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Search behaviour with reference point preferences: Theory and experimental evidence

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Search behaviour with reference point preferences: Theory and experimental evidence*

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Abstract: People are heterogeneous with respect to their behaviour in sequential decision situations. This paper develops models for search behaviour under the assumption of expected-utility maximisation and a search model that assumes sequential updating of utility reference points during the search process. I find experimental evidence that supports the new reference point model: Individual loss aversion is systematically related to the observed search behaviour in a way that is consistent with the predictions of the reference point model; that is, loss aversion helps to predict heterogeneity in search behaviour. Risk attitude is not related to search behaviour. The finding that many people set reference points in sequential decision tasks is of interest in, e.g. consumer economics, labour economics, finance, and decision theory.

Keywords: dynamic choice; sequential decision behaviour; reference points; loss aversion; preference elicitation; risk aversion

JEL classification: D83; C91

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1 Introduction

Search situations occur often in our everyday lives. For example, we use search strategies when we look for the best price of a certain product that we want to buy or when we search for a new job. Conceptually, search tasks are representative of dynamic choice situations in which we must decide between committing resources to an attractive proposition or deferring the decision in the hope of receiving a better deal. Search tasks are attractive for experimental studies in economics because of this simple decision structure that masks a complicated optimization problem that, in most cases, cannot be solved without a computer.

Behaviour in economic search situations has been investigated both theoretically and experimentally in the fields of economics, mathematics and psychology since the 1950's. Seminal theoretical work in the economic strand of this literature was done by Simon (1955) and by Stigler (1961). Since then, numerous authors have investigated variations of search problems, and they have focused on examining the search strategies that people use (e.g. Hey, 1981; 1982; 1987; Cox and Oaxaca, 1989; Kogut, 1990; Harrison and Morgan, 1990; Sonnemans, 1998; 2000; Houser and Winter, 2004).

In price search tasks as well as in lottery tasks, people make financial decisions under risk, and they thereby reveal their preferences. Do the preferences revealed by a simple preference elicitation mechanism inform us on behaviour in search situations that involve decisions in the same monetary range? In this paper, a lottery-based preference elicitation mechanism is combined with a price search task in an economic laboratory experiment to investigate the link between individual preferences and search strategies based on various utility-based models of search behaviour. The study provides evidence that people set utility reference points relative to which they evaluate future outcomes in sequential decision tasks.

This paper contributes to the theoretical development and experimental testing of various utility-based search models and provides evidence that loss aversion, and not risk aversion, helps explain observed search behaviour. More specifically, individual search behaviour is better explained by a model that assumes sequential updating of utility reference points than by search models that are based on expected-utility theory. The reference point model helps to explain individual heterogeneity in sequential decision behaviour.

The findings are of interest for decision theory. They help to understand the determinants and properties of individual search behaviour in markets (e.g. Zwick et al., 2003), and they 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 Bergh, 2005). The sequentially risky decision nature of the search problem makes the results interesting for theoretical and applied research in finance (Gneezy, 2003).

Finally, the findings complement research on rules of thumb in dynamic decision problems (e.g. Lettau and Uhlig, 1999, Houser and Winter, 2004).

This paper first establishes links between search behaviour and individual preferences by developing various search models, in particular the reference point model (Section 2). Then the experimental design (Section 3) and methodology to draw inferences about search behaviour and preferences based on the experimental data (Section 4) are described. Next, the link between the elicited preferences and the observed search behaviour is investigated (Section 5). The methodology and findings are discussed in Section 6; Section 7 concludes.

2 Models of Search Behaviour

In this Section I derive the optimal search behaviour of an expected-utility maximiser, both under risk neutrality (Section 2.1) and without restrictions on individual risk attitude (Section 2.2). 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 2.3, I develop the reference point model.

2.1 Optimal Stopping in Search Tasks under Risk Neutrality

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 value 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 (Lippman and McCall, 1976; Kogut, 1990) and 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:

$$G(m) = -\underbrace{[1 - F(m)]m}_{\otimes} - \underbrace{\int_{75}^{m} x dF(x)}_{\oplus} - c + m. \quad (1)$$

[1] For the remainder of the derivation in this Section, the currency units are skipped.

[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.

The term $\otimes$ accounts for the case in which a value 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 value than m is found and computes the expected value in this case. There exists *a unique* value 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:

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

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

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

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

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 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 receives a total payoff:

$$\Pi(S_t) = max\{0, 100 - m - t \cdot c\}. \tag{4}$$

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:

$$J_t(S_t) = max\{\Pi(S_t), E[J_{t+1}(S_{t+1})|S_t]\}. \tag{5}$$

$E(\cdot)$ 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.

2.2 Stopping Rules in Search Tasks Without Restrictions on Risk Attitudes

The derivations above are based on the assumption of a risk-neutral searcher. It is individually rational to use a risk-neutral optimal stopping rule *only* for risk-neutral subjects.

As a more general case, I therefore consider a searcher with an arbitrary, monotone utility function $u(\cdot)$. If the searcher ignores sunk costs and takes her decisions based on a one-step forward-looking strategy, the equation that determines her reservation price m^* then has the following form that follows from (2):[3]

$$u(100 - m) = (1 - F(m))u(100 - m - c) + \int_{75}^{m} u(100 - x - c)dF(x) \tag{6}$$

Equation (6) 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) η. The solution has the constant reservation price property. 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 her constant reservation price value is. 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.

Analogous to the derivation of the optimal search rule in the risk-neutral case, I now consider that subjects do not treat search costs as sunk costs. Again, this is a finite-horizon problem. After the agent has stopped searching, she buys the item and receives a total payoff:

$$\Pi^u(S_t) = max\{0, u(100 - m - t \cdot c)\}. \tag{7}$$

The recursive formulation of the dynamic discrete choice problem is:

$$J_t^u = max\{\Pi^u(S_t), E[J_{t+1}^u(S_{t+1})|S_t]\}. \tag{8}$$

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.

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.

[3] This equation does *not* characterize the optimal solution to the search problem. However, it gives the optimal strategy for a searcher who ignores sunk costs and who uses a one-step forward induction strategy and who has arbitrary risk attitudes.

2.3 The Reference Point Model

The reference point model (henceforth: *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-maximisation (see previous Subsection) implicitly assume that the reference point is always at zero payoff, the reference point model assumes a reference point which is always at the current payoff.

Concretely, the rp-model assumes that subjects consider the payoff that they have in hand for sure (i. e. the value of the good minus the best price observed minus the search cost incurred so far) as their reference point. Relative to this reference point, any lower payoff potentially obtained by continuing the search would be a loss, and any higher payoff would be a gain.

To formalize the model, 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, $u^-(\cdot)$:

$$u(x) = \begin{cases} u^+(x) & x \geq 0 \\ u^-(x) & x < 0. \end{cases} \tag{9}$$

Subjects have to decide whether to stop or to continue the search 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 $\bigotimes$ [$\bigoplus$] 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

$$\begin{aligned} G(m_t) &= \underbrace{\int_{-\infty}^{m_t - c} u^+(m_t - x - c)dF(x)}_{\bigotimes} \\ &+ \underbrace{\int_{m_t - c}^{m_t} u^-(m_t - x - c)dF(x) + (1 - F(m_t)) \cdot u^-(-c)}_{\bigoplus}. \end{aligned} \tag{10}$$

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

(6): The search behaviour is independent of time t since subjects focus on the marginal gain or loss of the next step but not on the total payoff from the search. Identical with the prediction of the forward optimal search model (6), this model results in a *constant reservation price over time.* As in the forward optimal search model, 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:

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

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

$$\begin{aligned} G(m_t) &= \int_{-\infty}^{m_t - c} u^+(p(x, m_t))dF(x) + \int_{m_t - c}^{\infty} u^-(p(x, m_t))dF(x) \\ &= \int_{-\infty}^{\infty} u(p(x, m_t))dF(x). \end{aligned} \tag{12}$$

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, as predicted by 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 $v(\cdot)$:

$$q(y) = \begin{cases} q(y) = y & y \geq 0 \\ 0 & y < 0 \end{cases} \tag{13}$$

$$v(y) = \begin{cases} v(y) = y & y \geq -c \\ 0 & y < 0 \end{cases} \tag{14}$$

The modified rp-payoff-function $p(x, m_t, t)$ now has the following form.[4]

$$p(x, m_t, t) = \begin{cases} q(100 - c \cdot t - x - c) & m_t \geq 100 - c \cdot t \\ v(m_t - x - c) & m_t < 100 - c \cdot t \wedge x \leq m_t \\ v(m_t - (100 - c \cdot t)) & m_t < 100 - c \cdot t \wedge x > m_t \end{cases} \tag{15}$$

With the modified version of the rp-payoff-function, the rp-model (12) is written as follows:

$$\begin{aligned} G(m_t) &= \int_{-\infty}^{m_t - c} u^+(p(x, m_t, t))dF(x) + \int_{m_t - c}^{\infty} u^-(p(x, m_t, t))dF(x) \\ &= \int_{-\infty}^{\infty} u(p(x, m_t, t))dF(x). \end{aligned} \tag{16}$$

I have now developed two search models, (16) and (10), that assume that subjects update their reference points during the search process. Both rp-models are based on two independent parts of the utility function, $u^+(\cdot)$ and $u^-(\cdot)$. The EU-based models presented in the previous Subsection, however, are less flexible in the sense that they are based on only one branch of the utility function, $u^+(\cdot)$. In order to be able to compare the two modelling approaches in the remainder of the paper, both models need the same number of degrees of freedom in the preference parameters. I therefore assume the following one-parameter form of the reference point utility function:[5]

$$u(x) = \begin{cases} u^+(x) = x & x \geq 0 \\ u^-(x) = \lambda \cdot x & x < 0 \end{cases} \tag{17}$$

Using this form of the utility function, the rp-model implicitly assumes that individuals are risk-neutral and that only the kink at the utility reference point plays a role for observed search behaviour. The crucial parameter that determines individual search behaviour is now the individual loss aversion parameter λ. Assuming utility specification (17), the *stationary rp-model* (10) implies a constant reservation price search rule; the level of the reservation prices is a function of loss attitude λ.[6]
Assuming utility specification (17), 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 λ: 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 equivalent with two classical search models that are based on EU-maximisation:

[4] A detailed derivation of the function $p(x, m_t, t)$ is given in the Appendix of the paper.

[5] This form was proposed by Benartzi and Thaler (1995) and subsequently used in various experimental studies that elicit individual loss aversion (see, e.g., Schmidt and Traub, 2002)

[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 $\lambda = 1$.

– The stationary rp-model (10) predicts the same search behaviour as the EU-based forward optimal search model (equation (6)), 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 behaviour, the *explanation* for the search behaviour 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). We will see later that due to the similar predictions of the two models, distinguishing between these two preference-based explanations for search behaviour requires independent measures for individual preferences. The following section describes how information on individual preferences and on search behaviour was elicited.

3 Experimental Design

The experiment 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 behaviour.
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. To create similar decision situations in both, the search task (Part B) and the preference elicitation parts (Part A and C), the preference elicitation parts have been designed such that subjects are faced with tasks that involve the comparison between a sure payoff, **s**, and a lottery, **c**.

The descriptions of the experimental design will begin with Part C, continue with Part A, and end with Part B. This makes some details of the design clearer.

3.1 Part C: Risk Attitude

In part C, a 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 and a sure payoff and 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_{min} =€0 and x_{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 $(x_{min}, p; x_{max}, (1-p))$.[7] 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 $(x_{min}, p; s_{0.5}, (1-p))$. Finally, in the last question, the subject is asked to reveal indifference between the lottery $(s_{0.5}, p; x_{max}, (1-p))$ 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, which allows for the estimation of the individual utility function, thereby obtaining a risk attitude index for each subject in the monetary domain between €0 and €24.[8]

3.2 Part A: Loss Attitude

Part A consists of two blocks, *(A-1)* and *(A-2)*, that are presented in random order. In block *(A-1)* subjects are again presented with a 50-50-gamble $(x, 50\%; y, 50\%)$ and a sure outcome **s** to the subjects. 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}. The 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).[9]
In block *(A-2)*, subjects are presented with three pure certainty-equivalent lotteries of the same type as in part C, but with x_{min} =€1 and x_{max} =€9.

3.3 Part B: Search Behaviour

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[10], and visiting a new location costs €1. On the instruction sheet, 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

[7] The value of p was set to 50% for all subjects, i. e. $p = 1 - p$. 50-50-lotteries are well-known to most decision-makers through events such as throwing coins.

[8] Note that the search task is designed such that subjects earn at least €0 and at most €24.

[9] Please see the Appendix, Figure 6, for the graphical presentation of the lotteries.

[10] In other words, participants 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.

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 minimise the impact of learning, 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:[11]
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 subdivision of the subject sample into two categories: 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 reference points.

A few remarks on the experimental design: 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 and 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

[11] 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. Furthermore, the two lotteries, I and II, are presented in random order.

properties of the search experiment (i.e. they are aware that their minimum payoff is €0 and that their maximum payoff is €24), the certainty-equivalent-method with the values x_{min} =€0 and x_{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_{min} =€0 and x_{max} =€24 on the answer to the search-model question.

3.4 Administration and Payoffs

The study was conducted in the Summer and Fall of 2004 in the experimental laboratory of the SFB 504, a national research center at the University of Mannheim. In eight sessions 119 students of the University of Mannheim participated in the experiment on search behaviour and preferences. All experiments were run entirely on computers using software written by the author. With regards to the specific tasks, subjects were instructed that (i) their payoff was truncated at €0 (i.e. subjects 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). Given this experimental design, the search models presented in this Section imply that any systematic relationship between individual loss aversion and search behaviour that cannot be explained by a correlation between loss aversion and risk aversion[12] is evidence that subjects set reference points during their search. Controlling for a relationship between risk aversion and loss aversion, *no* relationship between loss aversion and search behaviour is expected, if subjects behave according to EU-theory.

4 Inference about Preferences and Search Behaviour

This Section presents and discusses how risk and loss attitude is estimated from the data obtained in the lottery tasks of the experiment. I also describe how individual search behaviour is classified based on the data obtained in the search experiments and the search models developed above.

4.1 Estimation of Risk Attitude

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.

[12] I test for that correlation in a later Section. Furthermore, the duration model (Section 5.3) is a test of the relationship between preferences and search behaviour that controls for such a correlation.

Utility functions of the power form (e.g. Tversky and Kahneman, 1992; Abdellaoui, 2000) assume that subjects have constant relative risk aversion (CRRA):

$$u(x) = (\frac{x - x^G_{min}}{x^G_{max} - x^G_{min}})^{(\alpha+1)} \tag{18}$$

x^G_{max} is the largest elicited value of x in the gain domain, i.e. €24; x^G_{min} is the smallest elicited x-value on the gain domain, i.e. €0. The estimated coefficient α 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):

$$u(x) = \frac{1 - e^{-\gamma(x - x^G_{min})}}{1 - e^{-\gamma(x^G_{max} - x^G_{min})}} \tag{19}$$

For $\gamma = 0$ the function is defined to be linear, i.e. the subject is risk neutral. In the CARA-specification, the estimated coefficient γ 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.

4.2 Estimation of Loss Attitude

Based on the subjects' response in Part A of the experiment, an individual-specific index for loss aversion is calculated. The statistic $\lambda_x = -y/x$ is a measure for individual loss aversion, where $x \in$ {€-1,€-10,€-25,€-50,€-100} and y is the response to the lottery given in part A. This method of eliciting a coefficient of loss aversion is similar to the method in Tversky and Kahneman (1992).

4.3 Classification of Decision Rules Used in the Search Task

The next step in 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 behaviour best is attributed to each subject. Since utility-based search models developed in Section 2 establish a relationship between preference parameters and decision rules, I can assign preference parameters to the subjects based on the attributed search rules.[13]

The Universe of Search Rules

For the investigation of the relationship between individual preferences and search behaviour, I use as candidate decision rules all those search rules that can be derived from

[13] 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.

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 behaviour) 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 (6)), an 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 $r \in \{€78, .., €94\}$ which is constant during the search round. There are 17 *type-1-rules* denoted by $t1_{78}, t1_{79}, ..., t1_{94}$. Every rule corresponds to a certain risk attitude parameter α^{search} and γ^{search}.[14]

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. There are again 17 different *type-2-rules*, denoted by $t2_{78}, t2_{79}, ..., t2_{94}$, 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,..., and for the last rule it is €94 (see Figure 2). Each reservation price path corresponds to a certain α-interval. The 17 price paths $t2_{78}, t2_{79}, ..., t2_{94}$ correspond to a decreasing sequence of 17 α-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). Analogously, each reservation price path corresponds to a certain γ-interval, and the 17 paths correspond to an increasing sequence of γ-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 α^{search} and γ^{search} can be attributed to her. These coefficients are the risk attitudes that explain best the observed search behaviour.

Finally, the *type-3-rules* are based on the non-stationary rp-model (16), the rp-model developed under the assumption that subjects do focus on total payoffs from searching. The reservation price is a function of the search step t and of individual loss aversion λ (see Figure 4). Again, 17 different rules are considered, $t3_{78}, t3_{79}, ..., t3_{94}$: For the first rule, the reservation price at $t = 1$ is €78, for the second rule, it is €79,..., and for the last rule it is €94. The rules correspond to a decreasing sequence of λ-intervals taken from the interval $[0.042, 3.392]$. Based on the *type-3-rules*, I attribute to every individual a loss coefficient λ^{search}. The loss attitude coefficient assigned best explains the observed

[14] Under risk neutrality, one finds a constant reservation price of €86. The set of 17 constant reservation price rules, $t1_{78}, t1_{79}, ..., t1_{94}$, is sufficiently large to classify all observed behaviour (see Figure 5).

search behaviour conditional on the assumption that the subject uses the non-stationary rp-model.

Classification Procedure

To classify search behaviour, I determine for each subject the proportion of choices consistent with each decision rule and then maximise 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 pay-off tasks. This assumption seems reasonable in view of the fact that all subjects are experienced when they begin the 15 pay-off relevant tasks.

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 $d_{it} \in \{0,1\} : d_{it}^{c_i}(S_{it}) \rightarrow \{0,1\}$. Now, let d_{it}^{*} denote the observed decision of subject i in period t. Then, define the indicator function:

$$X_{it}^{c_i}(S_{it}) = 1(d_{it}^{*} = d_{it}^{c_i}(S_{it})) \tag{20}$$

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

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

5 Results

This Section starts with self-contained descriptions of the results of the utility function elicitation (Part A and Part C) and of the classification of the search behaviour (Part B). The main part of this Section is the joint analysis of the results of individual preferences and search behaviour based on the theoretical findings in Section 2.

5.1 Part C and A: Risk and Loss Attitude

Of the 119 subjects that participated in the experiment, thirteen were excluded.[15] From the data in Part C two indices of risk attitude, an index α (derived from a CRRA-specification) and an index γ (derived from a CARA-specification), were estimated *for each* subject. From the data obtained in part A, five indices of loss attitude, λ_1, λ_{10}, λ_{25},

[15] In contrast to all other subjects, the utility functions derived from the answers of these 13 subjects are not strictly monotone. This is evidence that they did not understand the lottery tasks correctly or did not take it seriously.

λ_{50}, and λ_{100}, were calculated *for each* subject.

Table 1 reports results of the nonlinear least squares estimation of the risk coefficients γ and α, 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 of the utility function.

Table 2 shows the results of the loss aversion elicitation part of the experiment. Participants were predominantly loss averse in their choices. I find mean loss aversion coefficients $\overline{\lambda_x}$ that are significantly higher than 1. As expected, there is a high and statistically significant degree of correlation between the individual answers to the various loss aversion questions (see Table 3). In fact, 39% of the subjects exhibited constant loss aversion, that is, their loss aversion coefficient is identical for all loss aversion questions. For 83% of all subjects, the hypothesis of constant loss aversion cannot be rejected based on fitting a power-function on the data. This simply means that no significant relationship between the level of the stimulus and the degree of loss aversion could be proven.[16]

5.2 Part B: Search Behaviour

Search behaviour differs considerably across individuals. I also find a preponderance of early stoppers compared to behaviour under the risk neutral stopping rules. This confirms results from earlier experimental studies (e.g. Hey, 1987; Sonnemans, 1998).

Considering (a) the universe of search rules (see Figures 1, 2, 3, and 4), (b) the rather low average number of search steps, and (c) the fact that only a finite number of search rounds per individual (namely 15 rounds) is observed, it is clear that based on the universe of 51 rules individual search rules are not (empirically) identified.[17] In essence, and in line with findings from Schunk and Winter (2004), the discrimination between very similar reservation price *rules*, that is *across* search rule types (e.g. between $t1_{80}, t2_{80}$, and $t3_{80}$), is hardly possible. It does not serve to identify the search models that subjects are using.[18] In contrast, the identification *within* a certain rule type is clear: For example, there is significant difference in whether a subject's behaviour is more consistent with, for example, $t1_{80}$ rather than with $t1_{81}$. In other words, individual risk attitude or loss

[16] 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). The studies are also in line with the experimental findings on constant loss aversion: Schmidt and Traub (2002) cannot reject the hypothesis of constant loss aversion for 78% of their subjects. Note, however, that the measurement of loss aversion is complicated by the fact that there is *no* agreed-upon definition of loss aversion in the literature (for reviews of this topic, see Abdellaoui, Bleichrodt, Parashiv (2004) and Koebberling and Wakker (2005)).

[17] Asymptotically, that is if an infinite number of search rounds per individual is observed, individual search rules are identified.

[18] For more details, please see the Appendix, Section 8.3.

attitude parameters can be attributed to the subjects based on their behaviour in the search task.

5.3 Analysing Search Behaviour and Individual Preferences

As mentioned above, the observed search behaviour 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 behaviour and individual preferences* that are testable based on the information gained in Parts A, B, and C of the experiment. Essentially, it is hypothesised that for subjects from P^R, individual loss aversion is systematically related to search behaviour, while for subjects from P^C, risk aversion is systematically related to search behaviour. Specific hypotheses are stated below:
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 λ_x in Part A – a subject from P^R is, the fewer search steps (denoted by *ss*) this subject should take in the search process.
(H2) For subjects from P^R, the index of loss aversion, λ_x, elicited in Part A, should be positively correlated with the index of loss aversion, λ^{search}, elicited in the search task, 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 γ or α in the preference elicitation Part C – a subject from P^C is, the fewer steps *ss* this subject should take in the search process.
(H4) For subjects from P^C, the indices of risk attitude γ and α elicited in the preference elicitation Part C should be positively correlated with the particular indices of risk attitude γ^{search} and α^{search}, respectively, revealed through the search behaviour.

To subdivide the sample into P^R and P^C, I use the answers to the search-model question (see Section 3.3): 39 subjects were categorised into group P^R, 67 subjects were categorised into group P^C.
Descriptive statistics on individual preferences and search behaviour by subgroup are reported in Table 4.

Descriptive Analysis

Before the above-mentioned hypotheses are investigated, it is helpful to compare the descriptive statistics on preference estimates (see Table 1 and Table 2) with the theoretical findings on the relationship between preference parameters and search behaviour (see Section 4.3):

Risk attitude (CRRA-specification): Table 1 shows that all estimates for α 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: $\{tX_{83}, .., tX_{87}\}$ for $X \in \{1, 2\}$.
Risk attitude (CARA-specification): Table 1 shows that all estimates for γ 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: $\{tX_{84}, .., tX_{87}\}$ for $X \in \{1, 2\}$.
Loss attitude: The estimated λ_x-values lie in the interval $[0.5, 20]$. This corresponds to reservation price paths that start between €83 (for $\lambda = 0.5$) and €94 (for $\lambda = 20$). The following search rules apply: $\{tX_{83}, .., tX_{94}\}$ for $X = 3$.
The first finding from this descriptive analysis is: The variance in the degree of curvature of the utility function is not sufficient to explain the heterogeneity in the observed search behaviour. As Figure 5 suggests, the complete universe of search rules is needed to describe the search behaviour of all observed individuals.[19] The second finding is that though the estimated loss aversion coefficient is compatible with a wider range of different search rules than estimated risk aversion, the variation in loss aversion is also not sufficient to capture the observed heterogeneity in search behaviour.

Correlation Analysis

Table 5 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. For the complete sample P, there are negative correlations of marginal significance between most estimates for individual loss aversion and the number of search steps (ss); this is consistent with (H1). In contrast, the estimates for individual risk attitude are not correlated with the number of search steps.
For the subgroup P^R, I find strong support for (H1): There are significant negative correlations between all estimates for individual loss aversion and the number of search steps (ss). Additionally, results from these analyses support (H2): The estimates for individual loss aversion derived from the lottery questions, λ_x, and the estimates derived from the observed search behaviour, λ^{search}, are correlated at the 10%-level (λ_1, λ_{10}, and λ_{25}), and some at the 5%-level (λ_{50} and λ_{100}). For P^C, no significant correlations were found, suggesting that none of the hypotheses (H3) and (H4) for this group are supported. The hypotheses (H3) and (H4) are not supported by any of the considered subgroups either.

[19] In fact, the lower and the upper boundaries of the universe of search rules, tX_{78} and tX_{94}, have been chosen based on the observed search behaviour. The universe consisting of $\{tX_{83}, .., tX_{87}\}$ would not be sufficient.

Duration Analysis

A further analysis of the relationship between individual preferences and search duration controls for a relationship between risk attitude and loss attitude parameters. As well, it exploits the discrete time-to-event-nature and multiple-spell-nature. The event is the stopping of the search, and the duration is measured discretely as the number of search steps. Furthermore, 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, which gives the probability of stopping the search in the next time step, conditional on not having stopped so far:

$$h_0(t) = P(T = t \mid T \geq t) \tag{22}$$

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.[20] 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:

$$h_0(t) = \begin{cases} h_1 & t < 25 \\ h_2 & t = 25. \end{cases} \tag{23}$$

To investigate the hypotheses derived above, I test whether the hazard can be explained by individual preference parameters. Therefore, two covariates X are chosen in the hazard function: one covariate that characterizes risk attitude (γ or α) and one covariate characterizing loss attitude ($\lambda_1, \lambda_{10}, \lambda_{25}, \lambda_{50}$ or λ_{100}). 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:

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

where, i = 1,.., 106. β is a parameter vector, h_1 and h_2 characterize the baseline hazard. Recall that every subject had to play 15 search rounds. All prices were drawn from a uniform distribution, and all subjects observed *the same* series of price draws in each search round. Therefore, I expect an unobserved effect for each search round, stemming from the series of price draws that are different across rounds but identical across individuals. To account for this unobserved heterogeneity, a random effect that is common to all

[20] The structural assumption of a constant hazard can be supported based on our empirical findings on the identifiability of different search rules and based on theoretical deliberations. Please see the Appendix, Section 8.4, for a discussion of the constant hazard assumption.

observations from a certain search round j ($j = 1, .., 15$) is included. The following model is considered:

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

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

Table 6 presents estimation results for the complete sample and for the subgroups. In all estimations a likelihood ratio test suggests that the included random 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 decrease in individual search time. This effect is significant at the 5%-level for λ_{10}, λ_{25}, and λ_{50}, it is marginally significant for λ_1, regardless of the specification of the risk attitude coefficient (α or γ). Risk attitude has no significant explanatory power for the search duration.
Considering the subsample P^R even stronger support for (H1) is found: Apart from λ_{100}, all estimates for individual loss aversion have explanatory power for search duration at least at the 2%-significance level. Individual risk attitude is always insignificant.
In the subgroup P^C, no preference parameter has significant explanatory power.[21]

There is considerable heterogeneity in subject's search behaviour. According to the analyses presented above, the estimated loss aversion coefficient has significant explanatory power for individual search behaviour, whereas risk attitude generally has no significant explanatory power, regardless of whether CARA- or CRRA-specifications of the utility function are considered. The findings on the explanatory power of loss aversion do not hold for the subgroup P^C, but they are very strong for the subgroup P^R. The results suggest that some subjects, in particular those from subgroup P^R, set reference points during their search in a way captured by the rp-model. Other subjects, in particular those from the subgroup P^C, might not set reference points during their search but solve the search task based on some other heuristic.

6 Discussion

This paper focuses on the development and experimental testing of various search models, in particular the reference point model. The results suggest that the rp-model is virtually identical with EU-based models in its predictions about reservation price paths, but it is considerably better than EU-based models in reconciling the experimental data on individual preferences with the data on individual search behaviour. Complemented with empirical information on individual preferences (e.g. the empirical distribution of loss

[21] The robustness of the results from the duration analysis has been checked. All results are very robust. Please see the Appendix, Section 8.4, for a brief discussion of different specifications of the duration model.

aversion in a population, see, e.g. Tversky and Kahneman, 1992; Pennings and Smidts, 2003), the rp-model is consistent with existing empirical findings on search behaviour, such as the large heterogeneity of search rules and the predominance of early-stopping in the population (Hey, 1987; Cox and Oaxaca, 1989; Sonnemans, 1998).

To further investigate individual heterogeneity, I hypothesise that at least a specific subgroup, P^R, of the subjects uses the proposed rp-model. Since identification of this subgroup merely based on the observed search behaviour of subjects is in practice not possible, the subgroup P^R is identified with the help of the search-model question. Under the assumption that subjects understand this question correctly and that they are able to relate this question to their actual search behaviour, the question is likely to be a good instrument for dividing the complete sample into the particular subgroups P^R and P^C. The main empirical result of this paper – namely that individual loss aversion is systematically related to search behaviour, whereas risk aversion is not related to search behaviour – is independent of this search-model question. Nevertheless, all further results concerning the subgroup differences in search behaviour are built on the assumption of the validity of this question.

The presented experimental setup is based on one specific search environment, which is characterized by the known price distribution, the search cost and the ability to recall. It is conceivable that subjects behave differently in a different search environment (e.g. in an environment where the price distribution is not known). In particular, the effect of loss aversion on search behaviour might become more or less pronounced if higher losses (i.e. higher search cost) are involved. In the context of a search environment with a considerably longer time between the search steps, the observed effect of loss aversion might rather be called an endowment effect (Kahneman, Knetsch and Thaler, 1991; Huck et al., 2005): If a person holds an object that she may keep for sure, the next step in the search is evaluated only relative to this endowment.

A further issue to be addressed is the recall option of the search task. To my knowledge, no search model or rule that explicitly predicts the recall option has been investigated in the literature so far; the rp-model is not able to predict recall decisions either. Indeed, 2.4% of all stop-or-go decisions in the sample are decisions to stop and recall a price that has been rejected.

In sum, the analyses lend support to the claim that subjects use different strategies when "solving" the search task. In line with findings in Schunk and Winter (2004)[22] I do not find evidence supporting the classical EU-based search models in the sample. Controlling for the effect of risk attitude, I do obtain support for the hypothesis that loss aversion is related to search behaviour, implying that people set reference points in the course of their

[22] The experimental design in Schunk and Winter (2004) differs from the design presented in this paper. They use an adaptive method to elicit utility functions, and they present a different search task to the subjects.

search. It is important to note that no *direct* empirical support for the specific reference point updating assumption that underlies the presented form of the reference point model can be found. The observed relationship between loss aversion and search behaviour is also consistent with subjects that set one constant utility reference point higher than €0 and evaluate the outcomes during the search relative to this reference point. This explanation cannot be rejected by the experimental data, but from a behavioural point of view there is no argument that would favor this model over the reference point model that is developed in this paper.

7 Conclusions

Subjects are heterogeneous with respect to their sequential decision behaviour. Based on data obtained in a controlled laboratory experiment, I have shown that to some extent, this heterogeneity can be linked to heterogeneity in individual preferences.
For the entire participant sample, loss aversion was shown to be systematically related to search behaviour, while risk attitude was not related to search behaviour. Given the experimental design, these findings suggest that people set reference points during their search relative to which they evaluate potential future outcomes. The proposed reference point search model describes overall observed behaviour better than search models derived from expected-utility theory.
To further investigate heterogeneity in search behaviour, an instrument was used to subdivide the sample into two subgroups. It is found that for the subjects from one subgroup, P^C, there was no relationship between individual preferences and search behaviour. However, for the other subgroup, P^R, individual preferences and search behaviour were strongly related in a way that is consistent with the predictions of the reference point model.

At least for subjects from the P^R subgroup, more than a third of the sample, observed search behaviour can be explained significantly better by a search model that assumes sequential updating of utility reference points during search, rather than by a model derived from the assumption of expected-utility maximising behaviour. This means, in addition to heterogeneity in the estimated individual preferences, there might also be heterogeneity in the way people solve the search task: Some people set reference points in sequential decision tasks, while others do not. The two subgroups of the sample use different models for solving the search task, and with the help of an instrument to separate these two subgroups, individual search behaviour is to a certain degree predictable, provided that information on individual preferences, specifically on loss aversion, is available.

The finding that people set reference points in sequential decision tasks is of interest for recent theoretical and applied research in many fields, e.g. marketing science (Zwick et al., 2003), labour economics (Eckstein and Van den Bergh, 2005), and finance (Gneezy, 2003).

8 Appendix

8.1 Graphical Presentation of the Lotteries on the Computer Screen

See figure 6.

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 2.3, i.e.

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

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

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: $x \geq m_t - c$

- $m_t \geq 100 - c \cdot t$
  $\Rightarrow p(x, m_t, t) = 0 = q(100 - c \cdot t - x - c)$
- $m_t < 100 - c \cdot t$
  - $m_t - c \leq x \leq m_t$
    $\Rightarrow p(x, m_t, t) = m_t - x - c = v(m_t - x - c)$
  - $m_t < x$
    - $m_t \leq 100 - c \cdot t - c$
      $\Rightarrow p(x, m_t, t) = -c = v(m_t - (100 - c \cdot t))$
    - $m_t > 100 - c \cdot t - c$
      $\Rightarrow p(x, m_t, t) = m_t - (100 - c \cdot t) = v(m_t - (100 - c \cdot t))$

8.3 Details on Search Behaviour

Descriptive Findings

In total, 8532 stop-or-go-decisions were observed in the experiment. The mean number of search steps for all 15 search rounds was 80.5, with a minimum of 49 steps, a maximum of 135 steps and a standard deviation of 18.1 steps. The mean number of search steps per search round was 5.4, with a minimum of 1, a maximum of 25 and with a standard deviation of 3.4 steps. The mean number of search steps was significantly lower than the expected number of search rounds 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) was 6.3 steps. Under a CARA-finite horizon model, expect 7.4 steps were expected and under the non-stationary rp-model 7.0 steps were expected. Figure 5 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 Behaviour

This brief Section presents some results of the procedure to classify search behaviour:
If the universe of search rules is limited to the 17 type-1-rules – the constant reservation price rules – 92.8% of all observed stop-or-go-decisions can be explained. When limited to the type-2-rules 93.0% are explained under the CARA-specification and 92.7% under the CRRA-specification. Finally, the type-3-rules explain 92.8% of all decisions. Under the CARA-specification, all 3 decision rules (type 1, type 2 and type 3) explain observed behaviour equally well for 83 (78%) of the subjects (i.e. I cannot discriminate between the 3 rule types for 83 subjects). Under the CRRA-specification, all 3 decision rules (type 1, type 2, and type 3) explain observed behaviour equally well for 89 (84%) of the subjects. 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 behaviour of all subjects in the sample but to estimate the preference parameters that best describe observed search behaviour. Therefore, the encountered problems of over-fitting, reflected in the lack of discrimination between different search rules, are 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.[23]

The findings presented here have again made clear that it is impossible to attribute search models to the subjects merely based on their revealed search behaviour; 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 $t1_p$ and rule $t1_q$ (for $p, q \in \{78, .., 94\}$) – I am able to attribute preference parameters (risk or loss attitude, depending on the

[23] Schunk and Winter (2004) use the same classification procedure. More sophisticated statistical methods for the joint determination of the universe of decision rules and the classification of decision rules that allow for errors are used by Houser and Winter (2004) and Houser *et al.* (2004).

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 behaviour. 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 behaviour. 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 structural duration model approach.
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? The worst case in terms of consistency with the constant reservation price assumption is that a subject is very risk averse *and* uses a CARA-finite horizon rule: It can be seen in Figure 3 that in this case the individual has 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 $1 - (1 - \frac{20}{76})^2 = 45.7\%$, that is, even in this "worst case", the constant hazard assumption is correct in 45.7% of all cases.
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 modelling approach that is nonparametric concerning the individual hazard function would effectively require the identification of reservation price paths. 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 all support the conclusions that are drawn in this paper.

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FIGURE 1
Constant reservation price path (type-1-rules) for different risk attitudes in CARA or CRRA-specifications of a utility function. The more risk averse a searcher is, the higher her reservation price level.

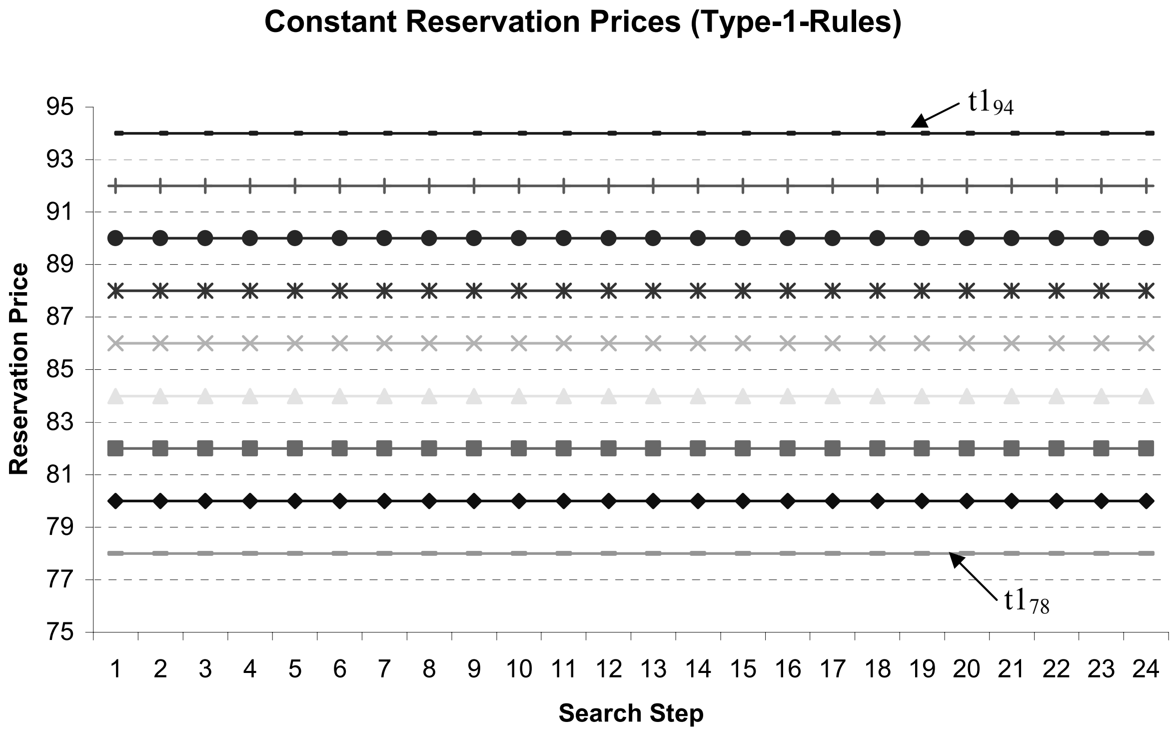

FIGURE 2
Reservation price path for type-2-rules for different risk attitudes. CRRA-specification of the utility function. The more risk averse a searcher is, the higher her reservation price level.

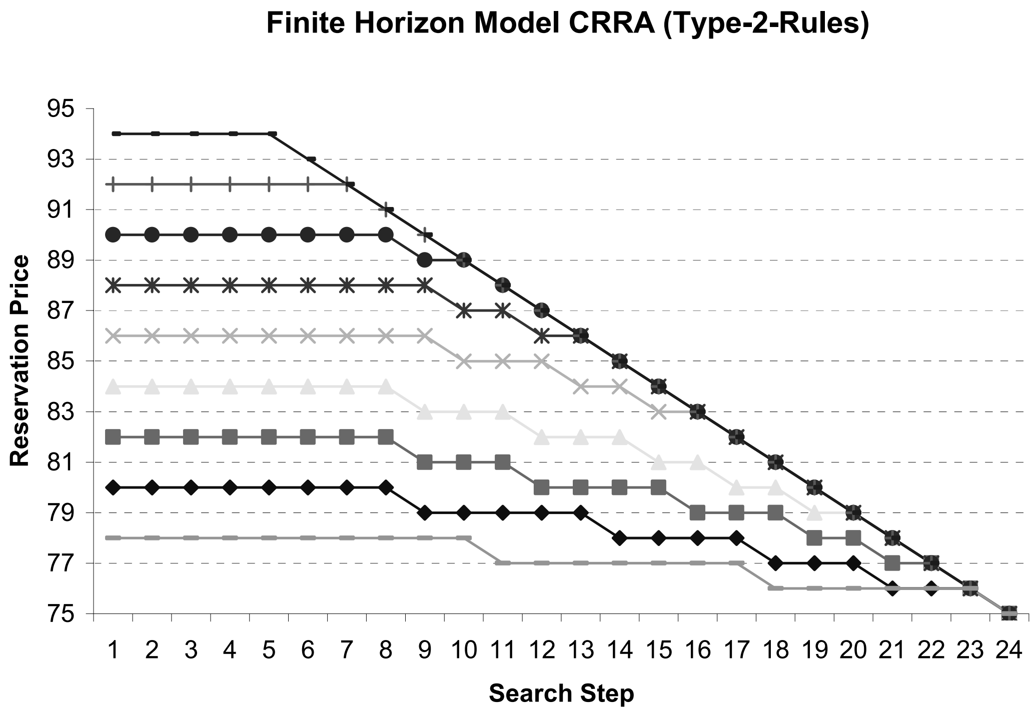

FIGURE 3
Reservation price path for type-2-rules and different risk attitudes. CARA-specification of the utility function. The more risk averse a searcher is, the higher her reservation price level.

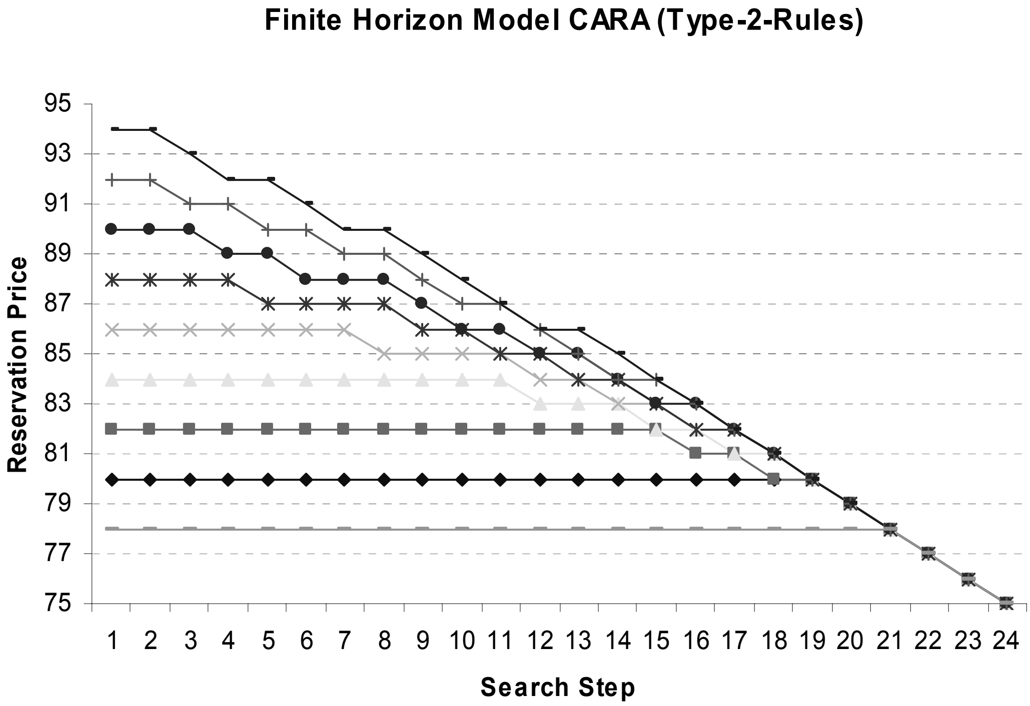

FIGURE 4
Reservation price path for type-3-rules: Nonstationary reference-point model under risk-neutrality. The more loss averse a searcher is, the higher her reservation price level.

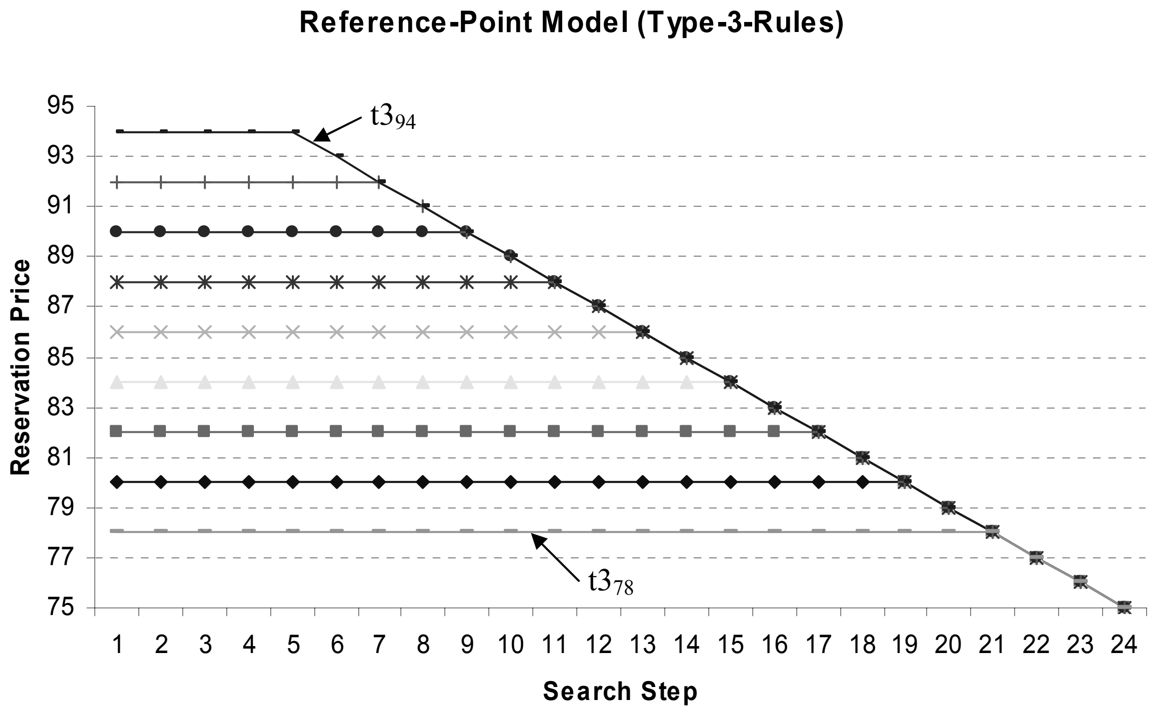

FIGURE 5
Imposing a constant reservation price rule on every subject, we obtain the following distribution of constant reservation price rules in the sample. The lowest observed reservation price is €78, the highest reservation price is €94.

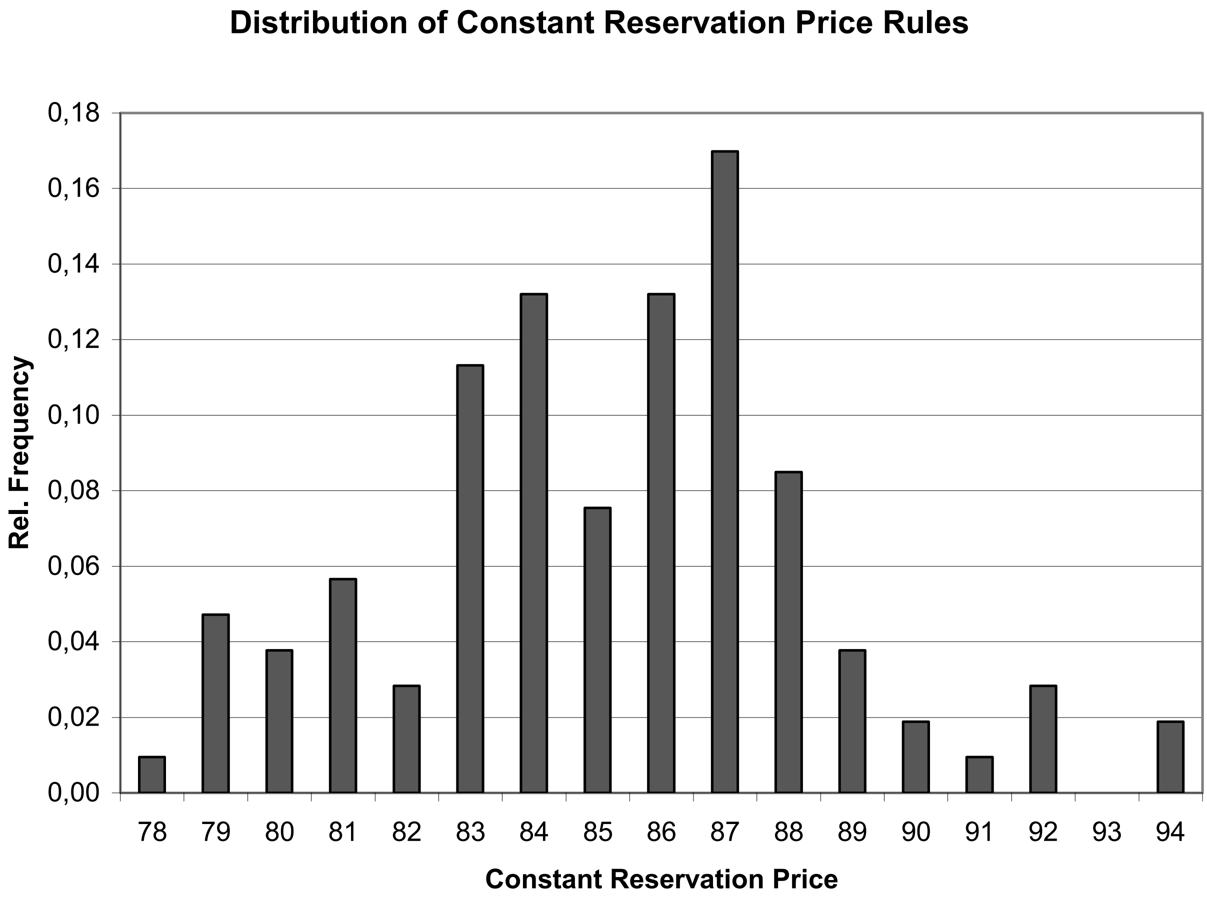

FIGURE 6
Graphical presentation of the lotteries on the computer screen.

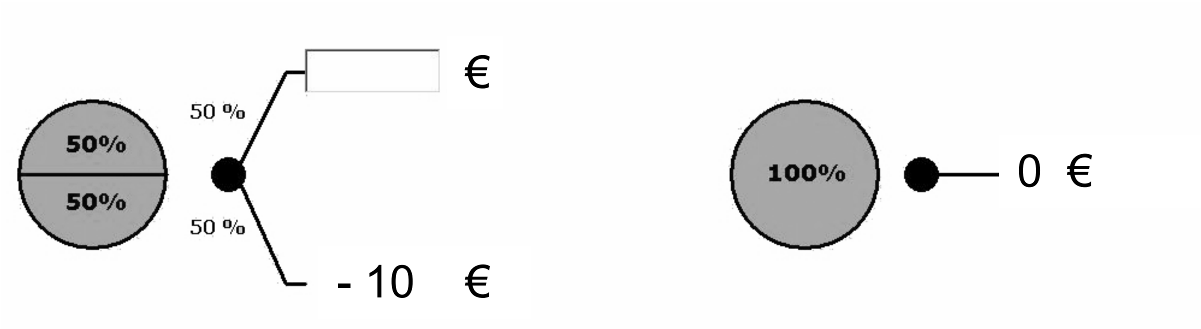

TABLE 1
Estimation results of CRRA and CARA utility function specification and classification of subjects according to their risk attitude

	Functional Specification	
	CRRA (α)	**CARA (γ)**
Minimum coeff. estimate	-0.457	-0.153
Maximum coeff. estimate	2.345	0.093
Mean R^2 of all estimations	0.998	0.998
Proportion Risk Averse	37%	37%
Proportion Risk Neutral	37%	37%
Proportion Risk Seeking	26%	26%

TABLE 2
Results of the loss aversion lottery questions.

	x-values				
	100	**50**	**25**	**10**	**1**
Minimum λ	1	.9	.96	.9	.5
Maximum λ	10	16	20	20	20
Mean λ	2.39	2.39	2.4	2.53	2.56
Median λ	1.68	1.6	1.6	1.85	1.5
Loss Averse	69%	69%	69%	70%	71%
Loss Neutral	30%	30%	30%	30%	28%
Loss Seeking	1%	1%	1%	0%	1%

TABLE 3
Pearson correlation between the different elicited loss aversion coefficients (all correlations are statistically significant at the 1%-level).

		x-values				
		100	**50**	**25**	**10**	**1**
x-values	**100**	1.00				
	50	0.88	1.00			
	25	0.82	0.95	1.00		
	10	0.80	0.94	0.96	1.00	
	1	0.66	0.73	0.72	0.74	1.00

TABLE 4
Descriptive statistics for the complete sample and the subgroups P^R and P^C.

	Complete Sample		P^R		P^C	
	Mean	**Std.Dev.**	**Mean**	**Std.Dev.**	**Mean**	**Std.Dev.**
λ_1	2.56	2.57	2.29	1.72	2.72	2.96
λ_{10}	2.53	2.63	2.19	1.41	2.74	3.12
λ_{25}	2.40	2.38	1.88	1.02	2.69	2.86
λ_{50}	2.39	2.27	1.98	1.21	2.63	2.68
λ_{100}	2.39	2.10	2.06	1.84	2.59	2.23
α	0.03	0.38	-0.03	0.26	0.07	0.44
γ	0.00	0.04	0.01	0.03	0.00	0.04
Search Steps(ss)	80.49	18.05	81.79	18.99	79.73	17.57

TABLE 5
Spearman Correlations between preference and search parameters

TABLE 5a -- P (106 subjects)

	Search steps (ss)		λ^{search}		γ^{search}		α^{search}	
	ρ	p-value	ρ	p-value	ρ	p-value	ρ	p-value
λ_1	-0.10	0.29	0.04	0.65				
λ_{10}	-0.17	0.08	0.11	0.28				
λ_{25}	-0.17	0.08	0.08	0.39				
λ_{50}	-0.16	0.10	0.10	0.29				
λ_{100}	-0.16	0.10	0.11	0.28				
α	0.02	0.87					0.03	0.78
γ	-0.01	0.88			0.06	0.63		

TABLE 5b -- P^R (39 subjects)

	Search steps (ss)		λ^{search}		γ^{search}		α^{search}	
	ρ	p-value	ρ	p-value	ρ	p-value	ρ	p-value
λ_1	-0.32	0.05	0.28	0.09				
λ_{10}	-0.40	0.01	0.30	0.06				
λ_{25}	-0.40	0.01	0.32	0.05				
λ_{50}	-0.38	0.02	0.32	0.05				
λ_{100}	-0.41	0.01	0.33	0.04				
α	-0.10	0.56					0.00	1.00
γ	0.10	0.56			0.00	0.99		

TABLE 5c -- P^C (67 subjects)

	Search steps (ss)		λ^{search}		γ^{search}		α^{search}	
	ρ	p-value	ρ	p-value	ρ	p-value	ρ	p-value
λ_1	0.03	0.80	-0.09	0.48				
λ_{10}	-0.03	0.82	-0.01	0.95				
λ_{25}	-0.04	0.77	-0.04	0.75				
λ_{50}	-0.03	0.83	-0.01	0.91				
λ_{100}	-0.02	0.89	-0.016	0.90				
α	0.07	0.55					0.03	0.81
γ	-0.07	0.57			-0.00	1.00		

TABLE 6
Duration analysis. Estimation results for various preference specifications and samples. We use two covariates in each duration regression: One covariate for loss attitude (**λ_1/ λ_{10}/ λ_{25}/ λ_{50}**, or **λ_{100}**) and one covariate for risk attitude (**α** or **γ**) That is, for each sample considered, we present 10 duration regressions.

CRRA **CARA**

TABLE 6a -- P (106 subjects)

CRRA:

Regressor	Coefficient	p-value
λ_1	0.02	0.07
α	0.02	0.73
λ_{10}	0.02	0.04
α	0.04	0.57
λ_{25}	0.02	0.03
α	0.02	0.75
λ_{50}	0.02	0.04
α	0.02	0.77
λ_{100}	0.02	0.12
α	0.02	0.74

CARA:

Regressor	Coefficient	p-value
λ_1	0.02	0.07
γ	-0.59	0.34
λ_{10}	0.02	0.03
γ	-0.76	0.23
λ_{25}	0.02	0.02
γ	-0.69	0.28
λ_{50}	0.03	0.02
γ	-0.68	0.28
λ_{100}	0.02	0.11
γ	-0.58	0.35

TABLE 6b -- P^R (39 subjects)

CRRA:

Regressor	Coefficient	p-value
λ_1	0.07	0.01
α	0.17	0.28
λ_{10}	0.09	0.00
α	0.18	0.26
λ_{25}	0.14	0.00
α	0.20	0.21
λ_{50}	0.09	0.01
α	0.15	0.35
λ_{100}	0.04	0.09
α	0.18	0.26

CARA:

Regressor	Coefficient	p-value
λ_1	0.07	0.01
γ	-1.67	0.15
λ_{10}	0.09	0.00
γ	-1.80	0.12
λ_{25}	0.14	0.00
γ	-1.91	0.11
λ_{50}	0.09	0.01
γ	-1.61	0.16
λ_{100}	0.04	0.08
γ	-1.72	0.14

TABLE 6c -- P^C (67 subjects)

Regressor	**Coefficient**	**p-value**
λ_1	0.02	0.17
α	-0.02	0.83
λ_{10}	0.02	0.17
α	0.00	1.00
λ_{25}	0.02	0.09
α	-0.01	0.94
λ_{50}	0.02	0.08
α	-0.01	0.94
λ_{100}	0.03	0.12
α	-0.01	0.86

Regressor	**Coefficient**	**p-value**
λ_1	0.02	0.18
γ	0.11	0.89
λ_{10}	0.02	0.18
γ	-0.09	0.91
λ_{25}	0.02	0.10
γ	-0.04	0.96
λ_{50}	0.02	0.08
γ	-0.06	0.94
λ_{100}	0.03	0.13
γ	0.10	0.90

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