Behavioral heterogeneity in dynamic search situations: Theory and experimental evidence

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Abstract

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Behavioral Heterogeneity in Dynamic Search Situations: Theory and Experimental Evidence

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Abstract: This paper presents models for search behavior and provides experimental evidence that behavioral heterogeneity in search is linked to heterogeneity in individual preferences. Observed search behavior is more consistent with a new model that assumes dynamic updating of utility reference points than with models that are based on expected-utility maximization. Specifically, reference point updating and loss aversion play a role for more than a third of the population. The findings are of practical relevance as well as of interest for researchers who incorporate behavioral heterogeneity into models of dynamic choice behavior in, for example, consumer economics, labor economics, finance, and decision theory.

Keywords: dynamic choice; behavioral heterogeneity; reference points; individual differences; loss aversion

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1 Introduction

Dynamic choice situations are prevalent in our everyday lives, for example when we go shopping, search for a new job, or trade on the stock market. Existing research finds that people are very heterogeneous with respect to their behavior in dynamic choice situations (see, e.g., Boswijk et al., 2007; Hommes et al., 2005a; Sonnemans, 1998, 2000), and economic theory suggests that this heterogeneity in dynamic choice situations is reflected in preference heterogeneity. For example, we would expect systematic differences in dynamic choice behavior between very risk averse and very risk seeking types of people. This raises the following questions: Does information on individual preferences help us predict how people behave in dynamic choice situations? Is there further heterogeneity in dynamic choice behavior that differences in individual preferences cannot explain, for example because behavior is not consistent with the predictions of standard preference-based economic models? The answers to these questions concern the foundations of dynamic choice behavior. However, while there is an enormous experimental literature on the foundations of decision behavior in static decision situations, the foundations of behavior in dynamic decision situations, despite being equally important, remain largely unexplored.

This paper explores the foundations of dynamic choice behavior by answering the questions above. I do so by using laboratory experiments that test various models of dynamic choice behavior, providing evidence on the link between preferences and real observed dynamic choice behavior. The specific contributions of this paper are as follows: First, I develop a new dynamic choice model that involves sequential updating of utility reference points. Second, I provide evidence from two experiments that this reference point model explains heterogeneity in individual search behavior better than search models based on expected utility theory. And third, I show that while heterogeneity in search behavior can be systematically linked to heterogeneity in individual preferences for many subjects, there is also a considerable fraction of subjects, whose search behavior is inconsistent with the predictions of utility-based economic models. In other words: preference heterogeneity alone cannot explain all heterogeneity in search behavior.

Economic science assumes that preferences are the key determinants of behavior. Therefore, knowing which preferences are related to real observed behavior is of inherent interest for the field. In fact, structural knowledge about the link between preferences and behavior is an important requirement for normative as well as for positive economics. More specifically, the findings of this paper are of interest for researchers who are building models of behavior in dynamic choice situations, and they are relevant for decision theory, since they help to understand the determinants and properties of individual search behavior in markets (e.g., Zwick et al., 2003). The findings also serve as a guide to theoretical and structural econometric specifications that explicitly allow for individual heterogeneity in applied search theory; these specifications are being developed in many fields, including research on consumer search and job search (Eckstein and van den Berg, 2007). Finally, since little is known about reference point formation over time in dynamically risky decision situations, my findings are relevant for numerous theoretical and applied issues in
finance, e.g. when it comes to stock selling decisions (Baucells et al., 2007; Gneezy, 2005; Grinblatt and Han, 2005), as well as for life-cycle savings decisions (Bowman et al., 1999).

The experimental and theoretical investigation of dynamic choice behavior requires a decision task that is representative of dynamic choice situations in our real life as well as implementable in the laboratory without loss of control. Such a task is a search task. First, the simple decision structure of search tasks masks a complicated optimization problem that – comparable to dynamic choice situations in our everyday lives – cannot be solved without a computer; at the same time, these tasks occur often in our everyday life, e.g. when we look for the best price for a certain product or when we search for a new job. Second, search tasks are attractive for laboratory investigations, because participants in a laboratory experiment understand immediately their simple sequential decision structure.

It is thus no surprise that decision behavior in search situations has been intensively investigated both theoretically and experimentally in the fields of economics, mathematics, and psychology since the 1950’s. Simon (1955) and Stigler (1961) completed seminal theoretical work in the economic strand of this literature. Since then, numerous authors (e.g., Cox and Oaxaca, 1989; Harrison and Morgan, 1990; Hey, 1981; 1982; 1987; Houser and Winter, 2004; Kogut, 1990; Schunk and Winter, 2009; Sonnemans, 1998; 2000) have investigated variations of search problems, and they have focused on examining which search strategies exist. However, the central question addressed by this paper, the extent to which theoretical models explain the link between individual heterogeneity in search strategies and heterogeneity in preferences, remains unexplored. Finally, it is also worth mentioning that there is a growing literature on dynamic models with heterogeneous expectations (see, e.g., the survey by Hommes, 2006); the behavioral foundations of this literature are also investigated experimentally (Heemeijer et al., 2009; Hommes et al., 2005b). While the price process is endogenous in this literature, the price distribution is exogenous in my experimental setup, i.e. it is neither affected by individual expectations nor by individual decisions. This allows me to focus only on the question how preference heterogeneity and dynamic choice strategies are linked.

This paper proceeds as follows. First, I develop various search models, in particular the reference point model, in order to discuss the links between individual preferences and search behavior (section 2). Then, the experimental designs (section 3) and the methodology for drawing inference about search behavior and preferences based on data from two experiments are described (section 4). Next, the link between elicited preferences and observed search behavior is investigated (section 5): I present descriptive information, a correlation analysis, and a structural econometric analysis that exploits the discrete time-to-event panel nature of the data. The methodology and possible explanations for the findings are discussed in section 6; section 7 concludes.

2 Models of Search Behavior

In this section I first derive the optimal search behavior of an expected utility maximizer (section 2.1). For the derivation of the decision rules, two cases are considered: In the first case, the cost of each completed search step is treated as sunk costs; in the second case,
I derive the finite horizon optimal stopping rule assuming that subjects do not treat past search costs as sunk costs. Finally, in section 2.2, I develop the reference point model.

2.1 Optimal Stopping Behavior in Search Tasks

Assume that a searcher’s goal is to purchase a certain good that she values at €100. The searcher sequentially observes any number of realizations of a random variable X, which has the distribution function $F(\cdot)$. In the current experiment, $F(\cdot)$ is a discrete uniform distribution with lower bound €75 and upper bound €150. Let the cost of searching a new location be €c. Assume that at some stage in the search process, the minimal price that the searcher has observed so far is €m.\(^1\) Basic search theory assumes that individuals treat the cost of each search step, once completed, as sunk costs (Kogut, 1990; Lippman and McCall, 1976) and that they compare the payoff of one additional search step with the payoff from stopping.\(^2\)

Then, subjects solve the problem based on a one-step forward-induction strategy and the expected gain from searching once more before stopping, $G(m)$, is generally given by:

$$G(m) = -\left[1 - F(m)\right]m - \int_{75}^{m} x dF(x) - c + m. \quad (1)$$

The term $\otimes$ accounts for the case in which a price larger than $m$ is found with probability $(1 - F(m))$. In this case, $m$ remains the minimum price. The term $\oplus$ stands for the case in which a lower price than $m$ is found and computes the expected value in this case. There exists a unique price $m^*$ with $G(m^*) = 0$, if $G(\cdot)$ is continuous and monotonic. Straightforward manipulation shows that the solution to this problem is identical to solving the following problem for $m$:

$$\pi(100 - m) = (1 - F(m))\pi(100 - m - c) + \int_{75}^{m} \pi(100 - x - c) dF(x) \quad (2)$$

Here, $\pi(\cdot)$ is the payoff-function from the search game. The payoff is truncated at 0 in the experiment:

$$\pi(x) = max\{0, x\} \quad (3)$$

The left-hand side of equation (2) is the payoff from stopping, and the right-hand side denotes the payoff from continuing the search. It is found that the optimal strategy is to keep searching until a price of $X$ less than, or equal to, the optimal price $m^*$ has been observed. For the search task considered in this paper, I find $m^* = 86$. That is, a risk-neutral searcher has the following decision rule: Stop searching as soon as a price less than or equal to 86 is found.

---

\(^1\) For the remainder of the paper, the currency units are skipped whenever possible. All monetary values are in euros.

\(^2\) Kogut’s (1990) findings show that a certain proportion of subjects does not treat search cost as sunk. A model in which search cost are not treated as sunk cost is presented later in this section.
Now assume a searcher with an arbitrary, monotone utility function \( u(\cdot) \). The equation that determines her reservation price \( m^* \) then has the following form that follows from (2):\(^3\)

\[
\begin{align*}
    u(100 - m) &= (1 - F(m))u(100 - m - c) + \int_{75}^{m} u(100 - x - c)dF(x) \\
    &\quad \quad \text{Equation (4)}
\end{align*}
\]

Equation (4) is solved numerically for the reservation price \( m^*(\eta) \), given the search environment and a utility function on gains that is parameterized entirely by a parameter (vector) \( \eta \). The solution has the constant reservation price property, independent of the functional form of \( u(\cdot) \). Figure 1 shows the constant reservation price decision rule for different risk attitude parameters of, e.g., a CRRA or a CARA utility function. The more risk averse the searcher is, the higher is her constant reservation price. Henceforth, I refer to rules of this type as forward optimal rules, keeping in mind that this rule is only optimal conditional on the individual utility function and on the assumption of a one-step forward strategy that ignores sunk costs.

** Include figure 1 about here **

Now, consider that subjects do not treat search costs as sunk costs. That is, for their decision whether to stop or to continue the search, they consider the total benefits and costs of the search; the agent stops searching only if the stopping value is higher than the continuation value. It follows that the problem is treated as a finite horizon problem that is solved backwards. Define \( S_t = \{t, m\} \) as the agents’ state vector after \( t \) search steps. After the agent has stopped searching, she will buy the item and she receives a total payoff:

\[
    \Pi(S_t) = \max\{0, 100 - m - t \cdot c\}. \quad \text{(5)}
\]

The agent stops searching only if the continuation value of the search is lower than the stopping value. The recursive formulation of the decision problem is therefore:

\[
    J_t(S_t) = \max\{\Pi(S_t), E[J_{t+1}(S_{t+1})|S_t]\}. \quad \text{(6)}
\]

\( E(\cdot) \) represents the mathematical expectations operator, and the expectation is taken with respect to the distribution of \( S_{t+1}|S_t \). Again, this problem has the reservation price property at every \( t \). The reservation price begins at 86, first stays constant, then starts decaying slowly, reaches 80 in the 19th round, and then decays at a rate of about one per round from that point forward.

For a searcher with an arbitrary, monotone utility function \( u(\cdot) \), the payoff function is then:

\[
    \Pi^u(S_t) = \max\{0, u(100 - m - t \cdot c)\}. \quad \text{(7)}
\]

The corresponding recursive formulation of the dynamic discrete choice problem is:

\[
    J^u_t = \max\{\Pi^u(S_t), E[J^u_{t+1}(S_{t+1})|S_t]\}. \quad \text{(8)}
\]

\(^3\) This equation does not characterize the optimal solution to the search problem. It gives the optimal strategy for a searcher with arbitrary risk attitude, captured by \( u(x) \), who ignores sunk costs, and who uses a one-step forward induction strategy.
This problem has, at every \( t \), the reservation price property. The monotonically falling reservation price implies that the agent should not exercise recall, i.e. she should not recall previously rejected prices. Figure 2 plots the reservation price paths for a CRRA-utility function specification; figure 3 assumes a CARA-specification. Henceforth, I refer to rules of this type as backward optimal rules. These rules are optimal search rules conditional on the individual utility function.

** Include figure 2 about here **

** Include figure 3 about here **

From the theoretical deliberations so far it can be inferred that – regardless of what type of rule subjects use, forward or backward optimal rules – the more risk averse a person is, the earlier she should stop search, i.e. the higher is the reservation price that she uses.

### 2.2 The Reference Point Model

When talking to people that are actually facing a search situation, for example graduate students on the job market, many people talk about their decision situation as if they were comparing their possible future offers from continuing the search with the current best alternative that they have already been offered. They consider everything that is worse than the current best payoff that they have for sure as a loss relative to that sure payoff, and everything that is better is considered as a gain relative to the sure payoff. The model that I develop in this section, the reference point model (henceforth: rp-model), captures this idea that future possible payoffs are compared to a reference point. The model is based on a concept from the psychology of decision-making, the concept of loss aversion, which plays a central role in Kahneman and Tversky’s (1979) descriptive theory of decision-making under risk. Loss aversion refers to the tendency of people to be more sensitive to reductions in their current level of well-being than to increases. The rp-model claims that during the search task, subjects set reference points relative to which the decision whether to stop or to continue the search is evaluated in terms of gains and losses. While the models based on EU-maximization (see previous subsection) implicitly assume that the reference point is always at zero payoff, the rp-model assumes a reference point which is always at the current best payoff.

To formalize these ideas, let \( u(\cdot) \) be the individual utility function. Following Kahneman and Tversky (1979), I decompose the function into the utility function on gains, \( u^+(\cdot) \), and the utility function on losses, \( u^- (\cdot) \):

\[
u(x) = \begin{cases} 
u^+(x) & x \geq 0 \\ \nu^-(x) & x < 0. \end{cases}
\]  

(9)

Subjects have to decide whether to stop or to continue the search at every search step \( t \). The reference point at time \( t \) is the payoff that they get from stopping when they realize the best price draw, \( m_t \), that they have in hand at time \( t \). The utility from continuing the search is evaluated relative to this reference point:
If subjects find a price lower [higher] than \( m_t - c \) in the next round \( t+1 \), they make a net gain [loss] relative to their current situation where they have \( m_t \) in hand – see the term \( \otimes \) [\( \oplus \)] in (10).

The model implicitly assumes that subjects solve the problem based on one-step forward-induction. In the rp-model the expected gain at time \( t \) from searching once more before stopping, \( G(m_t) \), is given by

\[
\begin{align*}
G(m_t) &= \int_{-\infty}^{m_t-c} u^+(m_t - x - c) dF(x) \otimes \\
&\quad + \int_{m_t-c}^{m_t} u^-(m_t - x - c) dF(x) + (1 - F(m_t)) \cdot u^-(c). 
\end{align*}
\] (10)

That is, the model assumes that people sequentially update their reference point in every time step. Model (10) is stationary in the same sense as the forward optimal model (4): The search behavior is independent of time \( t \) since subjects focus on the marginal gain or loss from the next step but not on the total payoff from the search. Identical with the prediction of the forward optimal search model (4), this model results in a constant reservation price over time. As in the forward optimal search model, the negligence of the sunk costs incurred during the search process is here responsible for the stationarity of the model.

I rewrite equation (10) for simplicity. For this purpose, define \( p(x, m_t) \) as the rp-payoff-function, i.e. the function that determines individual payoff (relative to the reference point) in the framework of the rp-model (10), conditional on having the best offer \( m_t \) in hand at time \( t \):

\[
p(x, m_t) = \begin{cases} 
    m_t - x - c & x \leq m_t \\
    -c & x > m_t 
\end{cases}
\] (11)

With the help of (11), the rp-model (10) is equivalently written as:

\[
\begin{align*}
G(m_t) &= \int_{-\infty}^{m_t-c} u^+(p(x, m_t)) dF(x) + \int_{m_t-c}^{\infty} u^-(p(x, m_t)) dF(x) \\
&= \int_{-\infty}^{\infty} u(p(x, m_t)) dF(x). 
\end{align*}
\] (12)

Several studies (e.g., Kogut, 1990; Sonnemans, 1998) find that many subjects also focus (to some extent) on total earnings from the search game, instead of only focusing on the marginal return of another draw. This translates into a reservation price that does not remain constant, but is falling when \( t \) increases, similar to the prediction of the backward optimal model (8).

In the framework of the rp-model, this means that subjects take into account that total payoff is left-truncated at 0. In other words, if subjects focus on total earnings, they take into account that when continuing the search, they do not risk losing money if their payoff...
at the current reference point is already 0. That is, the maximal loss that they can incur
is the search cost (if the payoff at the reference point is higher than the search cost), or
the payoff at the reference point (if the payoff at the reference point is less than the search
cost).
This idea, namely that subjects also focus on total earnings instead of only focusing on
the marginal return of another draw, is translated into the framework of the rp-model by
a modification of the rp-payoff-function.
For this purpose, I first define two functions \( q(\cdot) \) and \( v(\cdot) \):
\[
q(y) = \begin{cases} 
q(y) = y & y \geq 0 \\
0 & y < 0
\end{cases}
\]
\( (13) \)
\[
v(y) = \begin{cases} 
v(y) = y & y \geq -c \\
0 & y < -c
\end{cases}
\]
\( (14) \)
The modified rp-payoff-function \( p(x, m_t, t) \) now has the following form.\(^4\)
\[
p(x, m_t, t) = \begin{cases} 
q(100 - c \cdot t - x - c) & m_t \geq 100 - c \cdot t \\
v(m_t - x - c) & m_t < 100 - c \cdot t \land x \leq m_t \\
v(m_t - (100 - c \cdot t)) & m_t < 100 - c \cdot t \land x > m_t
\end{cases}
\]
\( (15) \)
With the modified version of the rp-payoff-function, the rp-model (12) is written as follows:
\[
G(m_t) = \int_{-\infty}^{m_t-c} u^+(p(x, m_t, t))dF(x) + \int_{m_t-c}^{\infty} u^-(p(x, m_t, t))dF(x)
= \int_{-\infty}^{\infty} u(p(x, m_t, t))dF(x).
\]
\( (16) \)
I have now developed two search models, (16) and (10), that assume that subjects update
their reference points during the search process. The EU-based models presented in the
previous subsection are based on only one branch of the utility function, \( u^+(\cdot) \), that is, in
these models, behavior can essentially be captured by a one-parameter functional form.
However, both rp-models are based on two independent branches of the utility function,
\( u^+(\cdot) \) and \( u^-(\cdot) \). In line with existing empirical studies on loss aversion (e.g., Benartzi
and Thaler, 1995; Schmidt and Traub, 2002; Tversky and Kahneman, 1992), I therefore
assume the following one-parameter form of the reference point utility function:
\[
u(x) = \begin{cases} 
u^+(x) = x & x \geq 0 \\
v^-(x) = \lambda \cdot x & x < 0
\end{cases}
\]
\( (17) \)
This functional form imposes that only the kink at the utility reference point plays a
role for observed search behavior. This assumption is introduced to reduce the reference
point model to only one preference parameter (as in the case of the EU-based models)
which can be identified with a standard experimental method, and I impose the same
assumption for the identification of loss aversion measures based on the experimental
data. The measurement of a parameter that characterizes loss aversion is, of course,
always connected to a functional form assumption and there is a discussion about the
definition and empirical measurement of an index for loss aversion (see Johnson et al.,

\(^4\) A detailed derivation of the function \( p(x, m_t, t) \) is given in the appendix of the paper which is available
in the JEDC Supplement Archive.
I will come back to this important issue later in this paper and I will also argue that the main conclusions from this paper are robust to this assumption. Based on utility specification (17), the crucial parameter that determines individual search behavior is now the individual loss aversion parameter $\lambda$. The stationary rp-model (10) implies a constant reservation price search rule; the level of the reservation price path is a function of loss attitude $\lambda$. The non-stationary rp-model (16) implies, in line with the stationary rp-model (10), a reservation price path that varies systematically with the loss aversion parameter $\lambda$: the higher loss aversion, the higher the reservation price. However, in contrast to the stationary rp-model, the reservation price starts falling after a certain number of time-steps (see figure 4).

The stopping rules derived from the reference point models (10) and (16) are comparable to two classical search models that are based on EU-maximization:

- The stationary rp-model (10) predicts the same search behavior as the EU-based forward optimal search model (equation (4)), and both models assume that subjects ignore sunk costs.

- Similar to the EU-based model (8), the non-stationary rp-model (16) predicts that the reservation price is first constant and starts falling after a certain number of time steps. In both models, subjects do not ignore sunk costs.

While EU-based models and the rp-model predict very similar search behavior, the explanation for the search behavior is different: In the rp-model, loss aversion explains the level of the reservation price path, whereas in the EU-models, risk aversion explains this level. The rp-model is built on the idea that “loss aversion [...] provides a direct explanation for modest-scale risk aversion” (Rabin, 2000, p. 1288). Due to the similar predictions of the models, distinguishing between these preference-based explanations for search behavior requires independent measures of individual preferences, which I elicit in the experiment for each subject using standard lottery procedures. I come back to this point in section 5.2.

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5 For example, equation (17) implies that $\lambda$ is a global measure of loss aversion, but it is obvious that under the assumption of more flexible functional forms for $u^+(\cdot)$ and $u^-(\cdot)$, loss aversion could also be defined locally, i.e. as a function of $x$. As section 3 shows, I estimate six different measures of loss aversion (based on six different $x$-values and one aggregate estimate for loss aversion) for each subject and the results of this paper are investigated for all six measures. This serves as a robustness check, because it underlines that the findings of this paper are independent of a specific local measure of loss aversion.

6 Algebraic transformations show that under (17) the rp-model (10) is identical to the classical risk neutral forward induction model (2) under the assumption that $\lambda = 1$.

7 It is tempting to find a parametrization of the decision environment (i.e., search cost $c$ and price distribution $F(\cdot)$), in which the (empirical) identification of the underlying preferences based on only the observed search behavior (and without additional and independent preference information) would be easier. This would require finding an environment, in which the models do not yield similar predictions over observed ranges of the underlying preference parameters. Further theoretical deliberations as well as simulation studies, obtainable from the author upon request, show that identification is not easier in other environments. The key issue is that at the search step where the models yield different predictions, most subjects have already stopped searching. For example, consider a risk neutral searcher. This person has a constant reservation price of 86 for 8 search steps (see figure 2 and figure 3), but if
3 Experimental Design

Two experiments have been conducted. Both experiments combine a lottery-based preference elicitation mechanism with a price search task, in order to link information from an independent measure of individual preferences with information on sequential decision behavior. Both experiments differ mainly in the preference elicitation method. Therefore, I describe the design of the first experiment (henceforth referred to as experiment I) in detail and I outline the design of experiment II only at the end of this section.

3.1 Experiment I

Experiment I consisted of three parts (A, B, and C) that were presented to the subjects in fixed alphabetical order. Parts A and C of the experiment served to elicit parameters that characterize subjects’ preferences, and part B consisted of a series of repeated price search tasks used to elicit subjects’ search behavior.

Note at this point that the decision in the price search task (part B), namely whether to stop (s) or to continue (c) the search, corresponds conceptually to the choice between a sure payoff (s) and a lottery (c) with several consequences. In order to create similar decision situations in both, the search task (part B) and the preference elicitation parts (part A and C), the certainty equivalent method (e.g., Wakker and Deneffe (1996) for risk aversion, and Tversky and Kahneman (1992) for loss aversion) has been used for preference elicitation. This way, subjects also deal with decision situations involving the comparison between a sure payoff (s) and a lottery (c) in the preference elicitation part of the experiment. The certainty equivalent method was used in this experiment since the decision situation used in this method is most similar to the decision situation in search tasks, as mentioned above. The method has been used with various starting parameters, both for the case of loss and risk aversion, to get an estimate of the robustness of the results.

The description of the design begins with part C, continues with part A, and ends with part B. This makes some details of the design clearer.

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8 Wakker and Deneffe (1996) used - also at the University of Mannheim where the present experiment takes place and at various other places - the same elicitation method with the same stimuli, identical number of iterations, and identical probability parameters, but with different starting values. This method has the advantage that subjects are exposed to only few lottery decisions and – specifically in this study – that it involves comparisons between sure payoffs and lotteries.

9 To further motivate the usage of the certainty equivalent method, note that it avoids using probabilities other than 50-50-probabilities. 50-50-probabilities have the advantage that they are well-known to most decision-makers through events such as throwing coins.
Part C: Risk Attitude

In part C, the certainty equivalent method (e.g., Wakker and Deneffe, 1996) is used to elicit individual risk attitude. That is, subjects are presented with a two-outcome lottery (c) and a sure payoff (s) and they are asked to enter one missing value such that they are indifferent between the sure payoff and the participation in the lottery. In total, only three lotteries are presented to the subjects.

Two values, $x_{\text{min}} = €0$ and $x_{\text{max}} = €24$, are defined. The subject is asked to enter a sure payoff, the certainty equivalent $s_{0.50}$, that is as attractive to her as the participation in the lottery ($x_{\text{min}}, 50% ; x_{\text{max}}, 50%$). In the second question, the subject is asked to enter the sure payoff $s_{0.25}$ that is as attractive to her as the lottery ($x_{\text{min}}, 50% ; s_{0.5}, 50%$). Finally, in the last question, the subject is asked to reveal indifference between the lottery ($s_{0.5}, 50% ; x_{\text{max}}, 50%$) and a sure payoff by stating the sure payoff $s_{0.75}$.

The values 0, $s_{0.25}$, $s_{0.5}$, $s_{0.75}$, and 24 are equally spaced in terms of their utility. This allows for the estimation of the individual utility function, and I obtain a risk attitude index for each subject in the domain between €0 and €24.

Part A: Loss Attitude

Part A consists of two blocks, (A-1) and (A-2), that are presented in random order, such that a direct order effect on the behavior in the search task can be excluded. In block (A-1) I use a method by Tversky and Kahneman (1992). Subjects are again presented with a 50-50-gamble ($x, 50% ; y, 50%$) and a sure outcome ($s$). In all five presented lottery tasks the sure consequence ($s$) has the value €0. One consequence of the two-outcome lottery has a value of $x \in \{-1,-10,-25,-50,-100\}$. These values are presented in random order. Subjects are asked to enter the monetary value $y$ of the other outcome of this 50-50-lottery such that the lottery and the sure payoff of €0 are equally attractive to them (i.e., they have to adjust a mixed prospect to acceptability).

In block (A-2), subjects are presented with three pure certainty-equivalent lotteries of the same type as in part C, but with $x_{\text{min}} = €1$ and $x_{\text{max}} = €9$.

Part B: Search Behavior

In part B subjects perform a sequence of search tasks. Each subject’s goal is to purchase a certain good that she values at €100. The good is sold at infinitely many locations.

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10 Note that the search task is designed such that subjects could also earn at least €0 and at most €24.

11 Please see the appendix, available in the JEDC Supplement Archive, figure 5, for the graphical presentation of the lotteries.

12 The lottery with $x_{\text{max}} = €24$ was intentionally not shown in part A (but only in part C) in order to exclude an effect on the behavior in the search task in which the maximum possible gain is €24. The main purpose of the lotteries in block (A-2) in the framework of this design, in which the order of (A-1) and (A-2) was randomized, was to exclude systematic effects of (A-1) on the search task. Note that the data from (A-2) can still be used to check the validity of the analyses presented in this paper: I find that the conclusions of this paper are independent of which risk attitude parameters, those stemming from part C or those stemming from part (A-2), are used in the analysis.

13 In other words, subjects are not prevented from searching as long as they want. It is not reasonable, however, to search for more than 25 steps, because, given the payoff structure, every search task lasting for more than 25 rounds ends with a zero payoff. No subject has searched for more than 25 steps.
and visiting a new location costs €1. Subjects are informed that the integer price at each location is drawn independently from a uniform price distribution with a lower bound of €75 and an upper bound of €150. After each price draw, subjects can stop and choose any price encountered so far, or they can continue their search at the incremental cost of another euro. The outcome of each search task is calculated as the evaluation of the object (100) minus the price at the chosen location minus the accumulated search cost. To ensure that subjects are experienced with the task and to minimize the observation of learning behavior, subjects are allowed to perform an unlimited number of practice search tasks before performing a sequence of 15 tasks that determine their payoff for part B of the experiment. Finally, after the experiment is completed, one of these 15 rounds is selected randomly to determine the payoff.

The search-model question.
After the search task is finished, there is one additional lottery question (henceforth referred to as the search-model question), worded as follows:

You have now dealt with lottery tasks and a price search task. Perhaps you have realized that the decision in the search task (to stop or to continue the search) is similar to the decision between the lotteries presented to you:

If you stop your search, you obtain a sure payoff, but if you decide to continue the search, you essentially play a lottery with a risky outcome.

Which of the two lotteries, I or II, is most similar to the lottery that you play when you continue the search from your point of view?

**Lottery I:** (€ A, p%; € B, (100-p)%)  
**Lottery II:** (€ X, p%; € Y, (100-p)%)  

(A, B, X, and Y denote arbitrary positive numbers, and p is a (percentage) number between 0 and 100).

This question is of importance: Search models that are based on expected utility theory (henceforth: EU-theory) assume that subjects evaluate the next search step as a pure lottery (cf. lottery I). In contrast, the new rp-model assumes that subjects evaluate the next search step as a mixed lottery (cf. lottery II). Therefore, the answer to the search model question allows for subdividing the subject sample into two groups: subjects behaving in a manner consistent with an EU-based model and subjects behaving in a manner consistent with a model in which subjects set utility reference points.

A few final remarks on the design of experiment I: First, the purpose of including both mixed (A-1) and pure (A-2) lottery tasks in the first part is to have subjects get used to both tasks before they have to answer the search-model question. Second, to make sure that subjects have sufficient experience with the search task and have been exposed to pure as well as mixed lotteries, the search-model question is presented directly after they have performed the search task. Third, since subjects are informed on the instruction sheet about the properties of the search experiment (i.e., they are aware that their minimum

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14 The graphical presentation of the two lotteries I and II presented in the search-model question is identical with the graphical presentation of all other lotteries (see appendix, available in the JEDC Supplement Archive). Furthermore, the two lotteries, I and II, are presented in random order.
payoff is 0 and that their maximum payoff is 24), the certainty-equivalent method with
the values $x_{\text{min}} = 0$ and $x_{\text{max}} = 24$ is used after they have answered the search-model
question (i.e. in part C). This avoids the potential influence of an exposure to lotteries
with $x_{\text{min}} = 0$ and $x_{\text{max}} = 24$ on the answer to the search-model question.

3.2 Experiment II

Experiment II focused only on the relationship between risk attitude and search behavior.
In particular, any confounding effects, e.g. due to the exposure to lotteries that involve
losses, were avoided in experiment II. Correspondingly, experiment II involved only parts
B (elicitation of risk attitude) and C (elicitation of search behavior) and the order of
both tasks was randomized. While part B (the search task) was implemented identically
to experiment I, part C measured risk aversion based on the price list procedure used
by Holt and Laury (2002), henceforth HL. The price list procedure involves ten choices
between the paired lotteries described in table 1. The payoffs are the same in all 10
choice situations and the payoffs for option A are less variable than the potential payoffs
for option B. While in the first row, the probability of the high payoff for both options
is 10%, it increases to 100% in the last row. A very risk seeking person should switch
to option B early, and an extremely risk averse person should switch over by decision
10 in the bottom row. Following the procedure in HL, payoffs for each subject were
determined by randomly implementing one of the ten lotteries and paying according to
the subjects decision on that lottery at the end of the experiment.

** Include table 1 about here **

3.3 Administration and Payoffs

Experiment I was conducted in the summer and fall of 2004 and experiment II was con-
ducted in February 2007. Both experiments were conducted in the experimental lab-
atory of the SFB 504, a national research center at the University of Mannheim, and
involved undergraduate and graduate students from the University of Mannheim. The
experiments were run entirely on computers using software written by the author. All
payoff procedures, including the random selection of the search round and of the lottery
that would be paid out, took place after the experiment was over. The instruction sheet
presented full information about the search task and it was emphasized that, (i), subjects’
payoff was truncated at €0 (i.e., they could not incur losses from the search task) and
that, (ii), they would not earn a show-up fee (i.e., no reference point was induced).

4 Inference about Preferences and Search Behavior

This section first presents and discusses how risk and loss attitude are estimated from the
data obtained in the lottery tasks of the experiments. Then, I describe how individual
search behavior is classified based on the data obtained in the search experiments.

Note that the maximum payoff from this task is €24, as in the search task. That is, risk attitude is
measured in the same domain in which we observe the search behavior.
4.1 Estimation of Risk Attitude

From the data obtained in experiment I I estimate individual risk attitude based on a parametric approach allowing for a specification of both constant relative and constant absolute risk aversion (CRRA and CARA, respectively). For both functional forms, the utility function is estimated from the data obtained in part C using nonlinear least squares. Utility functions of the power form (e.g., Abdellaoui, 2000; Tversky and Kahneman, 1992) assume that subjects have constant relative risk aversion (CRRA):

$$u(x) = x^{(\alpha+1)}$$

(18)

The estimated coefficient $\alpha$ characterizes each subject’s risk attitude under the CRRA-assumption. If $\alpha > 0$, the subject is risk seeking; if $\alpha < 0$, the subject is risk averse.

Utility functions of the exponential form (e.g., Currim and Sarin, 1989; Pennings and Smidts, 2000) assume that subjects have constant absolute risk aversion (CARA):

$$u(x) = 1 - e^{-\gamma x}$$

(19)

For $\gamma = 0$ the function is defined to be linear, i.e. the subject is risk neutral. In the CARA-specification, the estimated coefficient $\gamma$ characterizes each subject’s risk attitude in the sense of an Arrow-Pratt-measure of risk attitude (Pratt, 1964), that is: $-u''(x)/u'(x) = \gamma$. If $\gamma < 0$, the subject is risk seeking; if $\gamma > 0$, the subject is risk averse.

For the data obtained in experiment II, I follow Holt and Laury (2002) and use the total number of “safe” A choices as a measure of risk attitude.

4.2 Estimation of Loss Attitude

Based on the subjects’ responses in part A of the experiment, an individual-specific index for loss aversion is calculated. The statistic $\lambda_x = -y/x$ is a measure of individual loss aversion, where $x \in \{-1,-10,-25,-50,-100\}$ and $y$ is the response to the corresponding lottery given in part A. This method of estimating a coefficient of loss aversion is the method used in Tversky and Kahneman (1992) and its idea is to obtain a simple measure that captures the tradeoff between gains and losses. Note that because of the five $x$-values that are used for the elicitation, I essentially elicit five different measures of loss aversion, and I will use all five measures in the subsequent analyses. Additionally, I use OLS to estimate one aggregate measure of loss aversion, $\lambda_{OLS}$, from all five $x$-values, assuming the functional form specified in equation (17).\(^\text{16}\)

4.3 Classification of Decision Rules Used in the Search Task

The next step of the analysis is to determine the decision rule used by each subject in the search task. In order to do so, a fixed set of candidate decision rules is specified, the “universe of search rules”, and the decision rule that fits observed behavior best is attributed to each subject. Since the utility-based search models developed in section 2

\(^{16}\) I am grateful to an anonymous referee for this suggestion.
establish a relationship between preference parameters and decision rules, I can assign preference parameters to the subjects based on the attributed search rules.\textsuperscript{17}

**The Universe of Search Rules**

For the investigation of the relationship between individual preferences and search behavior, I use as candidate decision rules all those search rules that can be derived from the search models developed in section 2. The universe of search rules (i.e., the set of candidate search rules that are used in this paper to characterize search behavior) consists of the following 51 rules:

The first class of these decision rules, henceforth referred to as type-1-rules, share the constant reservation price property (see figure 1). These rules are either based on the assumption that subjects use the forward optimal search rule (equation (4), the EU-based model that neglects sunk costs), or the stationary rp-model (equation (10), the rp-model that neglects sunk costs). Each rule says that the subject uses a reservation price \( r \in \{78, \ldots, 94\} \) which is constant during the complete search round. The universe contains 17 type-1-rules denoted by \( t_{178}, t_{179}, \ldots, t_{194} \). Every rule corresponds to a certain risk attitude parameter \( \alpha_{\text{search}} \) and \( \gamma_{\text{search}} \).\textsuperscript{18}

The second class of decision rules is based on the finite horizon search model (i.e., the backward optimal search rules developed in section 2). According to these type-2-rules, the reservation price is a function of the search step \( t \) and of individual risk attitude. I assume again 17 different type-2-rules, denoted by \( t_{278}^{\text{CRRA}}, t_{279}^{\text{CRRA}}, \ldots, t_{294}^{\text{CRRA}} \), derived based on the assumption of a CRRA-specification of the utility function: For the first rule, the reservation price at \( t = 1 \) is 78, for the second rule, it is 79, etc., and for the last rule it is 94 (see figure 2). Each reservation price path corresponds to a certain \( \alpha \)-interval. The 17 price paths \( t_{278}^{\text{CRRA}}, t_{279}^{\text{CRRA}}, \ldots, t_{294}^{\text{CRRA}} \) correspond to a decreasing sequence of 17 \( \alpha \)-intervals taken from the interval \([-0.973, 25.20]\). Alternatively, the 17 type-2-rules can be derived based on the assumption of a CARA-specification of the utility function (see figure 3). Then, each reservation price path corresponds to a certain \( \gamma \)-interval, and the 17 paths correspond to an increasing sequence of \( \gamma \)-intervals taken from \([-2.028, 0.837]\). In the paper, it will always be clear from the context whether the particular type-2-rules are derived based on either a CRRA- or a CARA-specification of the utility function. Conditional on the assumption that a certain subject uses a finite horizon search model, risk coefficients \( \alpha_{\text{search}} \) and \( \gamma_{\text{search}} \) can be attributed to her. These coefficients are the risk attitudes that explain best the observed search behavior.

Finally, the type-3-rules are based on the non-stationary rp-model (16), the rp-model developed under the assumption that subjects focus on total payoffs from searching. The reservation price is a function of the search step \( t \) and of individual loss aversion \( \lambda \) (see

\textsuperscript{17} I can attribute only small intervals of preference parameters and not exact point-values, since the prices presented in the price search task are discrete.

\textsuperscript{18} Under risk neutrality, one finds a constant reservation price of 86. The set of 17 constant reservation price rules, \( t_{178}, t_{179}, \ldots, t_{194} \), is sufficiently large to classify all observed behavior, no subject is assigned a lower or higher reservation price, if I allow for a larger universe of rules (for further information, please see the appendix in the JEDC Supplement Archive).
Again, 17 different rules are considered, \( t_{378}, t_{379}, \ldots, t_{394} \): For the first rule, the reservation price at \( t = 1 \) is 78, for the second rule, it is 79, etc., and for the last rule it is 94. The rules correspond to a decreasing sequence of \( \lambda \)-intervals taken from the interval \([0.042, 3.392]\). Based on the type-3-rules, I attribute to every individual a loss coefficient \( \lambda_{\text{search}} \). The assigned loss attitude coefficient best explains the observed search behavior conditional on the assumption that the subject uses the non-stationary rp-model.

**Classification Procedure**

To classify search behavior, I determine for each subject the proportion of choices consistent with each decision rule and I maximize this proportion over the set of all candidate decision rules (i.e., a subject is assigned the decision rule that generates the largest fraction of correct predictions). It is assumed that each subject follows exactly one of the decision rules in the universe of candidate rules and that she uses the same rule in each of the 15 payoff tasks. This assumption seems reasonable in view of the fact that all subjects are experienced with the search task when they begin the 15 payoff relevant tasks (see section 3.1).

Formally, the classification procedure is described as follows: Each search rule \( c_i \in \mathcal{C} \), where \( \mathcal{C} \) is the universe of search rules described above, is a unique map from subject \( i \)'s information set \( S_{it} \) to her continuation decision \( d_{it} \in \{0, 1\} : d^c_{it}(S_{it}) \rightarrow \{0, 1\} \). Now, let \( d^*_{it} \) denote the observed decision of subject \( i \) in period \( t \). Then, define the indicator function:

\[
X^c_{it}(S_{it}) = 1(d^*_{it} = d^c_{it}(S_{it})) \tag{20}
\]

Let \( T_i \) be the number of decisions that are observed for subject \( i \). I attribute to each subject the search rule that maximizes the likelihood of being used by that subject:

\[
\hat{c}_i = \arg \max_{c_i \in \mathcal{C}} \sum_{t=1}^{T_i} X^c_{it}(S_{it}) \tag{21}
\]

**5 Results**

This section starts with self-contained descriptions of the findings from the utility function elicitation (part A and part C) and from the search task (part B). The main contribution of this section is the combination of the data on individual preferences and on search behavior, such that correlations on the subject level can be analyzed. Specifically, I test whether the hypotheses on the relationship between search behavior and preference parameters, derived in section 2, are supported by the data. This section starts with a detailed analysis of experiment I and ends with an analysis of experiment II which provides further evidence on the relationship between individual preferences and sequential decision behavior.
5.1 Part C and Part A: Risk and Loss Attitude

From the data in part C two indices of risk attitude, an index $\alpha$ (CRRA specification) and an index $\gamma$ (CARA specification), were estimated for each subject.\footnote{Alternatively, the data from part (A-2) can be used for the estimation of risk attitude. The data from part C are preferable, since in part C, the risk attitude index has been elicited in a monetary domain which is identical to the payoff domain of the search task. (Part (A-2) has in fact only been included to avoid order effects, see section 3.1). Therefore, only the results from part C are reported here. The conclusions of this paper are identical if the data from part (A-2) are used. The corresponding analyses can be obtained from the author upon request.}

From the data obtained in part (A-1), five indices of loss attitude, $\lambda_1$, $\lambda_{10}$, $\lambda_{25}$, $\lambda_{50}$, and $\lambda_{100}$, as well as an aggregate index, $\lambda_{OLS}$, were calculated for each subject.

Table 2 reports results of the nonlinear least squares estimation of the risk coefficients $\alpha$ and $\gamma$ of the 106 participants, including the mean coefficient of determination $R^2$ for those two estimations. The coefficients of determination are close to 1 for all nonlinear regressions. The proportions of different risk attitudes in the sample are independent of the functional form assumption of the utility function. The proportions of subjects in the particular categories is in line with findings in other experimental studies. For example, the proportion of risk seeking subjects is higher than the proportions reported by studies based on, e.g., price list elicitation methods (e.g., Harrison et al., 2005; Holt and Laury, 2002), and it is lower than the proportions reported by, e.g., Abdellaoui (2000).\footnote{Several empirical studies confirm the predominance of loss averse choices (e.g., Fishburn and Kochenberger, 1979; Tversky and Kahneman, 1992; Schmidt and Traub, 2002; Pennings and Smidts, 2003).}

Table 3 shows the results of the loss aversion elicitation part of the experiment. Across all loss aversion questions subjects were predominantly loss averse in their choices.\footnote{I find median loss aversion coefficients that are all significantly higher than 1. The values are higher than those reported in Schmidt and Traub (2002), but lower than the median values reported in Tversky and Kahneman (1992). As expected, there is a high and statistically significant degree of correlation between the individual answers to the five loss aversion questions (see table 4). In fact, 39% of the subjects exhibited constant loss aversion, that is, their loss aversion coefficient is identical for all loss aversion questions.}

5.2 Part B: Search Behavior

Search behavior differs considerably across individuals, detailed information by treatment is presented in the appendix (section 8.3, available in the JEDC Supplement Archive). Focusing on the average search duration of the subjects, I find overall a preponderance of early stoppers compared to behavior under the risk neutral optimal stopping rule. This confirms results from earlier experimental studies that have looked at search duration (e.g., Cox and Oaxaca, 1996; Hey, 1987; Sonnemans, 1998, see the appendix in the JEDC Supplement Archive for details).
Considering (a) the universe of 51 search rules (see figures 1, 2, 3, and 4), (b) the rather low average number of search steps compared to the optimal strategy, and (c) the fact that only a finite number of search rounds per individual (namely 15 rounds) is observed, it is clear that discrimination between very similar reservation price paths, that is across search rule types (e.g., between $t_{180}$, $t_{280}$, and $t_{380}$), is hardly possible. Individual search rule types are not (empirically) identified.\(^{21}\) In contrast, the identification within a certain rule type is clear: For example, there is significant difference in whether a subject’s behavior is more consistent with, for example, $t_{180}$ rather than with $t_{181}$.\(^{22}\) In other words, individual risk attitude or loss attitude parameters can be attributed to a subject based on her behavior in the search task, conditional on the assumption that the subject behaves according to a specific model. But, as I have already discussed at the end of section 2.2, this model itself cannot be identified based on the observation of the search behavior alone; independent measures of preferences that are elicited in part A and part C are needed additionally.

5.3 The Search-Model Question: Subdividing the Sample

As I have explained above (see section 3.1), the search-model question is used to subdivide the sample into $P^R$ and $P^C$: 39 subjects answered that they see a similarity between the search task and lotteries with gains and losses and were categorized into group $P^R$; 67 subjects think about lotteries with only gains and were categorized into group $P^C$. Descriptive statistics on individual preferences and search behavior by subgroup are reported in table 5.

** Include table 5 about here **

5.4 Analyzing Search Behavior and Individual Preferences

As mentioned above, observed search behavior alone is not sufficient to identify “users” of the reference point model. However, in order to discriminate between subjects that use the rp-model and subjects that use one of the classical EU-based models, I can derive hypotheses on the relationship between search behavior and individual preferences that are testable based on the information gained in parts A, B, and C of the experiment. Essentially, I hypothesize that for subjects from $P^R$, individual loss aversion is systematically related to search behavior, while for subjects from $P^C$, risk aversion is systematically related to search behavior:

*Conditional on the assumption* that a population $P^R$ of subjects uses the rp-model, the rp-model predicts that:

(H1) The more loss averse – measured as $\lambda_x$ in part A – a subject from $P^R$ is, the fewer search steps (denoted by $ss$) this subject should do in the search task.

(H2) For subjects from $P^R$, the index of loss aversion $\lambda_x$ – elicited in part A – should be positively correlated with the index of loss aversion, $\lambda_{search}$, elicited in the search task,

\(^{21}\) Asymptotically, that is if an infinite number of search rounds per individual is observed, individual search rules types are, of course, identified.

\(^{22}\) For more details about the classification, please see the appendix, section 8.3, available in the JEDC Supplement Archive.
part B.

*Conditional on the assumption that a population $P_C$ of subjects does not use the rp-model but one of the classical models (either the forward optimal search model or the backward optimal search model), it is claimed that:*

**H3** The more risk averse – measured as $\alpha$ and $\gamma$ in the preference elicitation part C – a subject from $P_C$ is, the fewer steps $ss$ this subject should do in the search task.

**H4** For subjects from $P_C$, the indices of risk attitude – measured as $\alpha$ and $\gamma$ in the preference elicitation part C – should be positively correlated with the particular indices of risk attitude $\gamma_{search}$ and $\alpha_{search}$, respectively, revealed through the search behavior.

In the remainder of this section, I study the correlation between preference parameters and search parameters in the sample. Then, I develop a structural econometric model that investigates which of the risk and loss aversion measures has better explanatory power for the observed search duration. Before these analyses, it is helpful to compare descriptive statistics on preference estimates (see table 2 and table 3) with the theoretical findings on the relationship between preference parameters and search behavior (see section 4.3). This gives a first impression of the relationship between the empirical findings and the theory.

*Risk attitude (CRRA-specification):* Table 2 shows that all estimates for $\alpha$ lie in the interval $[-0.457, 2.345]$. From the developed search models follows that these estimates correspond to reservation price paths that start between 83 (for $\alpha = 2.345$) and 87 (for $\alpha = -0.457$). That is, essentially only the following search rules are compatible with the preference estimates: $\{t_{X_{83}}, ..., t_{X_{87}}\}$ for $X \in \{1, 2\}$.

*Risk attitude (CARA-specification):* Table 2 shows that all estimates for $\gamma$ lie in the interval $[-0.153, 0.093]$. These estimates correspond to reservation price paths that start between 84 (for $\gamma = -0.153$) and 87 (for $\gamma = 0.093$). That is, only the following search rules are relevant: $\{t_{X_{84}}, ..., t_{X_{87}}\}$ for $X \in \{1, 2\}$.

*Loss attitude:* The estimated $\lambda_x$-values lie in the interval $[0.5, 20]$, see table 3. This corresponds to reservation price paths that start between 83 (for $\lambda = 0.5$) and 98 (for $\lambda = 20$). From the universe of search rules, the following rules apply: $\{t_{X_{83}}, ..., t_{X_{94}}\}$ for $X = 3$.

The first finding from this descriptive analysis is: The variation in the estimated levels of individual risk attitude is not sufficient to explain the heterogeneity in the observed search behavior. As I have already argued, the complete universe of search rules is needed and also sufficient to describe the search behavior of all observed subjects (please see the appendix in the JEDC Supplement Archive for further information). The second finding from the descriptive analysis is that the estimated loss aversion coefficients are compatible with a considerably wider range of different search rules than the estimated risk aversion coefficients. Except for one subject, the variation in loss aversion exactly captures the range of observed heterogeneity in search behavior.

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23 It was always the same subject who is responsible for the maximum value for $\lambda$ in all five cases (see table 3. Without this subject, reservation price paths between 83 and 95 would correspond to all estimated $\lambda_x$-values.
Correlation Analysis

Table 6 reports the results of an investigation of the above-mentioned hypotheses (H1)-(H4) based on a rank correlation analysis between observed preference and search parameters. A clear pattern emerges: For the complete sample \( P \), there are negative correlations of at least marginal significance between the different estimates of individual loss aversion and the number of search steps (ss); this is consistent with (H1). In contrast, measures of individual risk attitude (\( \alpha \) and \( \gamma \)) are not correlated with the number of search steps. For the subgroup \( P^R \), I find strong support for (H1): There are significantly negative correlations between all different estimates for individual loss aversion and the number of search steps (ss), demonstrating the robustness of the results. For four out of the six estimated values, the correlation is even significant at the 1%-level. Additionally, results from these analyses support (H2): The estimates for individual loss aversion derived from the lottery questions, \( \lambda_\ell \), and the estimates derived from the observed search behavior, \( \lambda_\text{search} \), are correlated at the 10%-level (\( \lambda_1 \) and \( \lambda_{10} \)), or at the 5%-level (\( \lambda_{25} \), \( \lambda_{50} \), \( \lambda_{100} \), and \( \lambda_{OLS} \)). For \( P^C \), no significant correlations are found at all. Furthermore, we find that the hypotheses (H3) and (H4) are not supported by any of the considered subgroups either.

** Include table 6 about here **

Unobserved Effects Duration Analysis

A structural econometric analysis of the relationship between individual preferences and search duration is presented in this subsection and controls for the simultaneous influence of risk and loss attitude on search behavior. Additionally, this analysis includes unobserved effects for each search round in order to capture possible behavioral differences that stem from the particular sequence of price draws that the subjects face in each single round. The analysis also exploits the discrete time-to-event-nature and multiple-spell-nature: The event is the stopping of the search, the duration is measured discretely as the number of search steps, and 15 spells (= search rounds) per subject were observed. For one specific search round, let \( T \geq 1 \) denote the search duration that has some distribution in the population. From the distribution function of \( T \), I derive the hazard function \( h_0(t) \) for \( T \). The discrete time hazard gives the probability of stopping the search in the next time step, conditional on not having stopped so far:

\[
h_0(t) = P(T = t \mid T \geq t)
\]  

(22)

Assuming that the subjects in the population use a constant reservation price rule, the hazard function \( h_0(t) \) is constant. That is, the stopping events are generated from a process without memory and \( h_0(t) = h_0 \), leading to a geometric duration distribution.\(^{24}\) To account for the finite horizon nature of the search problem (i.e., subjects stop their search in time step 25 if they have not been successful until then), a piecewise constant hazard function is used:

\[
h_0(t) = \begin{cases} 
  h_1 & t < 25 \\
  h_2 & t = 25.
\end{cases}
\]  

(23)

\(^{24}\) The constant hazard assumption can be motivated based on theoretical deliberations and based on empirical findings about the fit of constant reservation price paths. The constant hazard assumption is discussed in the appendix, section 8.4, available in the JEDC Supplement Archive.
To investigate the hypotheses derived above, I test whether the hazard, i.e. the conditional probability of stopping in the next time step, can be explained by individual preference parameters. Therefore, two covariates $X$ are used in the hazard function: one covariate that characterizes risk attitude ($\alpha$ or $\gamma$) and one covariate characterizing loss attitude ($\lambda_{10}, \lambda_{25}, \lambda_{50}, \lambda_{100}$, or $\lambda_{OLS}$). The idea of a proportional hazard is adopted (i.e., the conditional individual probability of stopping the search differs proportionately based on a function of the covariates). For discrete time data, this leads to the complementary log-logistic model (Clayton and Hills, 1993) and the discrete time hazard can be written as:

$$h_i(t, X) = 1 - \exp[-\exp(\beta'X_i + \delta_1 h_1 + \delta_2 h_2)], \quad (24)$$

where, $i = 1, ..., 106$. $\beta$ is a parameter vector, $h_1$ and $h_2$ characterize the baseline hazard.

Now, recall that every subject had to play 15 search rounds. All prices were drawn from a uniform distribution. The series of price draws are different across rounds but they are identical across individuals. Therefore, I expect an unobserved effect for each search round. To account for this unobserved heterogeneity, a random effect that is common to all observations from a certain search round $j$ ($j = 1, ..., 15$) is included. The following model is considered:

$$h_{i,j}(t, X) = 1 - \exp[-\exp(\beta'X_i + \delta_1 h_1 + \delta_2 h_2 + u_j)], \quad (25)$$

where $u_j$ is supposed to be normally distributed with mean zero.

Table 7 presents estimation results for the complete sample and for the subgroups. In all estimations a likelihood ratio test suggests that the included unobserved effect is highly statistically significant. For the complete sample of subjects, $P$, (H1) is supported: An increase in individual loss aversion is related to a significant increase in the conditional probability of stopping the search, i.e. to a decrease in search duration. This effect is significant at the 5%-level for $\lambda_{10}$, $\lambda_{25}$, and $\lambda_{50}$; it is marginally significant for $\lambda_1$, regardless of the specification of the risk attitude coefficient ($\alpha$ or $\gamma$). In all specifications, risk attitude has no significant explanatory power for search duration.

Considering the subsample $P^R$, stronger support for (H1) is found: Apart from $\lambda_{100}$, the estimates for individual loss aversion have explanatory power for search duration at the 5%-significance level ($\lambda_{OLS}$), or even at the 1%-level ($\lambda_1, \lambda_{10}, \lambda_{25},$ and $\lambda_{50}$). Again, individual risk attitude is insignificant in all specifications.

In the subgroup $P^C$, no preference parameter has significant explanatory power. I have performed all analyses presented in table 7 including higher order terms of the risk and loss aversion measures in order to test for possible nonlinear relationships. Similarly, I have included information on participant age, gender, and field of study. The same conclusions as those reported above are obtained. While the risk attitude terms are never jointly significant, the loss attitude terms are jointly significant in the same cases as reported in table 7. Furthermore, sociodemographic characteristics are always insignificant.\textsuperscript{25}

\textsuperscript{25} The robustness of the results from the duration analysis has been checked in detail. Please see the appendix (available in the JEDC Supplement Archive), section 8.4, for a brief discussion of different specifications of the duration model.
According to the analyses presented above, all estimated loss attitude coefficients have better explanatory power for individual search behavior than the estimated risk attitude coefficients, which are insignificant in all analyses. The findings concerning the explanatory power of loss aversion do not hold for the subgroup $P^C$, but they are very strong for the subgroup $P^R$, suggesting that members of the two groups behave differently when “solving” the search task.

Further Evidence from Experiment II

In experiment II, risk attitude of the subjects was measured according to Holt and Laury (2002) as the point where a subject switches from option A to option B. Very risk seeking subjects have a low switchpoint, risk averse subjects have a high switchpoint. The mean switchpoint is 6.6, suggesting that subjects are risk averse on average. Similar to Holt and Laury I also find that more than two thirds of the subjects choose more than 4 safe choices. Table 8 displays the distribution of risk attitudes for the 40 participants.

The most direct way of testing for a relationship between risk attitude and search behavior is to correlate the HL measure of risk attitude and the number of search steps on a subject level. A correlation coefficient $\rho$ of $-0.05$ and a $p$-value of 0.76 are found, suggesting that preference parameters and search behavior are not correlated.

6 Discussion

This paper focuses on the development and experimental testing of various models for dynamic choice behavior, in particular the reference point model (rp-model). The results suggest that the rp-model is similar to EU-based models in its predictions about reservation price paths, but it is better than EU-based models in reconciling the experimental data on individual preferences with the data on individual search behavior. Combined with established empirical results on individual preferences (such as the empirical distribution of loss aversion in a population, see, e.g., Johnson et al., 2006; Pennings and Smidts, 2003; Schmidt and Traub, 2002; Tversky and Kahneman, 1992), the rp-model – in contrast to EU-based models – is consistent with many existing findings on search behavior, for example the considerable heterogeneity of search rules and the predominance of early stopping in the population (Cox and Oaxaca, 1989; Hey, 1987; Sonnemans, 1998).

To further investigate individual heterogeneity, I hypothesize that at least a specific subgroup, $P^R$, of the subjects uses the proposed rp-model, and I find strong evidence for this hypothesis. The subgroup $P^R$ is identified with the help of the search-model question. Under the assumption that subjects understand this question correctly, the question is likely to be an instrument for dividing the complete sample into the particular subgroups

---

26 All except one of the 40 subjects (97.5%) switched only once. As in Holt and Laury (2002), the findings from the analysis reported in this paper do not change if the subject who switches from B back to A is dropped.
Note, however, that the main result of this paper – namely that individual loss aversion is systematically related to search behavior, whereas risk aversion is not related to search behavior – holds independently of this search-model question.

Two issues have to be kept in mind when interpreting the results from this study. First, the presented experimental setup is based on one specific search environment which is characterized by the price distribution, the search cost, and the option to recall previously rejected offers. It is conceivable that subjects behave differently in a different search environment, e.g., an environment, in which the price distribution is not known. A second modification would be to allow for considerably longer time between the search steps. In this case, the observed effect of loss aversion might rather be called an endowment effect (Huck et al., 2005; Kahneman et al., 1991): If a person holds an object that she may keep for sure for a certain time, she might consider this object as an endowment, and the next step in the search is evaluated only relative to this endowment.

The contribution of this paper is to link information on behavior in an elementary dynamic choice situation with information on individual preferences and to investigate correlations at the subject level. Controlling for the effect of risk attitude, I obtain support for the hypothesis that loss aversion is related to the observed heterogeneity in sequential decision behavior. However, there is no evidence that risk aversion is related to sequential decision behavior, i.e. there is no evidence that support the classical EU-based models. Note at this point that different measures for risk aversion have been used and the evidence is consistent: In experiment I, I used a measure based on the certainty equivalent method (Wakker and Deneffe, 1996) and in experiment II, a measure that is based on a price list method (Holt and Laury, 2002) was used. Finally, in a related contribution that focuses on people’s search heuristics and on a different dynamic choice context, Schunk and Winter (2009) use a parameter-free trade-off method (Abdellaoui, 2000).

There are two principal explanations for the findings of this paper: First, although the presented findings are based on three different risk elicitation methods, loss aversion could simply be better to measure than risk aversion. This explanation would concern all studies that use stakes at the laboratory level and that involve measures of individual preferences. A second explanation which is in line with existing laboratory and field evidence on myopic loss aversion in dynamic decision tasks, such as stock market decisions (e.g., Baucells, et al., 2007; Benartzi and Thaler, 1995; Odean, 1998), is that people set reference points during their search.

Future work investigating the link between preferences and behavior could extend this study by focusing on the question to what extent certain independently elicited preference measures (e.g. risk preferences elicited in lottery tasks) are able to exactly predict the usage of the corresponding stopping rule in the search task. Similarly, how people exactly form and update reference points in dynamic choice situations is still an important open question. This paper contributes to this literature through the laboratory analysis of a stylized and easily understandable, but sufficiently complex and representative dynamic choice task, which ensures full control for the researcher. While it is of very basic interest to get a better understanding of the foundations of dynamic choice behavior, the paper is also of direct relevance. For example, the findings of this paper can be combined with findings on the distribution of loss aversion in the population (see, e.g., Johnson et al.,
2006, who provide a large sample multivariate analysis of the distribution of loss aversion in the German, Austrian, and Swiss population). It follows, that older people as well as less educated people deviate more from optimality in their search behavior than others. That is, these people would stop too early when searching for the best price of a product or when searching for jobs on the labor market.

7 Conclusions

People are heterogeneous with respect to their dynamic choice behavior. Using data obtained in two controlled laboratory experiments that involved a search task as a simple representative of dynamic choice situations, I have shown that this heterogeneity can be linked to heterogeneity in individual preferences, specifically to loss aversion. In contrast, various measures for risk aversion have no explanatory power. The newly proposed reference point model describes observed search behavior better than models derived from expected utility theory. Overall, these findings suggest that in search tasks, many people set utility reference points tasks which they use to evaluate potential future outcomes. Interestingly, there is also a considerable fraction of people whose behavior seems inconsistent with utility-based decision models. Knowing the preferences (risk or loss attitude) of these people does not help us predict their behavior. In most cases, a few simple decision heuristics govern these people’s behavior. Houser and Winter (2004) and Sonnemanns (1998, 2000) classify those simple behavioral rules in a similar dynamic choice environment. Schunk and Winter (2009) show that the behavior of those individuals for whom there is no relationship with individual risk preferences, indeed often often corresponds to simple decision heuristics, such as satisficer heuristics or constant reservation price heuristics.

The finding that there is considerable heterogeneity in decision behavior is not new, and numerous studies have investigated the link between individual preferences and behavioral heterogeneity in static decision situations. The specific contribution of this paper is to provide information about the link between heterogeneity in individual preferences and heterogeneity in dynamic choice behavior via experimental tests of various models of dynamic choice behavior. The findings of this paper, particularly the result that many people set reference points in dynamic choice tasks, are of interest for researchers who incorporate behavioral heterogeneity into models of dynamic choice behavior. They are relevant for recent theoretical and applied research in, e.g., decision theory and marketing science (Zwick et al., 2003), labor economics (Eckstein and van den Berg, 2007), finance (Gneezy, 2005; Baucells, 2007), and life-cycle theory (Bowman et al., 1999).

Acknowledgement

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8 Appendix

8.1 Graphical Presentation of the Lotteries on the Computer Screen

** Include figure 5 about here **

Note: The instructions for the two experiments and the software for running the experiment can be obtained from the author upon request.

8.2 On the Function $p(x, m_t, t)$ in the RP-Model

The form of the rp-payoff-function $p(x, m_t, t)$ becomes clear under a rigorous case differentiation with respect to possible price draws. $q(\cdot)$ and $v(\cdot)$ are defined as in section 2.2, i.e.

\[
q(y) = \begin{cases} 
q(y) = y & y \geq 0 \\
0 & y < 0
\end{cases}
\]  
\[ (26) \]

\[
v(y) = \begin{cases} 
v(y) = y & y \geq -c \\
0 & y < -c
\end{cases}
\]  
\[ (27) \]

The following cases are possible:

**Case 1**

The price draw is better than the best price in hand minus the search cost: $x < m_t - c$

- $m_t \geq 100 - c \cdot t$
  \[ \Rightarrow p(x, m_t, t) = 100 - c \cdot t - x - c = q(100 - c \cdot t - x - c) \]
- $m_t < 100 - c \cdot t$
  \[ \Rightarrow p(x, m_t, t) = m_t - x - c = v(m_t - x - c) \]

**Case 2**

The price draw is worse than the best price in hand minus the search cost: $x \geq m_t - c$

- $m_t \geq 100 - c \cdot t$
  \[ \Rightarrow p(x, m_t, t) = 0 = q(100 - c \cdot t - x - c) \]
- $m_t < 100 - c \cdot t$
  \[
  \begin{align*}
  \bullet & \ m_t - c \leq x \leq m_t \\
  \Rightarrow & \ p(x, m_t, t) = m_t - x - c = v(m_t - x - c)
  \end{align*}
  \]
  \[
  \begin{align*}
  \bullet & \ m_t < x \\
  \begin{align*}
  \bullet & \ m_t \leq 100 - c \cdot t - c \\
  \Rightarrow & \ p(x, m_t, t) = -c = v(m_t - (100 - c \cdot t))
  \end{align*}
  \end{align*}
  \]
  \[
  \begin{align*}
  \bullet & \ m_t > 100 - c \cdot t - c \\
  \Rightarrow & \ p(x, m_t, t) = m_t - (100 - c \cdot t) = v(m_t - (100 - c \cdot t))
  \end{align*}
  \]
8.3 Details on Search Behavior

Descriptive Findings

In total, 8532 stop-or-go-decisions [3025 decisions in experiment II] were observed. The mean number of search steps for all 15 search rounds was 80.5 [75.6 in experiment II], with a minimum of 49 [37] steps, a maximum of 135 [107] steps and a standard deviation of 18.1 [17.5] steps. The mean number of search steps per search round was 5.4 [5.0], with a minimum of 1 [1], a maximum of 25 [25] and a standard deviation of 3.4 [3.3] steps. The mean number of search steps was significantly lower than the number of search steps which would be expected under the assumption of risk neutrality: The expected number of search rounds for an individual that uses the forward optimal search rule (i.e., a constant reservation price of 86) is 6.3 steps. Under a finite horizon model, 7.2 steps are expected. Figure 6 shows the distribution of mean search durations for the subjects from both experiments (experiment I and experiment II). Most of the mass of the distribution is to the left of a mean search duration of 7.2, i.e. there is a preponderance of early stoppers compared to the risk neutral optimal stopping rule. This is in line with results in earlier studies (e.g. Cox and Oaxaca, 1996; Hey, 1987; Sonnemans, 1998). Figure 7 shows the distribution of constant reservation price rules in the sample, conditional on the assumption that all subjects use such a rule.

Classification of Search Behavior

This section presents some results of the classification procedure:

If the universe of search rules is limited to the 17 type-1-rules – the constant reservation price rules – 92.8% [92.1% in experiment II] of all observed stop-or-go-decisions can be explained. When limited to the type-2-rules, 93.0% [92.3%] are explained under the CARA-specification and 92.7% [91.8%] under the CRRA-specification. Finally, the type-3-rules explain 92.8% [92.0%] of all decisions.

In this context, it is important to note that the main purpose of the classification method is not to determine a minimal universe of decision rules that best describes the behavior of all subjects in the sample but to estimate the preference parameters that best describe observed search behavior. Therefore, the possible over-fitting is not a problem for the analysis presented in this paper. In that, the presented method is akin to estimating other preference parameters from experimental data.

The findings presented here in the appendix have again made clear that it is impossible to attribute search models to the subjects merely based on their revealed search behavior unless we have much more observations per subject; i.e., discrimination across search rule types is infeasible. Since I can clearly discriminate within a certain rule-type – i.e., I can discriminate between, e.g., rule $t_1p$ and rule $t_1q$ (for $p, q \in \{78, \ldots, 94\}$ and $p \neq q$) – I am able to attribute preference parameters (risk or loss attitude, depending on the search model) to the subjects.
8.4 On the Duration Analysis

The Assumption of a Constant Hazard

The main motivation for the constant hazard assumption is the finding in section 5.2 and further detailed in the appendix (section 8.3) that a discrimination between the different search rule-types is hardly possible, since all search rules have a similar rate of consistency with the observed search behavior. It follows that the assumption of a constant reservation price, that is a type-1-rule, is generally a good proxy for the observed search behavior. A constant reservation price, in turn, implies a constant hazard in the duration model, as the reservation price path is interpreted as a hazard function in a duration model.

A glance at figures 1, 2, 3, and 4 reveals that all of the rules in the universe of search rules consist of an initial part that has a constant reservation price. What rule is least consistent with the assumption of a constant reservation price that is used for the duration analysis? Figure 3 reveals that if a subject uses a CARA-finite horizon rule and if the subject is very risk averse, it might be using the worst rule in terms of consistency with the constant hazard assumption. The subject might then have a reservation price of 94 at $t = 1$ and $t = 2$, and the price starts falling already from $t = 3$ on. The probability that this individual does not search for more than two steps is $1 - (1 - \frac{24}{76})^2 \approx 46\%$. That is, even in this “worst case”, the constant hazard assumption is correct in 46% of all cases, and this “worst case” characterizes only very few subjects, as figure 6 reveals.

Since a certain reservation price path in figure 1, 2, 3, or 4 can be interpreted as the hazard function of the particular individual that is using the corresponding search rule, a modeling approach that is nonparametric concerning the individual hazard function would effectively require the identification of reservation price paths. With the data at hand, this is practically impossible without further restrictions on the hazard function, given the identification problems encountered in section 4.3, which stem from the low number of observations per subject.

Robustness

Various alternative specifications for the duration model have been considered:

(a) It is tempting to include a random effect for each subject instead of including an effect for each search round. In this specification the unobserved effect term is highly insignificant. However, all results presented in this paper also hold in this specification, although in some cases they are statistically weaker.

(b) If the unobserved effect is left out from the estimated model, results are obtained that are virtually identical with results that are obtained based on the random effect specification for each subject (see specification (a) above).

(c) The hazard $h_1$ is highly significant in all estimations, but the drop-out term $h_2$ for time-step 25 is in general not significant, suggesting a specification without $h_2$ (i.e., a constant hazard instead of a piecewise constant hazard). All results are very similar to those reported in the paper; the effect of the loss aversion coefficient on search duration is even stronger than in the results reported in the paper.

In sum, the findings from alternative specifications support the conclusions that are drawn in this paper.
References


Tables and Figures

Table 1: *Experiment II*: The ten paired lottery-choice decisions.

<table>
<thead>
<tr>
<th>Option A</th>
<th>Option B</th>
</tr>
</thead>
<tbody>
<tr>
<td>10% of €12.50, 90% of €10.00</td>
<td>10% of €24.00, 90% of €0.60</td>
</tr>
<tr>
<td>20% of €12.50, 80% of €10.00</td>
<td>20% of €24.00, 80% of €0.60</td>
</tr>
<tr>
<td>30% of €12.50, 70% of €10.00</td>
<td>30% of €24.00, 70% of €0.60</td>
</tr>
<tr>
<td>40% of €12.50, 60% of €10.00</td>
<td>40% of €24.00, 60% of €0.60</td>
</tr>
<tr>
<td>50% of €12.50, 50% of €10.00</td>
<td>50% of €24.00, 50% of €0.60</td>
</tr>
<tr>
<td>60% of €12.50, 40% of €10.00</td>
<td>60% of €24.00, 40% of €0.60</td>
</tr>
<tr>
<td>70% of €12.50, 30% of €10.00</td>
<td>70% of €24.00, 30% of €0.60</td>
</tr>
<tr>
<td>80% of €12.50, 20% of €10.00</td>
<td>80% of €24.00, 20% of €0.60</td>
</tr>
<tr>
<td>90% of €12.50, 10% of €10.00</td>
<td>90% of €24.00, 10% of €0.60</td>
</tr>
<tr>
<td>100% of €12.50, 0% of €10.00</td>
<td>100% of €24.00, 0% of €0.60</td>
</tr>
</tbody>
</table>
Table 2: *Experiment I:* Estimation results of the CRRA and CARA utility function specification and classification of subjects according to their risk attitude.

<table>
<thead>
<tr>
<th>Functional specification</th>
<th>CRRA (α)</th>
<th>CARA (γ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum coefficient estimate</td>
<td>-0.457</td>
<td>-0.153</td>
</tr>
<tr>
<td>Maximum coefficient estimate</td>
<td>2.345</td>
<td>0.093</td>
</tr>
<tr>
<td>Median coefficient estimate</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean $R^2$ of all estimates</td>
<td>0.998</td>
<td>0.998</td>
</tr>
<tr>
<td>Proportion risk averse</td>
<td>37%</td>
<td>37%</td>
</tr>
<tr>
<td>Proportion risk neutral</td>
<td>37%</td>
<td>37%</td>
</tr>
<tr>
<td>Proportion risk seeking</td>
<td>26%</td>
<td>26%</td>
</tr>
</tbody>
</table>
Table 3: Experiment I: Estimation results of the loss aversion indices and classification of subjects according to their loss attitude.

<table>
<thead>
<tr>
<th></th>
<th>$\lambda_{100}$</th>
<th>$\lambda_{50}$</th>
<th>$\lambda_{25}$</th>
<th>$\lambda_{10}$</th>
<th>$\lambda_1$</th>
<th>$\lambda_{OLS}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum $\lambda$</td>
<td>1</td>
<td>.9</td>
<td>.96</td>
<td>.9</td>
<td>.5</td>
<td>1</td>
</tr>
<tr>
<td>Maximum $\lambda$</td>
<td>10</td>
<td>16</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>11.6</td>
</tr>
<tr>
<td>Median $\lambda$</td>
<td>1.7</td>
<td>1.6</td>
<td>1.6</td>
<td>1.9</td>
<td>1.5</td>
<td>1.6</td>
</tr>
<tr>
<td>Loss averse</td>
<td>70%</td>
<td>69%</td>
<td>69%</td>
<td>69%</td>
<td>61%</td>
<td>75%</td>
</tr>
<tr>
<td>Loss neutral</td>
<td>30%</td>
<td>30%</td>
<td>30%</td>
<td>30%</td>
<td>37%</td>
<td>25%</td>
</tr>
<tr>
<td>Loss seeking</td>
<td>0%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
<td>2%</td>
<td>0%</td>
</tr>
</tbody>
</table>
Table 4: *Experiment I*: Pearson correlation between the different loss aversion coefficients. All correlations are statistically significant at the 1%-level.

<table>
<thead>
<tr>
<th></th>
<th>$\lambda_{100}$</th>
<th>$\lambda_{50}$</th>
<th>$\lambda_{25}$</th>
<th>$\lambda_{10}$</th>
<th>$\lambda_{1}$</th>
<th>$\lambda_{OLS}$</th>
</tr>
</thead>
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<tr>
<td>$\lambda_{100}$</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda_{50}$</td>
<td>0.88</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda_{25}$</td>
<td>0.82</td>
<td>0.95</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda_{10}$</td>
<td>0.80</td>
<td>0.94</td>
<td>0.96</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda_{1}$</td>
<td>0.66</td>
<td>0.73</td>
<td>0.72</td>
<td>0.74</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>$\lambda_{OLS}$</td>
<td>0.99</td>
<td>0.94</td>
<td>0.88</td>
<td>0.86</td>
<td>0.70</td>
<td>1.00</td>
</tr>
</tbody>
</table>
### Table 5: Experiment I: Descriptive statistics for the complete sample (n=106) and subgroups $P^R$ (n=39) and $P^C$ (n=67).

<table>
<thead>
<tr>
<th></th>
<th>Complete Sample</th>
<th>$P^R$</th>
<th>$P^C$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_1$</td>
<td>1.5</td>
<td>2.57</td>
<td>1.5</td>
</tr>
<tr>
<td>$\lambda_{10}$</td>
<td>1.9</td>
<td>2.63</td>
<td>1.7</td>
</tr>
<tr>
<td>$\lambda_{25}$</td>
<td>1.6</td>
<td>2.38</td>
<td>1.5</td>
</tr>
<tr>
<td>$\lambda_{50}$</td>
<td>1.6</td>
<td>2.27</td>
<td>1.5</td>
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<tr>
<td>$\lambda_{100}$</td>
<td>1.7</td>
<td>2.10</td>
<td>1.5</td>
</tr>
<tr>
<td>$\lambda_{OLS}$</td>
<td>1.6</td>
<td>2.10</td>
<td>1.5</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.0</td>
<td>0.38</td>
<td>0.0</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.0</td>
<td>0.04</td>
<td>0.0</td>
</tr>
<tr>
<td>Search steps (ss)</td>
<td>80.49</td>
<td>18.05</td>
<td>81.79</td>
</tr>
</tbody>
</table>
Table 6: *Experiment I*: Spearman correlations between preferences and search parameters for the (sub)samples.

<table>
<thead>
<tr>
<th>Search steps (ss)</th>
<th>$P$ (106 individuals)</th>
<th>$P^R$ (39 individuals)</th>
<th>$P^C$ (67 individuals)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\lambda^\text{search}$</td>
<td>$\alpha^\text{search}$</td>
<td>$\gamma^\text{search}$</td>
</tr>
<tr>
<td>$\lambda_1$</td>
<td>-0.10 0.29</td>
<td>0.04 0.65</td>
<td></td>
</tr>
<tr>
<td>$\lambda_{10}$</td>
<td>-0.17 0.07</td>
<td>0.11 0.28</td>
<td></td>
</tr>
<tr>
<td>$\lambda_{25}$</td>
<td>-0.17 0.07</td>
<td>0.08 0.39</td>
<td></td>
</tr>
<tr>
<td>$\lambda_{50}$</td>
<td>-0.16 0.09</td>
<td>0.10 0.29</td>
<td></td>
</tr>
<tr>
<td>$\lambda_{100}$</td>
<td>-0.16 0.09</td>
<td>0.11 0.28</td>
<td></td>
</tr>
<tr>
<td>$\lambda_{OLS}$</td>
<td>-0.16 0.09</td>
<td>0.10 0.29</td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>-0.02 0.87</td>
<td>0.03 0.78</td>
<td>-0.01 0.88</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>-0.01 0.88</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

$\lambda$: Search steps, $\alpha$: Initial probability, $\gamma$: Commonality.
Table 7: Experiment I: Structural estimation. Results for various preference specifications and (sub)samples. I include 2 covariates and an unobserved effect in each panel regression: One covariate for loss attitude ($\lambda_1, \lambda_{10}, \lambda_{25}, \lambda_{50}, \lambda_{100}, \text{or} \lambda_{OLS}$) and one for risk attitude ($\alpha$ or $\gamma$), i.e., 12 regressions for each sample.

<table>
<thead>
<tr>
<th>CRRA</th>
<th>Regressor</th>
<th>Coefficient</th>
<th>p-value</th>
<th>CARA</th>
<th>Regressor</th>
<th>Coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\lambda_1$</td>
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[ P (106 individuals)]

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[ PR (39 individuals)]

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[ PC (67 individuals)]

Note: Inclusion of higher order terms of the risk and loss aversion measures (in order to test for possible nonlinear relationships) as well as inclusion of information on participant age, gender, and field of study in the panel regressions does not change findings.
Table 8: *Experiment II*: Risk aversion classifications based on the HL task.

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Figure 1: Constant reservation price path (type-1-rules) for different risk attitudes in, e.g., CARA or CRRA specifications of a utility function. The more risk averse a searcher is, the higher is her reservation price level.
Figure 2: Reservation price path for type-2-rules for different risk attitudes. CRRA specification of the utility function. The more risk averse a searcher is, the higher is her reservation price level.
Figure 3: Reservation price path for type-2-rules and different risk attitudes. CARA specification of the utility function. The more risk averse a searcher is, the higher is her reservation price level.
Figure 4: Reservation price path for type-3-rules: Non-stationary reference point model under risk neutrality. The more loss averse a searcher is, the higher is her reservation price level.
Figure 5: Graphical presentation of the lotteries on the computer screen.
Figure 6: Distribution of mean search durations for both experiments. We observe that most subjects stop earlier than predicted by the risk neutral optimal stopping rule.
Figure 7: Imposing a constant reservation price rule on every subject, I obtain the following distribution of constant reservation price rules in the sample. The lowest observed reservation price is €78, the highest reservation price is €94.