an example, a given round in which you are endowed with **e = 3**. You must choose how much of this you want to invest in the risky asset B (**i**) and how much you want to invest in the risk-free bond A (**e-i**).

The repayment factor for the risk-free bond A is 0.29 (**c**). The repayment for the risky asset B depends on the amount you invest (**i**) and on the market condition, good or bad whose probabilities, in the example, are 14% (**p**) and 86% (**1-p**) respectively. In particular, the repayment factor of the risk investment asset *i* is *e-i* in good market condition and *0* in bad market condition. Thus the repayment of the risky investment amount *i* is *0* in bad market condition and *(e-i)*i* in good market condition.

Given the total amount to be invested (in the example 3) and the repayment factor of the risk-free bond (in the example 0.29), your choice of how much to allocate in the risky asset (**i**) and how much to allocate in the risk-free bond (**e-i**) will determine your probability of gaining €14 or with the complementary probability of gaining €4, which both depend, of course, on good or bad market condition.

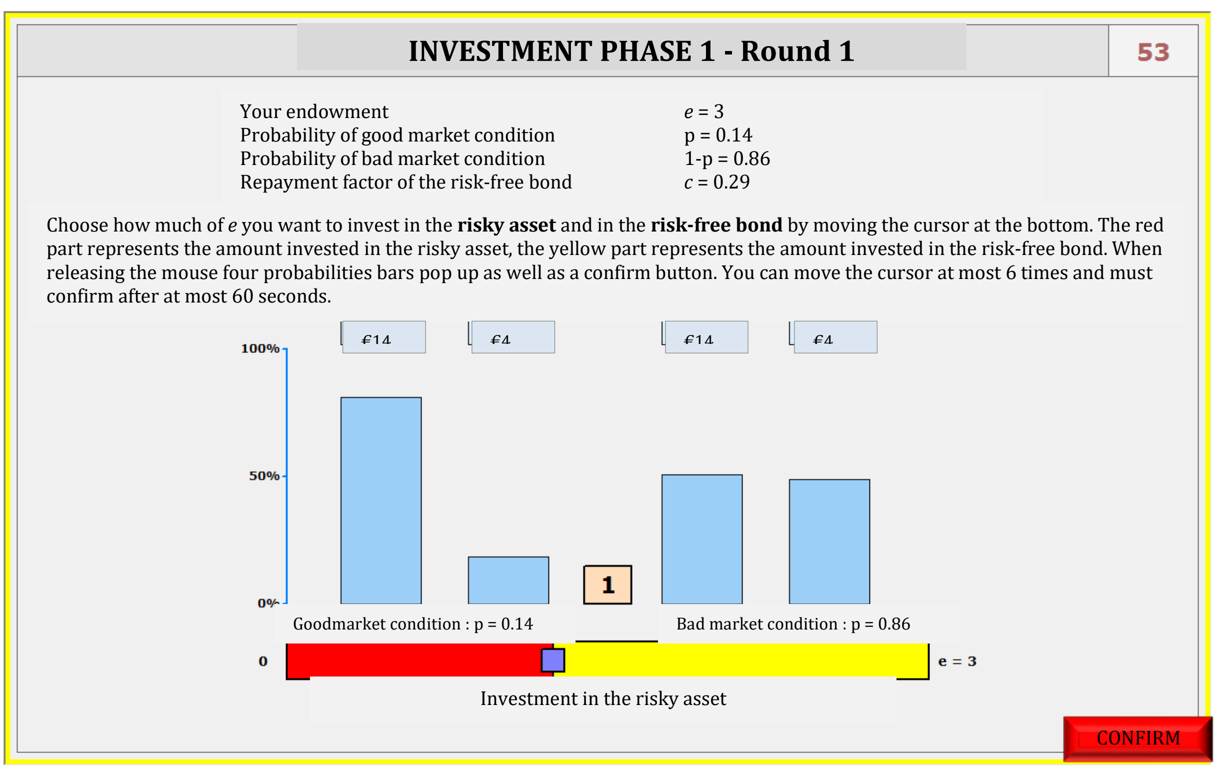
Warning: your choice will affect only the probability of gaining €14 or €4.

The probability for €14 and the complementary probability for €4 depend on your choice and on the market condition.

In the good market condition, the probability of obtaining €14 is the sum of the risk-free investment repayment **c*(e-i)** and the risky investment repayment **(e-i)*i**. The probability is shown in the screenshot by the height of the column corresponding to the good market condition, under €14, and the complementary probability of gaining €4 by the height of the column under €4. In the example, given the choice (investing about 1 in the risky asset), the probability of gaining €14 is near 80% and the probability of gaining €4 near 20%.

Alternatively, in the bad market condition, the probability of gaining €14 is only the risk-free investment repayment **c*(e-i)** which, in the example, is 50% as the complementary probability of gaining €4.

Before deciding how much to invest in investment B (**i**) you can try and see effects of your choice on the probability of gaining €14 or €4 in the two different market conditions by scrolling the cursor on the bar. You have several attempts before your final one which you must confirm. **You can move the cursor at most 6 times**. You can, of course, confirm also earlier attempts. The count of your attempts is shown in the very centre of the screen, by the number between the two columns each for the good respectively the bad market condition (in the example, 1 attempt). The number in the corner up on the right, instead, shows the time passed in the current round: for each round, you have **at most 60 seconds** to make your choice (in the example, you still have 53 seconds left).
Warning: if you do not confirm in time your payoff in that round is nil, i.e. you would not paid if this round would be randomly selected for payment.



YOUR GAIN IN THE EXPERIMENT

As already said, in this experiment **you can gain either €14 or €4**. Your actual gain in the randomly chosen payment round depends on your decision and on the market condition in that round. Furthermore, it depends on the final chance move between €14 and €4 with the success probability for €14 and the complementary probability for €4, depending on:

1. the round randomly chosen for final payment;
2. your investment choice (i) in that round;
3. the market condition in that round (either good or bad).

In addition, you will receive a show up fee of €4.

The total amount will be paid individually, privately and immediately to each participant after the experiment.

Appendix B

Figure 10: Investment choice in the experiment

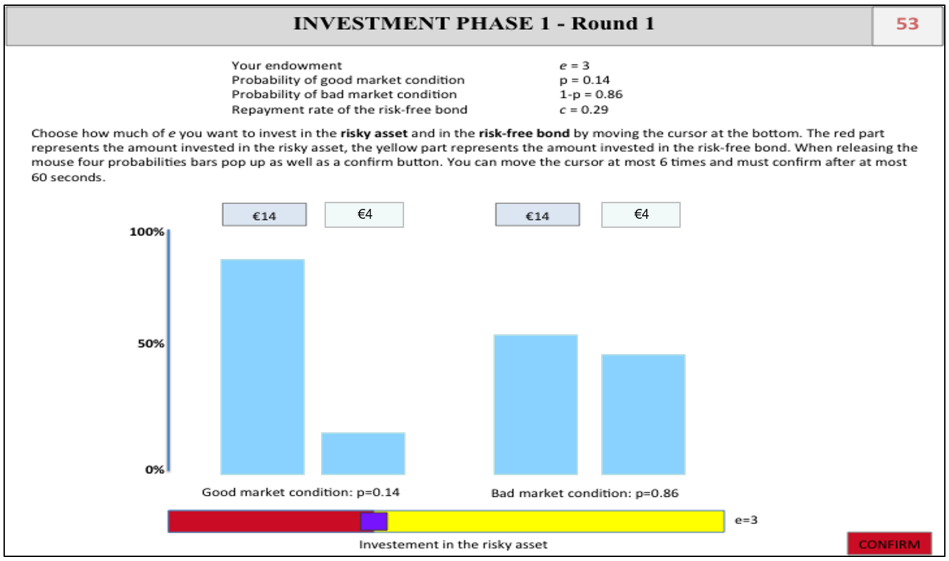


Table 13: Difference tests for probability p and probability $\hat{p}$ and payoff space deviation - T1 vs. T2

	T1 vs. T2		
	p in T1	$\hat{p}$ in T2	WRST Ho: Prob(T1) = Prob(T3)
Phase 1	0.289	0.555	0.00
Phase 2	0.289	0.539	0.00
WRST Ho: Prob(Ph1) = Prob(Ph2)	1.00	0.08	

Notes: The analysis refers to Wilcoxon Rank Sum Test (WRST) for two independent samples.

Figure 11: Investment choice in the experiment

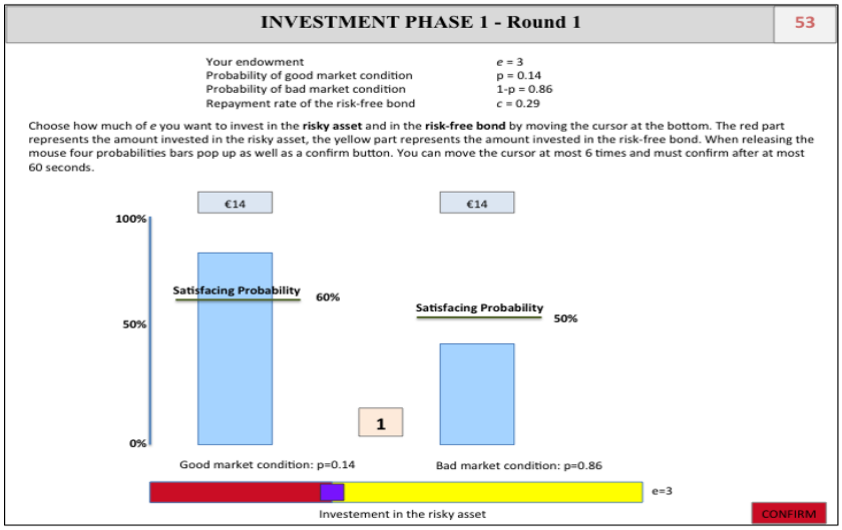


Table 14: Action and payoff space comparison - T2 vs. T4

	$i^* - i$			$P(i^*) - P(i)$			$\overline{P}(i^*) - \overline{P}(i)$			$\underline{P}(i^*) - \underline{P}(i)$		
T2 vs. T4	T2	T4	WRST(Ind.)	T2	T4	WRST	T2	T4	WRST	T2	T4	WRST
All sample	-0.282	-0.718	0.000(0.000)	0.070	0.152	0.000	0.043	0.030	0.000	0.069	0.175	0.000
Phase 1	-0.369	-0.749	0.000(0.000)	0.087	0.161	0.000	0.040	0.035	0.000	0.091	0.185	0.000
Phase 2	-0.195	-0.688	0.000(0.000)	0.054	0.142	0.000	0.045	0.025	0.000	0.046	0.165	0.000
KST(Ind.)	0.000(0.000)	0.000(0.000)		0.000	0.000		0.000	0.842		0.000	0.000	

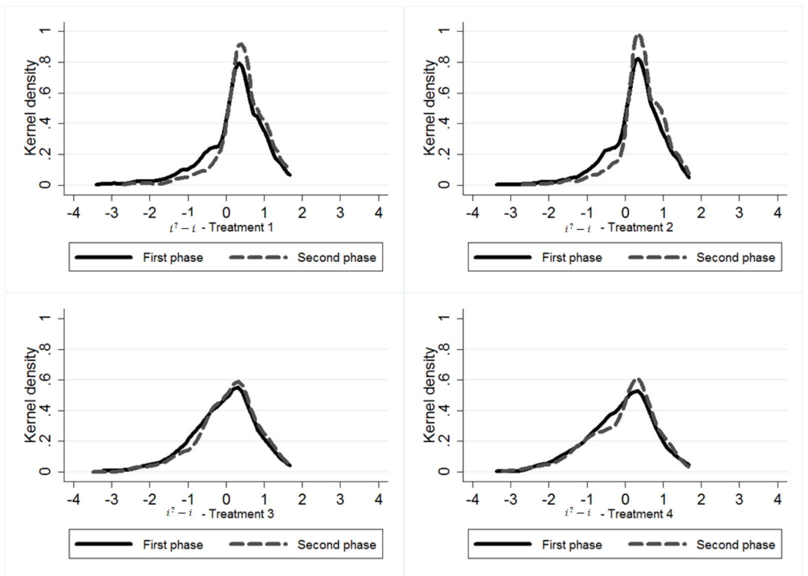
Notes: A Wilcoxon Rank Sum Test (WRST) for two independent samples was performed for comparison across treatments, and a Kolmogorov-Smirnov equality of distributions test (KST) was performed for the analysis across phases. We report the tests for individual averages in parentheses. For these tests, p-values are reported. In T2, $P(i^*)$ is computed by objective probabilities p.

Table 15: Action and payoff space comparison - T1 vs. T4

	$i^* - i$			$P(i^*) - P(i)$			$\overline{P}(i^*) - \overline{P}(i)$			$\underline{P}(i^*) - \underline{P}(i)$		
T1 vs. T4	T1	T4	WRST(Ind.)	T1	T4	WRST	T1	T4	WRST	T1	T4	WRST
All sample	-0.305	-0.718	0.000(0.000)	0.076	0.152	0.000	0.063	0.030	0.000	0.075	0.175	0.000
Phase 1	-0.409	-0.749	0.000(0.000)	0.095	0.161	0.000	0.056	0.035	0.000	0.102	0.185	0.000
Phase 2	-0.201	-0.688	0.000(0.000)	0.057	0.142	0.000	0.071	0.025	0.000	0.049	0.165	0.000
KST(Ind.)	0.000(0.000)	0.000(0.000)		0.000	0.000		0.000	0.842		0.000	0.000	

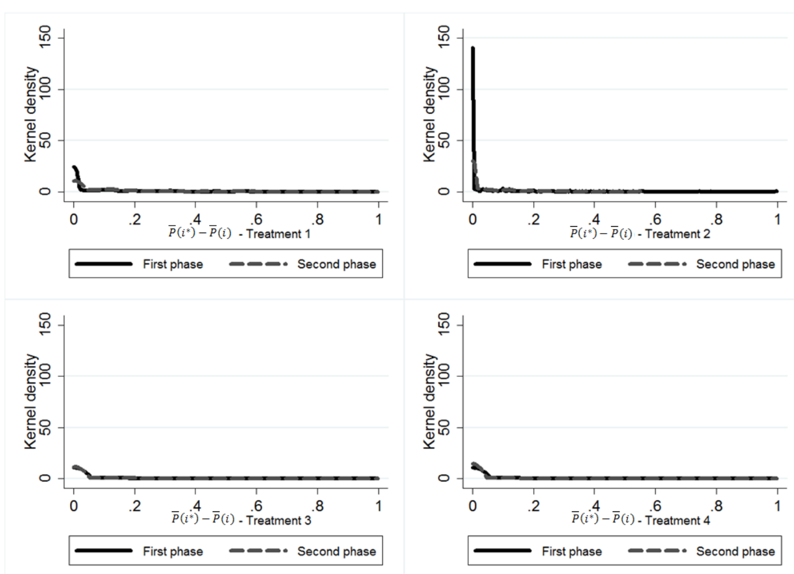
Notes: A Wilcoxon Rank Sum Test (WRST) for two independent samples was performed for comparison across treatments, and a Kolmogorov-Smirnov equality of distributions test (KST) was performed for the analysis across phases. We report the tests for individual averages in parentheses. For these tests, p-values are reported.

Figure 12: Deviation $i^{\circ} - i$ by Phase



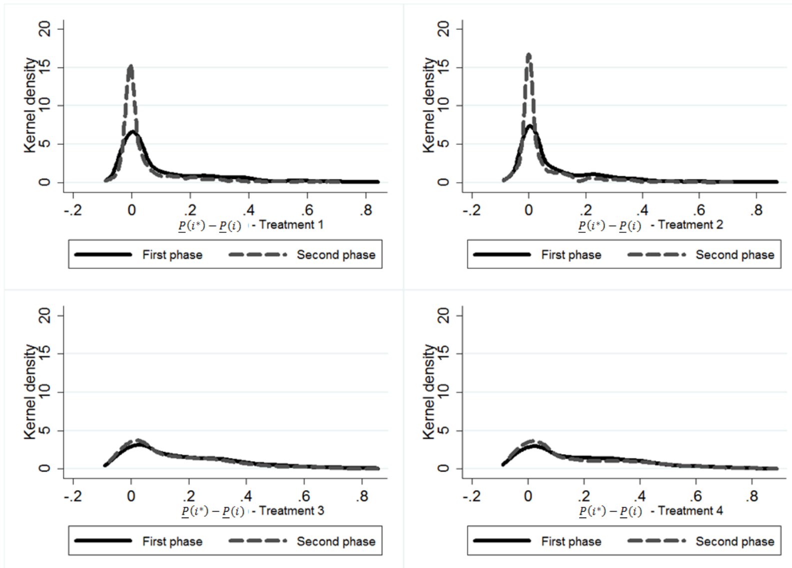
Notes: Kernel density function for cases where $c > 0$; Treatment 2 investment i° has been computed based on objective probabilities p.

Figure 13: Distance in payoff space: $\overline{P}(i^{*}) - \overline{P}(i)$ by phase



Notes: Kernel density function considering only cases where $c > 0$.

Figure 14: Distance in payoff space: $\underline{P}(i^{*}) - \underline{P}(i)$ by phase



Notes: Kernel density function considering only cases where $c > 0$.

Table 16: "Burning Money" and "Committing Suicide" if $c > 0$

	T3			T4		
	Phase 1	Phase 2		Phase 1	Phase 2	
% $\overline{P}(i) = \overline{A}$	0.31%	0.67%		2.35%	4.98%	
Observations	7	15		50	106	
% $\underline{P}(i) = \underline{A}$	0.00%	0.09%		0.00%	0.00%	
Observations	0	2		0	0	
		Burning Money				
	Phase 1	Phase 2	KST	Phase 1	Phase 2	KST
% $\overline{BM}$	48.31%	48.18%		46.38%	44.18%	
$\phi(\overline{BM})$	0.309	0.308	0.003	0.310	0.273	0.000
s.d.	0.146	0.176		0.157	0.177	
Observation	1087	1084		988	941	
% $\underline{BM}$	38.71%	40.98%		40.14%	41.97%	
$\phi(\underline{BM})$	0.212	0.231	0.271	0.165	0.149	0.070
s.d.	0.190	0.206		0.160	0.150	
Observation	871	922		855	894	
		Committing Suicide				
	Phase 1	Phase 2	KST	Phase 1	Phase 2	KST
% $\overline{CS}$	1.38%	1.16%		1.27%	0.85%	
$\phi(\overline{CS})$	0.351	0.212	0.020	0.369	0.152	0.031
s.d.	0.303	0.206		0.324	0.166	
Observation	31	26		27	18	
% $\underline{CS}$	11.29%	8.93%		9.86%	8.03%	
$\phi(\underline{CS})$	0.172	0.139	0.064	0.202	0.173	0.275
s.d.	0.150	0.130		0.171	0.139	
Observation	254	201		210	171	

Notes: The analysis refers to the p-values of Kolmogorov-Smirnov equality of distributions tests between phases. Cases with $c = 0$ are excluded.

Table 17: BM_ϵ and CS_ϵ comparison - T3 vs. T4

	$\overline{BM}_\epsilon$			$\underline{BM}_\epsilon$			$\overline{CS}_\epsilon$			$\underline{CS}_\epsilon$		
T3 vs. T4	T3	T4	WRST	T3	T4	WRST	T3	T4	WRST	T3	T4	WRST
Phase 1	0.318	0.326	0.343	0.272	0.226	0.000	0.401	0.493	0.237	0.226	0.239	0.823
Obs.	1055	936		663	594		27	20		188	175	
Phase 2	0.322	0.315	0.932	0.291	0.213	0.000	0.282	0.239	0.846	0.198	0.216	0.248
Obs.	1031	806		714	591		19	11		136	134	
KST	0.022	0.005		0.264	0.366		0.112	0.022		0.144	0.526	
T3 vs. T4	T3	T4	WRST	T3	T4	WRST	T3	T4	WRST	T3	T4	WRST
	$\overline{BM}$			$\underline{BM}$			$\overline{CS}$			$\underline{CS}$		
Phase 1	0.309	0.310	0.974	0.212	0.165	0.000	0.351	0.369	0.932	0.172	0.202	0.060
Obs.	1087	988		871	855		31	27		254	210	
Phase 2	0.308	0.273	0.000	0.231	0.149	0.000	0.212	0.152	0.390	0.139	0.173	0.015
Obs.	1085	941		922	864		26	18		201	171	
KST	0.003	0.000		0.271	0.070		0.020	0.031		0.064	0.275	

Notes: A Wilcoxon Rank Sum Test (WRST) for two independent samples was performed for comparison across treatments, and a Kolmogorov-Smirnov equality of distributions test (KST) was performed for the analysis across phases. Cases with $c = 0$ are excluded. The first part of the table considers the misspecification ϵ, while the second part does not.