Reference Point Formation over Time: A Weighting Function Approach*

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Abstract: Although the concept of reference point dependent preferences has been adapted to almost all fields of behavioral economics (especially marketing and behavioral finance), we still know very little about how decision makers form their reference points given a sequence of prices. Our paper provides both a theoretical framework on reference point formation over time, based on cumulative prospect theory's inverse s-shaped weighting function, and a new experimental method for eliciting subjects' individual reference points in a finance context. Consistent with our model, we document our student subjects' reference points to be best described by the first and the last price of the time series, with intermediate prices receiving smaller weights.

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1 Introduction

Empirical and experimental research over the past 25 years documents decision makers in general to be highly affected by whether they *perceive* a situation as a gain or as a loss. The general idea behind this behavior has a far-reaching tradition in psychology and was transferred into behavioral economics with Kahneman's and Tversky's (1979) prospect theory. According to prospect theory, decision makers derive their utility not from their current state of wealth but rather from changes in wealth relative to some reference point. If the decision maker perceives his current wealth to be higher than the reference point, he feels in the gain domain; conversely, if his current wealth falls short of his reference point, he suffers a painful loss. This thinking in gains and losses is assumed to affect subsequent decisions, with perceived gains leading to risk averse and perceived losses resulting in risk seeking behavior.

Reference dependency is reported to be of great importance in almost all fields of behavioral economics and everyday life (for a detailed literature overview, see Camerer 2000), including e.g. stock selling decisions (Shefrin and Statman 1985, Odean 1998, Weber and Camerer 1998, Grinblatt and Keloharju 2001), labor supply (Camerer, Babcock, Loewenstein, and Thaler 2000), consumers' purchase behavior (Lattin and Bucklin 1989, Putler 1992, Hardie, Johnson, and Fader 1993, Bell and Bucklin 1999, Bell and Latin 2000), savings behavior (Shea 1995, Bowman, Minehart, and Rabin 1999), racetrack betting (McGlothlin 1956, Ali 1977, Jullien and Salanié 2000), participation in state lotteries (Cook and Clotfelter 1993), and insurance purchases (Cicheti and Dubin 1994). Little is known, however, on how decision makers determine their reference points over time, and what they consequently perceive as a gain or as a loss. While Kahneman and Tversky (1979) interpret the reference point as either the decision maker's status quo or an expectation or aspiration level, these concepts remain ambiguous. Similarly, models in behavioral economics, especially marketing and finance, are based on the broad concept of reference dependency, but disagree on the formation and updating rule. Finance models, for example, usually assume the reference point to be some mixture of past purchase prices or historical prices, but fail to provide a coherent function on how different prices are aggregated by the investor.

Due to the great importance of reference point dependency in behavioral economics, a precise functional form is needed that captures how decision makers build their reference points as a reaction to different price path developments. Knowing e.g. stock market investors' formation and updating procedure could greatly enhance our understanding of investment biases and market anomalies. Although it is nowadays common in empirical analyses to assume some kind of reference point effect, there is actually no study that provides a direct horse race between competing reference point formation and updating rules. The present paper tries to fill the gap in the existing literature by proposing both a theoretical framework and an experimental design with which decision makers' individual reference points can be elicited in a time series context.

We think that there are two main reasons for why there is so little research on reference point formation and updating over time. First, reference points are barely measurable. While we are able to observe decision makers' choice behavior and may theorize on whether this behavior is driven by reference dependency, the reference point itself remains a black hole. Inferring reference points indirectly over decision makers' choices leads only to noisy signals, not precise point estimates. Second, one could consider a broad variety of different reference point candidates, starting with simple prices, like the purchase price or the historical peak of a time series, over diverse weighted averages, to more complicated conditional functions. As reference points are a subjective concept and solely depend on the decision maker's individual perception, many different reference points seem defensible.

The two problems culminate in severe multicollinearity: While there are so many possible reference points, researchers are severely hindered to disentangle just a few of them using a "normal" data set. If we, for example, want to find out whether investors' selling behavior and disposition effects (Shefrin and Statman 1985) could be better explained by the highest price or the equally weighted average historical price, most selling decisions do not let us differentiate between the two hypotheses. If the selling price marks the highest price of the time series, it is automatically also above the equally weighted average. Conversely, if the selling price lies below the equally weighted average, it cannot be the peak of the time series. Consequently, we need to base our horse race on only those situations in which the selling price lies between the average and the historical maximum, which eliminates approximately 50 % of a normal transaction data set. If we now introduce a second or third reference point candidate, e.g. the purchase price and the previous period's price, the multicollinearity problem gets progressively worse until we finally cannot reasonably run a regression on our set of competing reference point hypotheses.

As a solution to these problems, we propose the following approach: As a starting point, researchers looking for the "right" reference point should limit the space of possible reference prices to a small, selective number of more reasonable factors. We consequently base our horse race on the purchase price, current price, highest price, lowest price, and two different weighted average prices, and assume the reference point is a function of just these factors. Furthermore, price paths could be predetermined by the experimenter to artificially generate situations that let us disentangle factors that influence reference points. Optimally, this leads to ceteris paribus conditions, i.e. pairs of price paths that are the same in respect to all considered price path factors but one. Finally, researchers should not infer reference points through decisions (e.g. purchasing and selling), as this provides little information about the underlying reference points, but should rather directly ask subjects for point estimates of their current reference prices. The more precise the estimate, the easier it is to disentangle different reference point formation concepts.

In a first step, we seek to provide a theoretical framework. We believe that a theoretical model is important to interpret the empirical results, to have a guide for conducting follow-on studies, and to connect the current research with existing behavioral models of decision making. The theoretical framework we propose is based on the intuition that a reference point requires the decision maker to weight information. Hence, we borrow from the domain of decision making under uncertainty the idea of probability weighting (Tversky and Kahneman 1992), in our case interpreted as "information weighting".

In our formulation, the "probabilities", or given weights associated with each piece of information, are simply 1/n, where n is the number of observed prices. While in cumulative prospect theory, outcomes are rank-ordered before deriving decision weights, we instead sort outcomes following the time line, from the most recent outcome to the distant past. It is well known that an inverse s-shaped probability weighting function magnifies the decision weight of the extreme outcomes. In our setting, such inverse s-shaped weighting function pronounces the "information weights" given to the most recent and most distant piece of information, whereas intermediate outcomes are less important and thus receive a smaller weight. Finally, the summed product of information values times information weights produces the reference point.

In a second step, we set up a simple individual choice experiment for eliciting our student subjects' reference points over different price developments in a finance frame. In the experiment, subjects are confronted with one stock price path at a time and are asked to indicate the selling price for which they would feel neither happy nor unhappy. Although the experiment is framed with a finance story, we believe that results also shed light on other situations in which decision makers need to evaluate a time series of prices, for example, when purchasing consumption goods or buying insurances.

Based on our subjects' answers we run a horse race on competing reference point candidates and elicit the shape of the information weighting function discussed in the theoretical section of the paper. Consistent with our hypotheses and our model, we find our subjects focus on the purchase price and the current price of the time series. However, the two prices do not constitute the whole story. Instead, we also find some influence of the equally weighted average of the intermediate prices and a marginal impact of the historical peak. Lowest prices, on the other hand, are revealed to exhibit almost no influence on our subjects' decisions. Consequently, information weighting functions follow the inverse s-shaped form assumed in our model.

This paper proceeds as follows: In section 2 we provide an extensive literature overview on reference point formation and updating in various fields of behavioral economics. Based on the literature, we flesh out our research questions and hypotheses. Sections 3 and 4 present our model and the experimental design, while section 5 reports results on competing reference point candidates and elicits the information weighting function. Section 6 provides a discussion of our findings. Translations of the experimental instructions can be found in the appendix.

2 Related Literature and Hypotheses

In the following, we provide an overview on three strands of literature: First, we review theories and models on reference-dependent preferences, both general and more application-oriented. While these models are normally not deeply concerned with how reference points are formatted and updated over time, they may nevertheless provide testable hypotheses as a byproduct. Second, we overview empirical and experimental studies on the disposition effect, a prominent behavioral bias in the finance context that is usually assumed to be driven by reference dependency. We are interested in what these studies assume the reference point to be. Third, we summarize studies that are more closely related to our own design, i.e. empirical and experimental analyses concerned with reference point formation or updating over a time series of prices. Unfortunately, the last strand of literature is very thin and provides only limited insights on our research question.

For behavioral economics, prospect theory (Kahneman and Tversky 1979, Tversky and Kahneman 1992) constitutes the baseline model of reference-dependent preferences. In prospect theory, decision makers are assumed to base their decisions not on absolute wealth levels as proposed by expected utility theories but on changes in wealth relative to some reference point. Kahneman and Tversky consider the reference point to equal the status quo, but they also mention that in some situations the status quo could be replaced by an expectation or aspiration level. However, both concepts allow for different interpretations. If an investor e.g. purchased the same stock at different prices in the past, one may either assume his subjective status quo to equal the first, the most recent, or a mixture of both purchase prices. In addition, it remains unclear how the investor is going to form his future expectations about the stock and how these expectations interfere with past experiences.

Since Kahneman and Tversky (1979), reference dependency has also become a building block of more application-oriented models in behavioral economics, psychology, and sociology. While in psychology it is common to assume the reference point to be either the status quo (Kahneman and Tversky 1979, Tversky and Kahneman 1991, 1992, Hsee and

Abelson 1991) or some aspiration level (Dembo 1931, Hoppe 1931, Lewin, Dembo, Festinger, and Sears 1944, Siegel 1957), in marketing research, reference points are usually modeled as the consumer's expectation or aspiration concerning price, quality, or promotion of the consumption good (Lattin and Bucklin 1989, Putler 1992, Hardie, Johnson, and Fader 1993, Bell and Bucklin 1999, Bell and Latin 2000). Initiated by Shefrin and Statman (1985), in behavioral finance, reference points are generally referred to as a function of past purchase prices of the financial asset, not historical prices. This implies the assumption that prices at which the investor actually made a decision are more important than prices at which the investor did not act. Other models in diverse disciplines assess the reference point to be a mixed function of an aspiration level and some critical survival point (March 1988, March and Shapira 1992), or simply as the weighted average of past stimuli (Helson 1964, Lim 1995, Kopalle, Rao, and Assuncao 1996, Chen and Rao 2002, Compte and Jehiel 2003). Despite this variety in assumptions, these models rarely justify why their reference point is the "right" one or how exactly their reference point is formed and updated given a time series of prices.

Although there are many strands of literature that empirically test for behavioral biases that are assumed to be driven by reference dependency, for this literature overview, we focus on the disposition effect (Shefrin and Statman 1985) as this bias is more closely related to our research design. A test of the disposition effect is inevitably a joint test of how investors act in the presence of gains and losses and how investors form and update their reference points over time.[2] Thereby, most studies on the disposition effect assume the reference point to be a function of past purchase prices. Most often the equally weighted average purchase price is considered to be a good proxy (see e.g. Odean 1998, Grinblatt and Keloharju 2001, Garvey

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[2] See Barberis and Xiong (2006) for a detailed formal discussion on this prospect theory explanation.

and Murphy 2004, or Feng and Seasholes 2005). Much more rarely, the first purchase price (FIFO) or the most recent purchase price (LIFO) are applied as standard measures (see Weber and Camerer 1998 and Frazzini 2006). Non-purchases prices like previous period's historical prices or historical peaks are quite uncommon and are mainly used if there are no purchase prices available, e.g. when studying the disposition effect in management stock option exercise behavior (see e.g. Heath, Huddart, and Lang 1999, Core and Guay 2001, and Ben-David and Doukas 2006). As a robustness check, most authors also apply alternative reference point formation rules besides their standard measures, usually the highest, the first, and the most recent purchase price. Results are mainly unchanged due to the high correlation between these different specifications (see our multicollinearity argument in section 1).

In sum, models and empirical studies only marginally concerned with reference-dependent preferences strongly disagree on how the reference point is set up. In the following we review those few studies that focus on the question how reference points emerge given a time series of prices. These studies may provide first insights for our own research question.

Chen and Rao (2002) test close encounters of two kinds: "False alarm" and "dashed hope". In the false alarm setting, subjects are confronted with an intermediate decrease in wealth, which is reverted after some time. Similarly, in the dashed hope setting, subjects' wealth increases intermediately followed by a rebound to the initial level. The authors find that subjects are more happy following an intermediate decrease in wealth rather than an intermediate increase. This finding is consistent with an at least partial reference point adaptation to the intermediate wealth level. Arkes, Hirshleifer, Jiang, and Lim (2006) replicate a similar setting with a different methodology. Using the Becker, DeGroot, and Marschak (1964) procedure for eliciting their student subjects' willingness to accept for selling a lottery ticket, the authors show that updating is faster following gains than following losses.

In a very different experimental approach by Gneezy (2005), student subjects are given a hypothetical financial asset. The price of the asset follows a random walk, and subjects need to indicate every period whether or not they want to sell their asset for its current price. Gneezy reports that subjects are more willing to sell if the current price equals the historical peak. He interprets subjects' selling behavior as a proxy for their reference point and concludes that reference points are more a function of the highest historical price rather than of the asset's initial price. Maybe due to the multicollinearity problem discussed in the introduction (section 1), Gneezy does not provide statistical tests or horse races between competing reference point candidates.

Finally, Lin, Huang, and Zeelenberg (2006) report results of an experimental study conducted with individual investors. Investors are asked which stock they purchased most recently, what they expected the performance to be, and which two other stocks they considered purchasing instead. After answering these questions, subjects are shown the real performance of all three stocks and asked how sorry and regretful they feel having chosen the first stock. The authors document regret to be mainly a function of the chosen stock's performance relative to a zero-performance reference point. Investors thus seem to compare their situation to a mental counterfactual of not having purchased the stock at all. Conversely, comparing realized returns across stocks seems rather uncommon.

While these prior studies provide some insights on our research question, they analyze only very few price paths. For instance, Chen and Rao (2002) and Arkes, Hirshleifer, Jiang, and Lim (2006) study only two paths with three points in time, varying solely in their intermediate prices. Furthermore, we think that prior designs are not selective enough. Studying reference point formation and updating over time requires subjects to give point estimates. Asking for happiness or regret as done by Chen and Rao (2002) and Lin, Huang, and Zeelenberg (2006) or analyzing subjects' selling behavior as done by Gneezy (2005) leads to noisy proxies, which are of limited use for disentangling different reference point specifications. The design of Arkes et al. (2006) does give point estimates but applies the Becker, DeGroot, and Marschak (1964) procedure, which primes decision makers to rationalize about their behavior. This does not seem appropriate to capture the intuitive meaning of reference-dependent preferences. Hence, we develop a new experimental design with a variety of different price paths and a more intuitive reference point elicitation procedure in the following sections.

Based on this literature, we work out our research design and hypotheses as follows: As a starting point, and to reduce complexity, we only investigate reference point formation instead of reference point updating over time. In addition, we consider very simple price paths with one purchase decision only. We then choose simple price path factors as possible reference points, i.e. the purchase price, the current price, the highest historical price since the purchase, the lowest historical price since the purchase, and two different weighted average prices since the purchase (one giving identical weights to all prices and one giving higher weights to more recent prices). These path factors are assumed to be important in the literature. To fully disentangle which of these properties exhibit the strongest influence, we predefine price paths so that two paths are equal in respect to all of these reference point candidates but one.

We expect two groups of effects: Purchase price and current price are assumed to exhibit the main effects on the reference point. They mark the start and the end of the time series and are therefore likely to capture the decision maker's attention. Furthermore, the purchase price is linked to the purchase decision and is thus important from an accounting perspective. Conversely, the current price is the best estimate of future value and should be essential for the subject's expectation. Hence, the higher the two prices, the higher the reference point should be. Highest price, lowest price, and equally weighted average price are also expected to affect the reference point, but to a lower degree. The peak and the low of the time series may be especially eye-catching while the weighted average captures the mean perception of past stimuli. In addition, we test whether subjects weight more recent prices more strongly than older prices, i.e. whether reference points are path-dependent. Highest price, lowest price, equally weighted average price, and path-dependent average price therefore form our second group of hypotheses.

3 An Information Weighting Model of Reference Point Formation

In this section, we introduce a formal model of reference point formation. We base our model on the premise that a reference point is the outcome of a mental process in which decision makers essentially weight information. In our simple setup of a price process, this means that the reference point is some weighted average of observed prices. However, there could be multiple ways to attach weights to any given price path, and the task is to develop a model that yields a prediction on how such weighting will take place for any given sequence of prices.

We are inspired by developments in an area that has similarities to our problem, namely, decision under risk. Research on decision under risk seeks to understand how decision makers choose between prospects. A typical prospect is a set of outcomes $(x_1,x_2,\ldots,x_n)$ with received probabilities $(p_1,p_2,\ldots,p_n)$ that add up to 1. We now review the mainstream behavioral model of how (most) decision makers evaluate such prospects, i.e. cumulative prospect theory (Tversky and Kahneman 1992). For our purposes, it is sufficient to consider that all outcomes x_i, i = 1,..,n, are strictly positive.

Cumulative prospect theory views the evaluation of prospects as a dual task, in which decision makers first assign each outcome x_i some (utility) value $v(x_i)$. The value function v is usually thought of as concave, reflecting the principle of diminishing sensitivity. The second task consists of attaching decision weights π_i to each value $v(x_i)$. Here, probabilities are taken as the inputs. In the first step, outcomes are sorted highest to lowest. Let $(x_1^*,x_2^*,\ldots,x_n^*)$ be such that $x_1^* \geq x_2^* \geq \ldots \geq x_n^* > 0$, and let $(p_1^*,p_2^*,\ldots,p_n^*)$ be the corresponding probabilities. Then, probabilities are accumulated such that

(1) .

In the third step, a probability weighting function is introduced which transforms the entries in $(P_1^*,P_2^*,\ldots,P_n^*)$ into cumulative decision weights $(w(P_1^*),w(P_2^*),\ldots,w(P_n^*))$. The probability weighting function is any given increasing and continuous function with w(0) = 0 and w(1) = 1. In the fourth and final step, and with the understanding that $P_0^* = 0$, individual decision weights are calculated as

(2) .

The probability weighting function is usually thought as inverse s-shaped. This implies that both p_1^* and p_n^* will be magnified as compared with $p_2^*,\ldots,p_{n-1}^*$. In other words, the highest and lowest outcomes will receive decision weights higher than their received probabilities, while the intermediate outcomes will tend to receive decision weights lower than their received probabilities.

We view the rank-dependent model as a model of information weighting. If the formation of reference points is also a process of information weighting, one may speculate on how the rank-dependent model can be applied to this problem. Here is our proposal. First, we need to specify what the equivalent of a prospect is. Clearly, the replacement for the vector of outcomes is the given price path $(y_1,y_2,\ldots,y_n)$, which is sorted according to time. For the received probabilities, which we can call "received weights", we propose the simplest of all options: equal weighting. Hence, the "viewed from the outside" weight that the subject is supposed to give to each piece of information is 1/n, with n as the total number of prices in the price path.

Once the prospect is specified, we can now proceed to apply a concave transformation of prices, $v(y_i)$, $i = 1,\ldots,n$, reflecting diminishing sensitivity in weighting the outcomes. Next, we can calculate the decision weights. To do so, we introduce an important modification in the first step of the application of the weighting function. As information in the finance context is ordered by time, we find it psychologically much more plausible that (most) subjects do not naturally sort prices from highest to lowest, but rather sort them along the time line, from the most recent past to the most distant past. Hence, $y_i^* = y_{n-i+1}$ and

(3) .

The rest of steps are now standard. The second and third steps yield

(4) , and

(5) .

Rather than "probability weighting function", for our application, we shall call w the "information weighting function". Similarly, the "information weights" will be calculated as

(6) ,

or undoing the reverse-time ordering, the weight attached to y_i, is given by

(7) .

Using an inverse s-shaped information weighting function, we predict that more weight will be given to the most recent and most distant prices. Intermediate prices will receive less weight, regardless if those prices are the highest or the lowest in the sequence.

4 Experimental Design

We investigate reference point formation experimentally in a financial frame. In an individual choice task, subjects see one stock price path at a time and are asked to indicate their reference points in Euros. In the following, we explain the experimental design and the procedure in detail.

4.1 Individual Choice Task: Elicitation of Reference Points

A simple example of a reference point decision maker in a time series context is a stock market investor. The investor needs to decide which assets to purchase and sell at what time and is likely to be affected by past price developments. Hence, the general idea of our individual choice task is the following: We show our subjects a single predefined stock price path at a time. We want them to imagine that they purchased the stock for the first price shown in the graph and that since this purchase the price developed in the way presented.

Based on these stimuli, subjects are then asked to indicate their current reference points in Euros as point estimates.

Applying this methodology in the laboratory requires a more detailed specification: We cannot use the term “reference point” in the elicitation question as our subjects are unlikely to be familiar with this concept. From the definition of the reference point, one may be tempted to instead ask subjects for the selling price they would personally consider “neither a gain nor a loss”. However, as a pretest demonstrated, this elicitation question performs poorly as subjects focus almost exclusively on the purchase price. We assume that this is driven by the different meaning of “gains” and “losses” in prospect theory and everyday language. While in everyday language the two terms are related to mathematical calculation and accounting, in prospect theory “gains” and “losses” constitute a broader concept of individual perception and feelings. We therefore need to circumscribe the idea intuitively and instead ask for the selling price for which subjects would feel “neither happy nor unhappy”. In addition, the financial situation discussed above is quite artificial. We e.g. need a good explanation why the subject did not sell the stock in the meantime, i.e. between the purchase and now. We solve this problem by giving our subjects a real life background story in which they were not able to trade the stock in the past due to vacation.

In the real life background story, our subjects are told that a few days ago, on day 0, they purchased a stock traded in Euros. On the same day they went on vacation. In their vacation resort they could monitor the price development of the stock but could not trade it. Today, on the day before their return journey, they again take a look upon the stock’s price development since the purchase on day 0. They are told in the instructions that they assume the future stock price to rise or fall up to € 50 every day and regard all possible price changes between € +50 and € -50 as equally likely. Subjects are then requested to state the selling price for which they would feel indifferent, i.e. neither happy nor unhappy about selling the stock the next day. Great care is taken to ensure that our subjects understand the concept of indifference.

Figure 1 shows the computer screen. We show subjects a graphical representation of the price path instead of simple Euro values to make it easier for them to assess the price development of the stock. Every price path is presented on an individual computer screen. To make sure that our subjects are made aware of the whole price development process, the price path is drawn with a time lag of some seconds from left (the purchase price on day 0) to right (the current price of the stock). After the path is drawn, the subject could click on the graph area to indicate his reference point.

(insert figure 1 about here)

Our subjects are confronted with 63 different price paths, varying both in price path factors, e.g. the purchase price and the current price, as well as in length. While all subjects see the same price paths in the experiment, we randomize the order in which subjects pass through situations 1 to 63 to avoid order effects. Table 1 provides detailed information on all 63 price paths analyzed.

(insert table 1 about here)

Price path factors are chosen carefully to disentangle the influence of the purchase price, the current price, the highest price, the lowest price, and the equally weighted average price on the reference point. By predetermining price paths, we are able to artificially generate ceteris paribus conditions, i.e. pairs of price paths that are identical in respect to all investigated path factors but one. As an example, compare path numbers 1 and 2: The two paths share the same current price (€ 200), the same highest price (€ 250), the same lowest price

(€ 150), and the same equally weighted average price (€ 200). They only vary in their purchase prices (€ 250 in path 1 vs. € 150 in path 2). Hence, given that our set of price path factors is complete, differences in reference points between paths 1 and 2 need to be driven by differences in their purchase prices.

Overall, our 63 predefined price paths provide us with five ceteris paribus pairs that only vary in their purchase prices. In addition, there are five pairs that only vary in their current prices, their highest prices, their lowest prices, or their equally weighted average prices. Three additional pairs test for the influence of intermediate prices in general, while five pairs are designed to answer the question whether more recent intermediate prices are more important than older intermediate prices, i.e. whether reference points are path-dependent. Furthermore, paths 61 to 63 provide additional control for path lengths of three, four, or five days.

4.2 Questionnaire

After completing the individual choice task and before receiving their financial reward, subjects are asked to answer a short questionnaire. The questionnaire contains two open questions on the subject's decision behavior, questions in which we ask subjects directly whether e.g. the purchase price or the current price were important for their decisions, and another general open question at the end.

4.3 Procedure

The experiment was conducted in October and November 2006 at the SFB computer laboratory at the University of Mannheim. We did a pretest on October 13 and ran the main experiment on October 30 to November 3.

Our subjects were 35 male and 20 female students. Approximately half of them studied economics and business administration while the other half's fields of study were not related to economics, e.g. computer science, sociology, or law. The average age was 23, the average academic year was 2.7. Due to graphical requirements, the experimental software was programmed in Blitz Basic, applying its graphical user interface. After the experiment, subjects were asked to indicate on a scale whether or not the instruction were comprehensible, lasting from 1 (barely comprehensible) to 9 (very comprehensible). The average scale value was 8.22, so that we think that subjects indeed intuitively understood our elicitation procedures. The average processing time was 38 minutes, including instructions and some open questions at the end. Subjects received a fixed payment of € 8 for their participation. A translation of the German instructions can be found in the appendix.

5 Results

For the data analysis we proceed in the following way: In section 5.1 we first run univariate tests on those price paths that constitute ceteris paribus pairs, i.e. paths that only vary in one considered price path property. We also prove these results to be stable under a multivariate regression analysis in section 5.2. Section 5.3 elicits our subjects' information weighting functions taking all observations as decisions from one representative agent. Finally, section 5.4 questions in how far individual subjects deviate from this average behavior.

5.1 Univariate Analysis

Our price paths given in table 1 form ceteris paribus pairs as documented in table 2 that help us avoid the multicollinearity problem discussed in the introduction.

(insert table 2 about here)

A conservative way of analyzing the effect of different reference point candidates is to run univariate tests on these pairs. As discussed in section 2, we expect two groups of effects: In the first group, we assume the purchase price and the current price to exhibit the main effect on the reference point. However, we do not believe these prices to be the only factors in the reference point formation function. In the second group we therefore test for the influence of the highest price, the lowest price, and the equally weighted average price. In addition, we also study whether more recent prices are more important than older prices. As we have five ceteris paribus pairs for each the purchase price, the current price, the highest price, the lowest price, the equally weighted average price, and the path-dependent average price, we do not document results for all paths but focus on representative examples.

Purchase Price

We start studying the influence of the purchase price, taking paths 1 and 2 as examples. While paths 1 and 2 are the same concerning their current price, highest price, lowest price, and equally weighted average price, the purchase price of path 1 exceeds that of path 2 by € 100.[3] As our experiment shows, these purchase prices forcefully translates into reference points, with mean values of € 235.04 for path 1 and € 182.22 for path 2. This difference in reference points is highly significant using a matched-pairs signtest (p = 0.0000).

The other four ceteris paribus pairs confirm these results: While pairs number 2 and 3 are similar to the example documented above, they lead to smaller differences in reference points of € 20.13 (p = 0.0000) and € 26.87 (p = 0.0000) which is roughly equivalent to the

[3] Path factors can be looked up in tables 1 and 2.

halved distances in purchase prices of now € 50. Comparison 4 shows robust results in a situation in which a simple believe in price trends as an alternative explanation would lead to the opposite behavior (difference of € 44.31, p = 0.0000). Comparison 5 finally provides a robustness check in which the two price paths recently moved simultaneously (difference of € 46.64, p = 0.0000).

Current Price

Compared to purchase prices, we find a weaker but still economically and statistically significant effect for current prices. While path 11 leads to an average reference point of € 216.11, path 12 results in a reference point of € 182.22 (p = 0.0000). The mean difference is thus € 22.96. For ceteris paribus pairs number 7 and 8 the difference in reference points is roughly halved as are differences in current prices (p = 0.0401 and p = 0.0000). The two comparisons also eliminate both trend chasing and believe in mean reversion as possible explanations. Similarly, results are robust under the more complicated comparison conditions 9 and 10 (differences of € 13.87 and € 17.73, p = 0.0000).

Intermediate Prices

While both purchase price and current price exhibit a strong effect on the reference point, we do not believe these prices to constitute the whole story. Consequently, we study price paths that are the same in respect to both purchase and current price but differ in their intermediate prices. A very simple example provides ceteris paribus pair 11, consisting of paths 6 and 3. On average, subjects indicate reference points of € 208.33 following an intermediate price increase and € 198.07 succeeding an intermediate decrease. The difference in reference points is with € 10.25 still both economically and statistically significant (p = 0.0000). We receive similar results for ceteris paribus pair number 12 (difference of

€ 11.15, p = 0.0000), while pair 13 leads to even stronger differences in reference points (difference of € 20.15, p = 0.0000).

For further insights we compare paths 6 (€ 200 - € 250 - € 200) and 3 (€ 200 - € 150 - € 200) to path 61 (€ 200 - € 200 - € 200). Path 61 leads to an average reference point of € 202.22, which is significantly higher than that of path 3 (p = 0.0000) and lower than that of path 6 (p = 0.0000). In response to Chen and Rao (2002) and Arkers, Hirshleifer, Jiang, and Lim (2006) we conclude that reference points are indeed influenced by intermediate changes in wealth. Furthermore, while decision makers update their reference points both as a reaction to intermediate price increases and decreases, updating following gains is faster (difference of € 6.11) than updating to losses (difference of € 4.15).

In summary, we find strong effects for both the purchase price and the current price. The first and the last price seem to be the main factors of how decision makers assess a time series. Nevertheless, intermediate prices matter, and we should continue investigating to what extent intermediate prices are important in the examples discussed above. Paths 6 and 3 e.g. could be perceived differently because of differences in highest prices, lowest prices, or equally weighted averages. We go on disentangling these reference point candidates in our second group of hypotheses.

Highest Price and Lowest Price

Paths 23 and 24 lead to reference points of € 185.44 and € 181.38 and thus to an average difference of € 4.06 (p = 0.0481). In ceteris paribus pair 15, 16, and 18, effects are a bit smaller (differences of € 1.47, € 1.09 and € 2.13), and in pair 17 a bit stronger than in the baseline example (difference of € 4.18). The effect, however, is not significant for pairs 16, 17, and 18.

Conversely, we do not find clear results for the lowest price. Path 33 even leads to a lower reference point than path 34 with € 228.09 and € 237.58. Similarly, in pairs 20 to 23, reference points are either insignificantly different or higher in the second path.

Equally Weighted Average Price

Path 43 receives an average reference point of € 238.15 compared to € 235.20 for path 5 ($p = 0.1958$). The magnitude of the effect increases for pairs 25, 27, and 28, and decreases only slightly for pair 26. Effects are significant for pairs 25, 26, and 27.

Alpha Weighted Average Price

Finally, we test for path dependency. We therefore explore pairs 29 to 33 that are the same in respect to all considered price path factors and only differ in the ordering of prices. Reference points, however, do not seem to be systematically influenced by this ordering. While effects switch signs, differences are only statistically significant for pair 33, in which path 58, not 57, receives the higher reference point – contrary to our hypothesis.

Questionnaire Item

In a final question at the end of the experiment, we ask subjects directly for the importance of different reference point candidates. Subjects are required to answer on a 9-point-scale whether e.g. the purchase price had no influence (value of 1) or a strong influence (value of 9) on their decisions. We randomize the order in which different prices appear on the screen to control for order effects. Table 3 reports the results.

(insert table 3 about here)

Consistent with their behavior in the individual choice task, subjects assign the purchase price the highest value, followed by the current price. Lowest prices, highest prices, and equally weighted average price are perceived to be only marginally important. Surprisingly, subjects overestimate the influence of path-dependency and consider it to be the third most important aspect. Ignoring the weight for path-dependency, our subjects' answers agree with our univariate results. We interpret this as a sign that subjects do not only act intuitively but rationalize about their behavior.

5.2 Multivariate Regression Analysis

As further robustness checks we run regressions on all point estimates simultaneously. Regression analyses here have a couple of important advantages: They are based on many different price paths, decisions, and subjects at once, leading to more robust estimates. They also serve as horse races between competing price path factors, and regression coefficients can be easily transformed to decision or information weights, which capture the impact of every reference point candidate in percentages. However, regressions on path properties also lead to multicollinearity as discussed in the introduction. While this makes regressions with "normal data sets" virtually impossible, our predefined price paths reduce these problems to a great extent.

As documented in equation 8, we regress individual reference points (RP) for all subjects i and all price paths j on the purchase price (PP), the current price (CP), the highest price (HP), the lowest price (LP), the equally weighted average price (EP), and the alpha-weighted average price with an alpha of 50 % (AP).

(8)

We use ordinary least squares regressions without intercept so that coefficients could easily be interpreted as weights that should roughly add up to one. As there is still some collinearity between the highest, the lowest, and the two weighted average prices, we run two different regressions: One including all variables mentioned above and one excluding the equally weighted and the path-dependent average price. Table 4 documents the results.[4]

(insert table 4 about here)

Our multivariate results are consistent to our univariate findings. Relatively high weights are given to the purchase price (about 47 %), the current price (about 24 %), and the equally weighted average price (about 30 %), while highest, lowest, and the path-dependent average price[5] are more or less negligible or even lead to negative coefficients. Contrary to a "peak-end rule" (Fredrickson and Kahneman 1993, Kahneman, Fredrickson, Schreiber, and Redelmeier 1993, Kahneman, Wakker, and Sarin 1997, Kahneman 1999), the highest price clearly loses the horse race against the equally-weighted average price and only increases in importance if we exclude the two weighted average prices in the second regression.

5.3 Fitting the Information Weighting Function

We now calibrate our information weighting model presented in section 3 following two different approaches: First, we elicit the weights of stepwise cumulative weighting functions for different path lengths. In these functions, every price of the price path receives an own weight and the inverse s-shaped functional form must arise endogeneously. Second, we estimate curvature and elevation of Prelec's (1998) two parameter model using all price paths

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4 We do not report R-squares as these are biased in regressions without intercept.

5 Results are robust for different alphas as long as alphas do not approach 0 or 1. In these cases, alpha weighted prices mimic the purchase or the current price, leading to collineariry.

at once. The resulting continuous information weighting functions capture our subjects' general behavior and provide a broader framework for predicting financial decisions in these and other contexts.

We expect all information weighting functions to exhibit an ordinary s-shaped form as known from Tversky's and Kahneman's (1992) probability weighting function. In cumulative prospect theory, positive and negative outcomes are sorted separately from high absolute values to low. The maximum and minimum outcome thereby receive above-average decision weights, while intermediate outcomes are assumed to be only marginally important. The idea is that decision makers – due to perception or to reduce the complexity of the choice problem – usually focus on the highest and lowest possible outcome when valuating a lottery. Conversely, in our time series setting not the highest and lowest price but the first and the last price of the series are assumed to be excessively important (see section 2). Hence, we sort prices along the time line from most recent to the first price at which the subject acquired the stock.

Our methodology for eliciting stepwise cumulative weighting functions is as follows: For paths of length 3, we regress subjects' reference points on the first, the second, and the third price of the path. For path lengths of 4, the right-hand side of the regression function is set up as the first, the last, and the mean of the two intermediate prices,[6] and paths consisting of 5 prices are regressed on all individual prices 1 to 5. As we only have few paths with lengths higher than 5, we run a combined regression on paths with lengths 6 to 10 with the right-hand side consisting of the first, the second, the second-last, the last, and the mean of

[6] For path lengths of 4, multicollinearty prohibits us from assigning the second price and the third price individual weights.

remaining intermediate prices. All regressions are ordinary least squares without intercepts so that regression coefficients already roughly add up to one.

Received weights are assumed to equal 1/n, with n being the path length in prices. Cumulative received weights therefore add up to (n-i+1)/n with i being the number of the considered price. Behavioral information weights on the other hand are computed as renormalized regression coefficients and cumulated backwards over time. If the regression took only the mean of intermediate prices into account, we split the resulting weight among those prices that constitute the mean. Figure 2 shows resulting cumulative information weighting functions for paths with 3, 4, 5, and 6 to 10 prices.

(insert figure 2 about here)

We obtain characteristic weighting functions. Current prices and purchase prices receive the highest weights for all path lengths. Second and second-last prices are important – but to a lesser extent, while the other intermediate prices are more or less negligible. As an example consider the weighting function for path lengths of 6 to 10: The purchase price receives the highest weight with approximately 47 %, the current price is the second most important price path property with an average weight of 34 %, while the second to last price, intermediate prices (here: prices 3 to 6), and the second price are weighted with 6 %, 2 %, and 4 %, respectively. Cumulative weighting functions do not only exhibit an s-shaped form but also equal general probability weighting functions in elevation and curvature, crossing the 45 degree line at a cumulative received information weight of approximately 1/3 (compare Tversky and Kahneman 1992). There is also some evidence that the sum of weights given to intermediate prices increases with the length of the path – consistent with our models' prediction. In price paths of length 3, the second price receives an average weight of 12 %. If the path is extended to 4 prices, the two intermediate prices share a weight of again approximately 12 %. For paths with 5 prices or 6 to 10 prices, the weight sum of intermediate prices increases to 26 % or 20 %.

As curvature and elevation of weighting functions do not vary strongly with the length of the path, we now fit a parametric model. Several parametric forms of probability weighting functions have been proposed. We take the two-parameter model introduced by Prelec (1998), which is given by the following equation:

(9)

Out of the many different weighting functions that have been discussed in the literature, Prelec's model has the advantage to provide an axiomatic foundation, to be consistent with empirical and experimental findings, and to be relatively parsimonious. The parameter α regulates the curvature (for $\alpha = 1$, the probability weighting function is linear; as α decreases, w becomes more inverse s-shaped). The second parameter, β, determines the elevation: For $\beta = 1$, $w(P) = P$ for $P = 1/e \approx 0.37$. For $\beta < 1$, the elevation increases, and w(P) crosses the identity axis at a higher P. As the crossing around $P = 0.37$ has been found to be empirically plausible in other areas of decision making, the one-parameter version with $\beta = 1$ and $\alpha \approx 0.6$ would be a good candidate function to represent a typical decision maker.

We fit Prelec's weighting function based on all price paths and all subjects and use a solver program to estimate α and β so that prediction errors are minimized. Received weights are again defined to equal 1/n. Figure 3 shows the resulting cumulative information weighting function.

(insert figure 3 about here)

Our information weighting function has an elevation of 1.07 and a curvature of 0.25. While the elevation is very close to elevations elicited for probability weighting functions, the curvature is quite low. Bleichrodt and Pinto (2000) report a curvature of 0.94 and an elevation of 0.60, whereas Jullien and Salanié (2000) elicit parameters of 1.14 and 0.88 for Prelec's (1998) two parameter model.

This parametric weighting function implicitely also provides us with a simple updating rule, we want to illustrate with a short example: Imagine, an investor purchases a stock at € 100. At the time of the purchase the investor will value this single price information with 100 %, so that his reference point also equalls € 100. If, on the second day, the stock price drops to € 90, the purchase price receives a weight of 62.33 %, while the new price is weighted with 37.67 %, leading to a reference point of € 96.23. If, on the third day, the price reverts to € 110, the purchase price receives 57.42 %, the second price 9.14 %, and the current price 33.44 %, leading to a reference point of € 102.43. Over time, the purchase price thus looses of importance and gives more and more weight to more current prices.

5.4 Individual Differences

The analysis documented above is based on all subjects at the same time, taking all observations as decisions from one representative agent. An interesting follow-on question is in how far individual decision makers deviate from this average behavior. We therefore repeat our analyses from sections 2 and 3 on the individual level.

We rerun ordinary least squares regressions without intercept from section 2 for every subject separately and perform simple cluster analyses on resulting regression coefficients. For the cluster analyses we follow the hierarchical algorithm proposed by Ward (1963). Results are nevertheless similar for other hierarchical and nonhierarchical clustering methods.

We then compose three different clusters to provide a simple overview on individual differences. Table 5 documents the results.

(insert table 5 about here)

Table 5 reveals relatively strong differences across subjects. 16 subjects use the purchase price as their reference point, 8 the current, and 30 a mixture of the purchase, the current, and the weighted average price. All clusters, however, pay only little attention to the peak and the low of the time series, so that even individual level behavior seems to be in line with our information weighting model presented in section 2. Although decision makers differ quite strongly in whether they derive their reference points from the start, the end, or the average of a time series of prices, all clusters can be easily modeled with an inverse s-shaped information weighting function, differing only in elevation and curvature.

To provide further insights on this statement, we fit weighting functions on the individual level. As we neither want to differentiate between path lengths nor to run a cluster analysis on Prelec's two-parameter model, i.e. on elevation and curvature, we regress individual reference points on the purchase price, the current price, and the remaining intermediate prices for all price paths and every subject. Regressions are again ordinary least squares without intercept. Resulting regression coefficients are finally renormalized to add up to one and can be interpreted as information weights similar to section 3, with the only difference that intermediate prices receive one weight for all instead of individual weights. On these weights we then perform another cluster analysis following the Ward (1963) algorithm. Table 6 shows the results for clusters 1 to 3.

(insert table 6 about here)

Over clusters 1 to 3, subjects shift more and more weight from the purchase price over the mean of intermediate prices to the current price. This shift in weights is with roughly 50 % from cluster 1 to cluster 3 both economically and statistically highly significant.

Insights on individual differences can thus be summarized as follows: While information weighting functions elicited in section 3 capture decision makers' general behavior when faced with a time series of prices, individual investors might deviate strongly from this general pattern. This insight is both important for empirical research based on reference point dependent preferences and agent based modeling. Assuming that all investors are captured by only one representative agent might lead to wrong or imprecise predictions and poor individual decision or market models.

6 Discussion

Based on an individual choice experiment run with 55 students, we document first insights on how investors form their reference points as a reaction to a time series of prices. We conduct a horse race between the purchase price, the current price, the highest price, the lowest price, the equally weighted average price, and one path-dependent average price. Our subjects' reference points can be best described as a function of the first and the last price of the time series, with the equally weighted average price receiving a lower but remarkable third weight. Formally, investors' behavior can be captured by an inverse s-shaped information weighting function, sorting prices backwards along the time line from recent to past. We provide the theoretical framework for this approach and elicit the shape of the weighting function both stepwise and following the parametric form of Prelec (1998). On average, the purchase price receives a weight of 50 %, the current price 30 %, and the remaining intermediate prices share approximately 20 %. While the peak-end rule (Fredrickson and Kahneman 1993, Kahneman, Fredrickson, Schreiber, and Redelmeier 1993, Kahneman, Wakker, and Sarin 1997, Kahneman 1999) could have been a competing hypothesis on how subjects' value a time series of prices, the highest price clearly loses the horse race against the "first-last and equally weighted average rule".

Besides these empirical results, our paper also contributes to the literature by documenting a new methodology for eliciting decision makers' individual reference points. We propose that researchers interested in reference point formation should circumvent the multicollinearity problem discussed in the introduction by limiting the space of possible reference points, predetermining price paths, and asking subjects' for point estimates of their reference prices instead of just analyzing their choice behavior. We define three different elicitation questions that are easily understood by subjects and mimic the intuitive concept of reference point dependency.

As reference point formation and updating is still an open field in behavioral economics, further research is needed in diverse dimensions: While our study, for the sake of simplicity, analyzes the impact of price paths with one purchase decision only, the research design could be easily extended to more complicated time series, including further purchases or selling decisions, longer time series, or time series in non-finance contexts. Another promising idea would be to manipulate or control for future expectations and their impact on today's reference points. Follow-on studies could also focus on the individual level, explaining how different investor groups form and update their reference points over time. In this respect, trading habits or personality traits like overconfidence could enhance our understanding of individual formation and updating rules.

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Table 1: Price paths

This table contains all 63 price paths used in the experiment. Columns p_i contain the i-th price of the respective path in Euros.

Path nr.	p_0	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9
1	250	200	150	200						
2	150	200	250	200						
3	200	150	200							
4	150	200	200							
5	250	200	200							
6	200	250	200							
7	250	200	150	200	160	200	240	200		
8	150	200	250	200	240	200	160	200		
9	250	200	150	210	190	210	200			
10	150	200	250	210	190	210	200			
11	200	150	200	250						
12	200	250	200	150						
13	200	200	150							
14	200	200	250							
15	200	150	170	200	250	230				
16	200	250	230	200	150	170				
17	170	220	270	220	190	220	250			
18	170	220	270	220	250	220	190			
19	200	250	250	200						
20	200	150	150	200						
21	200	250	200	250	200					
22	200	150	200	150	200					
23	150	150	200	250	200					
24	150	200	200	200	200					
25	200	250	200	150	150					
26	200	200	200	200	150					
27	200	190	190	190	190	190	200	250	200	190
28	200	200	200	200	200	200	200	200	200	190
29	190	200	250	200	190	190	190	190	190	200
30	190	200	200	200	200	200	200	200	200	200
31	200	150	200	160	200	240	200			
32	200	150	200	190	200	210	200			
33	250	200	200	200	200					
34	250	250	200	150	200					
35	200	200	200	200	250					
36	200	150	200	250	250					
37	200	200	200	200	200	200	200	200	200	210
38	200	210	210	210	210	210	200	150	200	210
39	210	200	200	200	200	200	200	200	200	200
40	210	200	150	200	210	210	210	210	210	200
41	250	230	200	200	200	200	200	200		
42	250	230	200	220	220	200	160	200		

43	250	250	200					
44	150	150	200					
45	200	150	200	250	250	250	250	200
46	200	250	200	150	150	150	150	200
47	200	250	250	250	250	200	150	200
48	200	150	150	150	150	200	250	200
49	150	200	250	240	240	240	240	220
50	150	200	250	200	200	200	200	220
51	200	200	200	250	200			
52	200	250	200	200	200			
53	200	150	200	200	200			
54	200	200	200	150	200			
55	200	150	200	250	200			
56	200	250	200	150	200			
57	200	150	150	200	250	250	200	
58	200	250	250	200	150	150	200	
59	200	180	200	200	250	210		
60	200	250	200	200	180	210		
61	200	200	200					
62	200	200	200	200				
63	200	200	200	200	200			

Table 2: Ceteris paribus pairs

This table contains information on how ceteris paribus pairs are set up. The columns "Path A" and "Path B" link the pairs in this table to the paths specified in table 1. The column "Comment" discusses in how far paths A and B differ.

Pair nr.	Path A	Path B	Comment
1	1	2	Paths A and B are the same in respect to the current price, the highest price, the lowest price, and the equally weighted average price. The purchase price, however, is higher in path A than in path B.
2	3	4	
3	5	6	
4	7	8	
5	9	10	
6	11	12	Paths A and B are the same in respect to the purchase price, the highest price, the lowest price, and the equally weighted average price. The current price, however, is higher in path A than in path B.
7	3	13	
8	14	6	
9	15	16	
10	17	18	
11	6	3	Paths A and B are the same in respect to the purchase price and the current price. Intermediate prices, however, are higher in path A than in path B.
12	19	20	
13	21	22	
14	23	24	Paths A and B are the same in respect to the purchase price, the current price, the lowest price, and the equally weighted average price. The highest price, however, is higher in path A than in path B.
15	25	26	
16	27	28	
17	29	30	
18	31	32	
19	33	34	Paths A and B are the same in respect to the purchase price, the current price, the highest price, and the equally weighted average price. The lowest price, however, is higher in path A than in path B.
20	35	36	
21	37	38	
22	39	40	
23	41	42	
24	43	5	Paths A and B are the same in respect to the purchase price, the current price, the highest price, and the lowest price. The equally weighted average price, however, is higher in path A than in path B.
25	4	44	
26	45	46	
27	47	48	
28	49	50	
29	51	52	Paths A and B are the same in respect to the purchase price, the current price, the highest price, the lowest price, and the equally weighted average price. More recent prices, however, are higher in path A than in path B.
30	53	54	
31	55	56	
32	57	58	
33	59	60	

Table 3: Importance of price path factors

At the end of the experiment, subjects are asked how important they consider the following price path factors. Answers are given on a 9-point-scale reaching from 1 (totally unimportant) to 9 (extremely important). The following table reports the mean, the standard deviation, and the median for all price path factors.

	Mean	Std. dev.	Median
Purchase price	7.91	2.01	9
Current price	6.96	1.92	7
Highest price	4.96	2.65	5
Lowest price	4.82	2.59	6
Equally weighted average price	5.05	2.48	6
Path-dependent average price	6.20	1.92	6

Table 4: Multivariate replication of univariate results

The table documents the results of simple ordinary least squares regressions without constants. In regression 1 we regress individual reference points for all paths on simple price path factors, i.e. the purchase price, the current price, the highest price, the lowest price, the equally weighted average price, and the alpha-weighted average price with an alpha of 50%. Regression 2 is the same as regression 1 but omits both the equally weighted and the alpha-weighted average price. P-values are in parentheses.

	Reg. 1	Reg. 2
Purchase price	0.47 (0.000)	0.50 (0.000)
Current price	0.24 (0.000)	0.28 (0.000)
Highest price	0.06 (0.000)	0.18 (0.000)
Lowest price	-0.04 (0.009)	0.04 (0.002)
Equally weighted average price	0.30 (0.000)	
Alpha-weighted average price (Alpha = 50%)	-0.02 (0.610)	
# of observations	3,465	3,465

Table 5: Cluster analysis on price path factors

For every subject we regress individual reference points on simple price path factors, i.e. the purchase price, the current price, the highest price, the lowest price, and the equally weighted average price. We again apply ordinary least squares regressions without constants. Resulting regression coefficients are then analyzed using a Ward algorithm cluster analysis. The following table provides average regression coefficients for three different investor types. We do not report a fourth cluster containing one outlier subject. P-values in parentheses are based on t-tests comparing average regression coefficients of the considered cluster with average regression coefficients of all clusters.

	Cl. 1	Cl. 2	Cl. 3
Purchase price	0.80	0.40	0.08
	(0.000)	(0.095)	(0.000)
Current price	0.08	0.23	0.60
	(0.009)	(0.437)	(0.000)
Highest price	0.01	0.10	0.10
	(0.060)	(0.131)	(0.244)
Lowest price	-0.07	-0.03	0.01
	(0.219)	(0.233)	(0.109)
Equally weighted average price	0.18	0.30	0.25
	(0.084)	(0.450)	(0.354)
# of observations	16	30	8

Table 6: Cluster analysis on information weighting function weights

For every subject and every price path we regress individual reference points on the purchase price, the current price, and the mean of remaining intermediate prices. We again apply ordinary least squares regressions without constants. We then compute individual level information weighting function weights by renormalizing regression coefficients to add up to one. Information weights are then analyzed using a Ward algorithm cluster analysis. The following table provides average information weights for three different investor types. P-values in parentheses are based on t-tests comparing average information weights of the considered cluster with average weights of all clusters.

	Cl. 1	Cl. 2	Cl. 3
Purchase price	0.80 (0.000)	0.47 (0.149)	0.14 (0.000)
Intermediate prices	0.12 (0.110)	0.20 (0.227)	0.19 (0.378)
Current price	0.08 (0.000)	0.33 (0.268)	0.67 (0.000)
# of observations	16	31	8

Figure 1: Computer screen

The figure shows a translation of the computer screen. In the graph area, the price path is drawn with some time lack from left (purchase price) to right (current price). After the graph is drawn completely, subjects need to click into the graph area to indicate for what price they would be neither happy nor unhappy to sell the stock. After indicating the price, subjects could click on the "Continue" button at the lower right-hand corner of the screen to move on to the next situation. The screen was explained to subjects in the instructions. The path shown in the figure is path 56 in table 1.

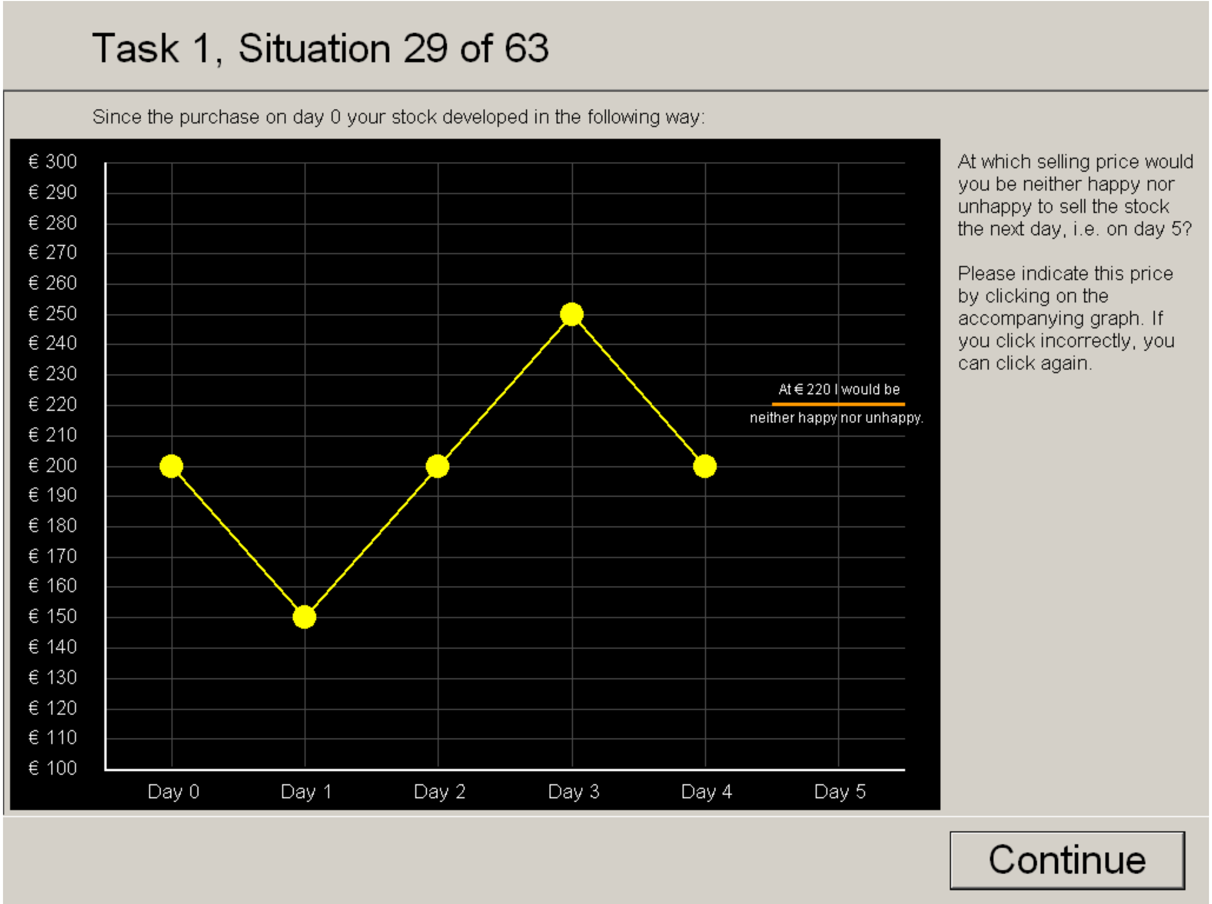


Figure 2: Fitted cumulative information weighting functions

The following graph shows fitted cumulative information weighting functions. Behavioral information weights are obtained by regressing individual reference points on successive prices and normalizing resulting regression coefficients to add up to one. Cumulative weights are then aggregated starting with the most recent price. Received weights are assumed to equal 1/n. We apply ordinary least squares regressions without constants for price path lengths of 3 (solid line), 4 (long dashed line), 5 (short dashed line) and 6 to 10 (lines with dashes and dot).

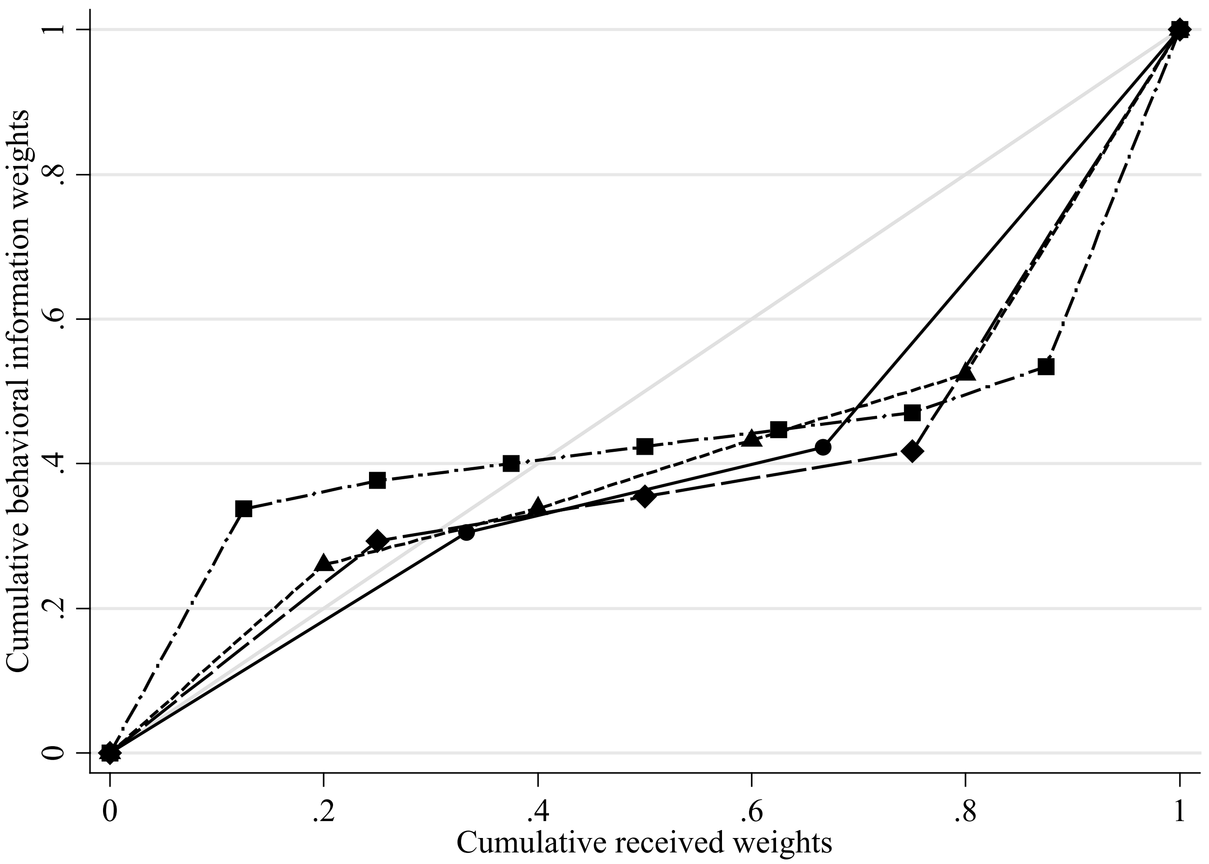
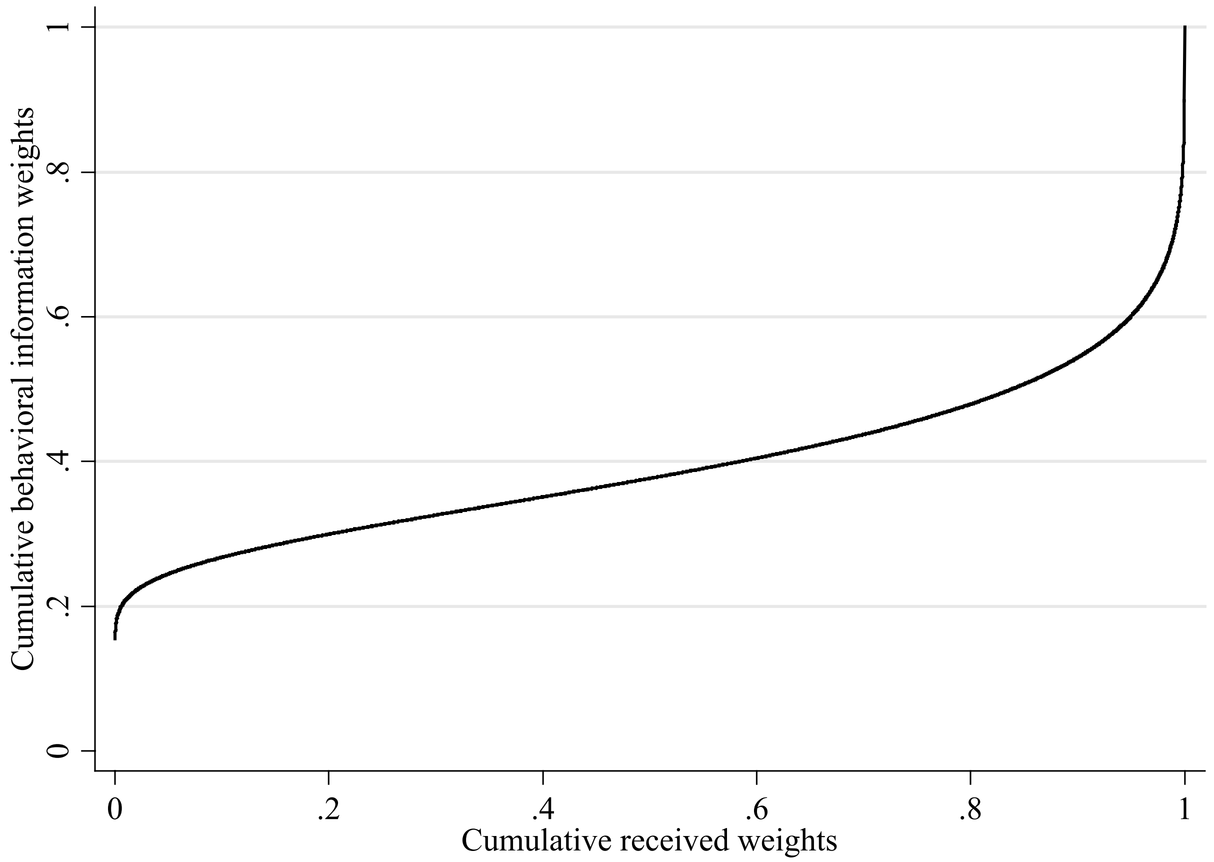


Figure 3: Fitted Prelec (1998) function

The following graph shows the fitted cumulative information weighting function as proposed for prospect theory by Prelec (1998). Elevation and curvature are obtained by fitting both parameters to the data using a multiparameter solver. Received weights are assumed to equal 1/n.



Appendix: Instructions

The following instructions were translated from German.

General Instructions

You are participating in an experiment of the Sonderforschungsbereich 504 of the University of Mannheim, financed by the Deutsche Forschungsgemeinschaft. The experiment consists of multiple tasks which you are going to process consecutively. For your participation you receive a financial reward of € 8.

The experiment lasts approximately 40 – 50 minutes (including time for reading instructions). We kindly ask you not to communicate with other participants. When you leave this computer screen you are in the first task of the experiment. The instructions for the other tasks appear on the screen when you begin the respective task.

Please signal us if you have problems understanding the instructions.

Instructions for the Individual Choice Task

Please consider the following situation: A few days ago, on day 0, you purchased a stock. Yet on the same day you went on vacation. In your vacation resort you could monitor the price development of the stock but could not trade it.

Today, on the day before your return journey, you once again take a look upon the stock's price development since your purchase on day 0. Since you can trade the stock again the next day back home, you ask yourself how you would feel if you were going to sell the stock the next day. You ask yourself at what selling price you would feel neutral about the sale of the stock, i.e. being neither happy nor unhappy about the sale. You assume the stock price to rise or fall up to € 50 every day and regard all possible price changes between € +50 and € –50 as equally likely.

On the following screens you will be confronted with several decision situations of this kind. You will be shown the stock's price development chart starting from the purchase on day 0 until the day before your return journey. The price for which you can trade the stock the next day back home is today still unknown. After the price path is plotted, you will be asked to indicate at what tomorrow selling price you would just feel neutral regarding the sale. Hence, we want you to indicate the selling price at which you would neither have positive nor negative emotions about the sale of the stock, therefore being neither happy nor unhappy. You chose the price for which you would feel exactly neutral by clicking on the corresponding price in the graph.

This task is not about your mathematical skills and there are no right or wrong answers. Instead, we request you to estimate at most intuitively at which selling price you would be neither happy nor unhappy about the sale of the stock.