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Exit timing: Real-options reasoning, heuristics, or precognition?

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Abstract

We experimentally analyze the importance of heuristics and precognition as predictors of exit choices and test this against the formal benchmark provided by real-options theory (consistent with optimal stopping). Unlike previous research, our experiment employs a real-time quantum process to generate future payoffs from the investment, and also determines counterfactual developments, i.e., future payoffs that would have been relevant had the respondent not exited, and actually shows the latter to her. We find evidence for the importance of all predictors. The real-options benchmark has some predictive value for exit choices, heuristics too, and also precognition plays a significant role. Implications for future research are discussed.

Keywords

Exit timing, real options, heuristics, precognition, economic experiment

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1. Introduction

Disinvestment decisions are an important case of dynamic decision problems where there is a risky future payoff from some activity, varying from round to round, and where an individual can decide to exit this activity in each round, or to continue. Practical applications are numerous, including questions when to terminate a relationship, when to sell a stock, when to abandon a business idea, or when to stop an innovation project. Recent papers have theoretically and experimentally analyzed this situation (Sandri et al. 2010; Musshoff et al. 2013). These authors use real options (or optimal stopping) as the economic benchmark for 'optimal' choices in this situation, and have empirically demonstrated some consistency with this 'benchmark', but also a pronounced tendency of most individuals to hold on for too long. Finally, in a recent working paper by Schade and Snir (2012) personality dimensions have successfully been linked to exit timing. Although those papers do contribute to a better understanding of individuals' behavior in disinvestment scenarios, they leave a large part of variance in behavior unexplained.

This paper hence looks at two other behavioral drivers that might contribute to a better understanding of disinvestment decisions: heuristics and precognition. Regarding the usage of heuristics, the paper follows the paradigm that heuristics might be providing useful shortcuts for individuals (see, e.g., Gigerenzer and Todd 1999). Consistent with this, Musshoff et al. (2013) mention that some heuristic, specifically, exiting if the payoff had dropped in two subsequent periods, worked quite well as a predictor of exit choices, but they neither provided any details nor looked at various possible heuristics in a more systematic manner. Precognition means individuals' potential ability to anticipate future developments without information being transferred by any 'classical' means. There is anecdotal evidence that some stock traders 'simply know when to sell', or that some people follow their 'gut' in those types of choices. But does this really mean that they are using 'non-classical' means – whatever they might be – to make them? In financial market transactions, for instance, one would often suppose the usage of insider information. Hence, how does this play out in a controlled experiment, when the information provided can perfectly be controlled?

Our experimental design replicates the one used in Sandri et al. (2010) and Musshoff et al. (2013) (and is somewhat similar to the one used in Schade and Snir (2012)), but with two important modifications. First, instead of using pseudo random numbers for generating the future payoffs in the experiment, we use a combination of a pseudo-random number series and a real random number generator, *quantis*, employing a real-time quantum process (http://www.idquantique.com/random-number-generators/products/quantis-usb.html). Second, we continue the development of the investment even after the respective individual has disinvested and show this to her; or in other words, individuals get precise information on the 'what if', the counter-factual part of her choice.

Employing this experimental design, we surprisingly find evidence for *all* behavioral drivers analyzed. The real options benchmark we are testing heuristics and precognition against, turns out to be a significant predictor of exit choices (hence replicating the results by Sandri et al. (2010), Musshoff et al. (2013) and Schade and Snir (2012)), some heuristics are also an important driver of exit choices, and, most thrilling, we have evidence for individuals being able to somehow ‘use’ future payoff information without the existence of any ‘classical’ means to do so. We are putting the latter result under scrutiny of an important alternative explanation. Specifically, since most exit choices are considerably delayed, consistent with the above research, and since using future information would also (based on our calculations) indicate later disinvestments, correlations of exit behavior and the seemingly usage of ‘future’ information could be spurious. Hence, we calculate and integrate in the regressions an individual waiting parameter and observe our findings to be robust. Moreover, future-directed heuristics, completely independent from any such explanation, turn out to be highly significant predictors of exit choices. We conclude that our ‘non-classical’ findings are robust enough to warrant future replications and derive some tentative implications.

This contribution is organized as follows. The next section outlines all underlying theories for our experiment: real options theory, heuristics, and precognition. The following section concerns itself with a detailed description of the experimental design. This section is followed by a section on experimental findings. The paper concludes with a section containing discussion, conclusions, limitations, and future research.

2. Theory

2.1. Real-options theory

The formal, economic benchmark underlying the (experimental) setup and (mathematical) analysis of exit choices in this contribution is real-options theory or optimal stopping. According to this benchmark, disinvestment is considered under conditions of irreversibility, which gives rise to a value of waiting before the "plug is finally pulled" for whatever risky project. As in Sandri et al. (2010) (the following formal development closely follows those authors), an existing project with a finite lifetime is analyzed. We show the mathematical modeling for a lifetime of three periods only, but qualitatively identical results can be derived for an infinite time horizon. In each period, the project earns a cash flow in value of X_0, and the cash flow develops according to a binomial tree. That is, in period 1 the cash flow may increase by a value $h > 0$ to reach $X_0 + h$ with probability p, or it may decrease to $X_0 - h$ with probability $1 - p$. In period 2 the cash flow may increase to $X_0 + 2h$ with probability p^2, fall to $X_0 - 2h$ with probability $(1 - p)^2$, or stay constant at X_0 with the rest probability $2p(1 - p)$. We assume a risk-neutral decision maker[1] who has the choice between continuation and abandonment of the project. Termination of the project yields a salvage value L in addition to the cash flow of the current period. Once terminated, the project cannot be restarted, so the disinvestment decision is irreversible.

[1] In the context of real-options, risk preferences come into play at least if it is impossible to set up a replicating portfolio of traded assets that duplicates the stochastic outcome of the (dis)investment project under consideration (see Dixit and Pindyck 1994). The formal analysis of exit times for different risk propensities of decision makers is available from the authors upon request. See also Musshoff et al. (2013), for a theoretical and empirical analysis of the effect of risk propensity on exit choices. In this contribution, risk propensity is taken care of simply by integrating it as a control variable in the hierarchical regression analyses (see the results section).

For better comprehension, we are presenting our optimal stopping benchmark in contrast to the benchmark that would be provided by traditional investment theory, although the latter is not used as an explicit benchmark in the later analysis of the findings.[2] According to traditional investment theory and its corresponding net present value (NPV) approach, the project should be abandoned if the liquidation value $L + X_0$ exceeds the continuation value $\hat{C}$. The decision rule which formally expresses the NPV approach is D_1, where

$$D_1 : \max(\hat{C} \,;\, L + X_0) = \hat{F}_0 \tag{1}$$

and the continuation value equals

$$\begin{aligned}\hat{C} = X_0\big(p(X_0 + h) + (1-p)(X_0 - h)\big)q^{-1} + (p^2(X_0 + 2h) \\ +2(p(1-p)X_0) + (1-p)^2(X_0 - 2h) + L)\, q^{-2}\end{aligned} \tag{2}$$

Here $q^{-1} = 1 / (1 + r)$ is a discount factor and r denotes the interest rate. Decision rule D_1 means that stopping the project is preferable if the salvage value L exceeds the expected value of the discounted cash flows, and the calculation of the expectation is based on information available in period 0. Therefore, decision rule D_1 disregards any further information which might be obtained in subsequent periods. This decision is a simple comparison between the two alternatives "continuation of the project" and "termination of the project in period 0".

[2] It performed poorly in previous studies (Sandri et al. 2010; Musshoff et al. 2013) and also performed poorly when tested on our experimental data. Results are available from the authors upon request.

The situation changes if the decision on termination of the project can be delayed to period 1, a realistic case that is also underlying our experiment. Now the decision maker has an abandonment option in period 0, which she can exercise or keep alive until period 1. Delaying the decision has the potential advantage that it allows for the arrival of new information in period 1, which offers more flexibility. Of particular interest is the situation in which $X_0 - h < Lr < X_0 + h$, meaning that continuation will be the optimal decision if the cash flow increases in period 1 and termination will be optimal if the cash flow decreases. This leads to a different stopping rule:

$$D_2 : \max(\tilde{C} ; L + X_0) = \tilde{F}_0 \tag{3}$$

with a continuation value

$$\begin{aligned}\tilde{C} &= X_0 + \big(p(X_0 + h) + (1-p)(X_0 - h + L)\big)q^{-1} \\ &\quad +(p^2(X_0 + 2h + L) + p(1-p)(X_0 + L))\, q^{-2}\end{aligned} \tag{4}$$

The myopic decision rule D_1 yields $\hat{F}_0$, the classical net present value of the project, while the optimal stopping rule D_2 produces $\tilde{F}_0$, the so-called strategic (expanded) net present value (Trigeorgis, 1996). Since $\hat{F}_0$ is less than or at most equal to $\tilde{F}_0$, deviations from the myopic rule D_1 to the optimal stopping rule D_2 are expected. This becomes obvious by comparing the respective disinvestment triggers. A disinvestment trigger marks the threshold level of the cash flow at which it becomes optimal to disinvest. In each period the decision maker compares this normative threshold with the realized value of the random cash flow. Whenever the realized cash flow is larger than the disinvestment trigger, the project should be continued but the latter should be stopped if the cash flow falls under the value of the trigger. We can compute the disinvestment triggers by equating the continuation value and the termination value and solving for X_0. According to decision rule D_1 and the NPV approach, the project should be terminated if the current cash flow falls below:

$$\hat{X}_0 = Lr - h(2p - 1)\left(1 + \frac{1}{1 + q}\right) \tag{5}$$

The optimal disinvestment trigger referring to decision rule D_2 and the real options approach is:

$$\tilde{X}_0 = Lr - h\left(2p - \frac{q}{p + q}\right) \tag{6}$$

This shows that the myopic NPV approach will differ from the real options approach, and the difference between the two triggers amounts to:

$$\hat{X}_0 - \tilde{X}_0 = \frac{h(1 - p)(2p + q)}{(1 + q)(p + q)} > 0 \tag{7}$$

Notice that $\tilde{X}_0$ is smaller than $\hat{X}_0$ for any $p > 0$, meaning that a decision maker following the real options approach will tolerate lower levels of the cash flow before irreversibly terminating the project. By comparison, a myopic decision maker following the NPV would need higher cash flow levels to keep her from disinvesting.

The following example illustrates the difference between the two disinvestment triggers and decision rules. As in the later experiment, we assume an initial cash flow X_0 = 1,000, an upward movement of the cash flow h = 500 with probability p = 0.5, a salvage value L = 11,000 and an interest rate r = 0.1. As in the experimental situation, we assume a larger number of periods (i.e., ten) than we did in the formal development (i.e., three). The experimental situation is depicted in Figure 1. The disinvestment trigger according to the NPV is $\hat{X}_0$ = 1,100 (pink line). The initial cash flow already falls below this trigger, and thus the project should be immediately terminated in period 0. Differently, the real options approach suggests a much lower disinvestment trigger (blue line), i.e., 495, as can be seen in Figure 1, which is far below the initial cash flow and thus waiting for future information is preferable.

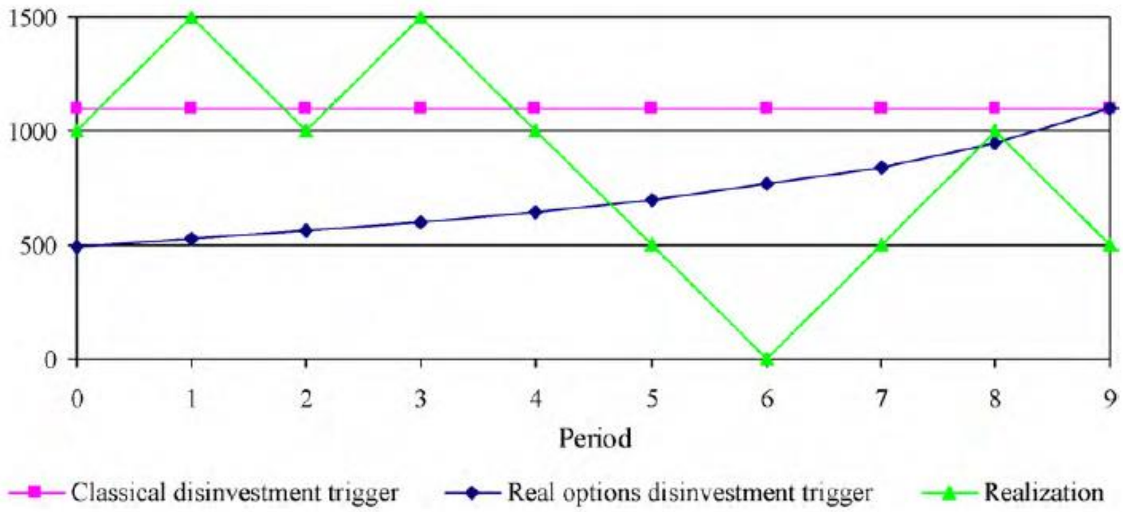

Figure 1: Binomial development of the cash flow and disinvestment triggers
(Source: Sandri et al. 2010)

When should the individual disinvest, given the sample random path of the payoff variable in Figure 1 (green line)? In this example, the optimal disinvestment time according to the real options approach would be period 5; since here the green line undercuts the blue one.

The above reasoning leads us to formulate the following real-options hypothesis:

H_{RO}*: *Rational disinvestment behavior is determined by decision rule D_2 and the according disinvestment trigger given in equation (6).

2.2. Heuristics

Most individuals are likely not to apply the above described, sophisticated real options approach, neither in their daily decision-making nor in our experiment, at least not in a formal, i.e. mathematical, way, but are rather inclined to use heuristics. Gigerenzer and Todd (1999, p. 26) describe heuristics within cognitive psychology as "[…] a useful shortcut, an approximation, or a rule of thumb for guiding search, such as a strategy that a chess master uses to reduce the enormous space of possible moves at each point in a game." Consequently, simple heuristics might help individuals to process large amounts of complex information leading to accurate and valuable conclusions. In this paper, we follow Gigerenzer and Todd's (1999) line of reasoning (which is in contrast to Tversky and Kahneman's (1974) original approach[3] who rather link heuristics to biases, leading to problematic inferences etc.) and try to assess whether certain heuristics (defined in the form of certain payoff events) might help or guide our respondents in determining the optimal disinvestment choice. In our analysis of experimental findings (see section 4.), we tested three simple heuristics that appeared to us most plausible, considering the experimental task (see section 3.1. for the detailed design of the task). Based on the experimental design, it should be emphasized that only payoff-based heuristics should be relevant as no additional information or cues were provided between the decision scenarios or time periods

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[3] Kahneman's more recent thinking slightly differs from his previous position. Specifically, he now puts a lot of emphasis on the great power of heuristic processes in the problem solving activities of individuals (Kahneman 2011).

within the scenarios[4]. The following three payoff-based heuristics will be used in the analysis to test whether they might drive exit choices and thus constitute three hypotheses:

(8) $$X_{t\ \mathrm{current}} = 0$$ ***H_{H1}:*** *The respondent exits if she for the first time (in the currently played round) experiences a zero value payoff.*

(9) $$X_{t\ \mathrm{current}} < 0$$ ***H_{H2}:*** *The respondent exits if she for the first time (in the currently played round) experiences a negative payoff.*

(10) $$X_{t\ \mathrm{current}} = X_{t-2} - 2h$$ ***H_{H3}****:The respondent exits if she experienced (in the currently played round) a decrease in the payoff for the second time in a row.*

Underlying those payoff-based heuristics might be more general behavioral principles, such as the usage of stop-loss rules (in particular relevant for the payoff event defined in (10) but also relevant for the payoff event defined in (8)), or the principle of salience (in particular relevant for the payoff event defined in (9) but also relevant for the payoff event defined in (8)).

Stop-loss reasoning

Stop-loss rules are commonly used by investors in the financial market in order to manage the level of their investment risk, whereby the underlying threshold variable

[4] Note: Heuristics were included in several regression models with exit times as dependent variable. However, based on the fact that the applied heuristics are all payoff based, they were excluded from those regression models where payoff is the dependent variable in order to avoid endogeneity problems.

differs (e.g. a 2 percent loss rule would lead to an equity sale, once the share has lost two percent of its purchase value). Such rules are, among others, applied in order to protect investors from emotional responses to losses, as for example described by the disposition effect (holding losing stock for too long in the portfolio while selling value increasing stock too early; see Shefrin and Statman 1985). We propose that individuals might also hold some heuristic stopping rules in order to have some kind of self-control mechanism that prevents them from falling prey to behavioral biases.

We now explain how such a behavioral bias might eventuate in our experiment based on prospect theory (Kahneman and Tversky 1979) and how a stop-loss rule might potentially prevent respondents from such bias. Please revisit Figure 1 to better appreciate the following reasoning. Assume that our respondents hold a reference point of 0 points[5]. In such a case, the respondent, in the "editing phase", will identify all negative values as losses and all positive values as gains. Assume that the respondent in this period realized a negative payoff of -500 points and is faced with the decision to disinvest (and realize the loss of 500 points)[6] or to continue with the investment. Should she decide for the latter option, she could, based on the experimental design, in the next period either break even (0 points) or realize a loss of -1000 points, both events having an equal probability of occurrence. Prospect theory predicts that our respondent would decide to continue playing, as the above choice is taking part on the

[5] An analogous line of reasoning would hold for a reference point of 1,000. As this is the starting point of the payoff variable in the RO experiment, one could clearly defend this to be the reference point. Also, both might be reference points (see Cyert and March (1963), for the case of holding two reference points).
[6] Without a loss in generality, the following example is based on a reference point of 0.

convex part of the value function[7]. However, holding some intuitive, “self-controlling” rules (which the respondent might have developed throughout her life once she became aware of her tendencies to gamble with losses) might cause respondents to disinvest contrary to what prospect theory would suggest. We argue that in particular the payoff events $X_{t\,current} = 0$ and $X_{t\,current} = X_{t-2} - 2h$ could stimulate such internal rules.

Salience effects

We further argue that salience effects could influence respondents’ behavior. Salience is underlying several cognitive biases and means that a certain aspect stands out from the rest. In the words of Taylor and Thompson (1982), “Salience refers to the phenomenon that when one's attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments". Hence, in our exit scenarios, not all potential developments of the cash-flow might be perceived on equal footing. Instead, achieving a cash-flow of zero ($X_{t\,current} = 0$) or a negative cash-flow ($X_{t\,current} < 0$) might weigh more in the exit decisions those individuals are making (see also Bordalo et al. 2010).

2.3. Precognition

Different terms are used to describe individuals’ supposed ability to anticipate future developments – in situations characterized by an absence of any ‘classical’ way of

[7] Once the “editing stage” has been completed, the decision maker enters the “evaluation stage”. Whereby the value function is characterized by an S-shape: concave in the gain domain and convex in the loss domain. This shape implies individuals to be risk averse with gains but risk taking when dealing with losses.

information transfer: *precognition*, *premonition*, and *anticipatory physiological responses (APR)* are the most prominent of them and describe slightly different variations on this theme. Whereas precognition describes getting cognitive knowledge on future developments, premonition is rather concerned with feelings, and APR with anticipatory body reactions.

In our case, where people make exit choices, it is somewhat unclear what kind of anticipation would potentially take place. Precognition is thus used as a simplifying label here, without actually being able to judge whether such choices make use of precognition, premonition, or APR. In fact, the two most well-known results so far are those for premonition and those for APR. Premonition findings have recently inspired a public debate. The reason: First, striking experimental findings from nine successful premonition experiments were reported by Cornell emeritus Daryl Bem (2011) and published in a mainstream top journal (*Journal of Personality and Social Psychology*). Second, various unsuccessful replications followed (e.g., Ritchie et al. 2012), for three negative trials on the last of Bem's nine experiments; and Galak et al. (2012) for a small meta study with null results on three of Bem's experiments).

Far more robust appear to be the results on APR. Mossbridge et al. (2012) provide a meta study analyzing a total of 26 reports (from 1978 to 2010). The authors find strong evidence for individuals' abilities to physiologically anticipate future events without any 'classical' information transfer on them (randomly ordered arousing vs. non-arousing stimuli or guessing tasks with correct/incorrect feedback). This holds for many different physiological measures: heart rate, 'electrodermal activity, pupil dilation, blood volume, electroencephalographic activity, blood oxygenation level dependent (BOLD) activity' (p. 1). In a fixed effect model, the overall statistical significance for predictive physiological anticipation turned out to be $p < 2.7 \times 10^{-12}$. The evidence is so clear, that at least 87 unpublished contrary reports would have been necessary to reduce this evidence to a chance level ($p > 0.05$). Hence it is safe to conclude that individuals' bodies are able to anticipate future developments. Admitting that the exact mechanism how 'knowledge' might propagate from the body level to individuals' exit decisions is somewhat unclear, we feel that the strong evidence on APR warrants the following hypothesis to be tested (note that 'CF' stands for 'cognition future'):

$\boldsymbol{H_{CF}}$: *Individuals' are able to pick the overall optimal exit time, taking into account all future developments.*

3. Experimental design

The experiment was conducted at a major German University in August 2012 with university students from various study backgrounds. Respondents were recruited via a psychological experimental database. In total eight experimental sessions were run, resulting in a sample size of N=100. The duration of the experiment was about 120 minutes and consisted of four different sections.

In the first section of the experiment, respondents had to make choices in several (i.e., 20) rounds of an optimal stopping problem: They could always continue with a project, whose payoff developed according to a binomial distribution, or abandon it and receive a constant termination value. Each optimal stopping problem was automatically terminated after ten periods, and then a new, independent round started (for the details, see below). In the second section, participants were confronted with decisions that determined their risk attitudes, in an implementation of the procedure by Holt and Laury (2002). In the third section, respondents had to answer psychological questionnaires that tested their tendency of sensation seeking (Zuckerman, 1979) as well as some decision-making patterns (buck-passing vs. vigilance inclinations). Additionally, some demographic data was collected. All aforementioned sections were programmed with the experimental software z-Tree (Fischbacher, 2007). In the last section of the experiment, which was conducted using the software e-prime, respondents were presented subliminally shown, emotionally laden pictures. In the following each section of the experiment is outlined separately in detail.

3.1. Real-options experiment

Decision scenario

This section of the experiment mostly follows the experimental design by Sandri et al. (2010) and Musshoff et al. (2013). However, one of the important departures of the current experiment from those studies is the implementation of a 'what if' development of the binomial tree, once respondents had decided to terminate the project. The random mechanism (which will be described in detail below) continued to run even after a respondent's exit decision and the – then hypothetical! – outcomes were shown to her. This additional feature provides us with a large amount of data on hypothetical payoffs – the payoffs that participants would have received, had they decided to continue to play and not decided to terminate the project. As will become obvious later in the paper, these hypothetical payoffs play an essential role in our data analysis.

In this part of the experiment, respondents were faced with 20 identical optimal-stopping scenarios (rounds), whereby each round consisted of 10 time periods. Before commencing with the actual payoff-relevant scenarios, respondents were carefully instructed regarding the parameters describing the scenarios (e.g. the interest rate, initial payoff (endowment), probabilities, termination value)[8]. Respondents had to answer comprehension questions and play a trial round before the actual experiment commenced, to ensure respondents understood the rules and potential development of the game.

As in our above example (see the Theory section as well as Figure 1), each of the 20 rounds started with a payoff of 1,000 points in period 0, and evolved throughout the following 10 periods according to a binomial process with p = 0.5, no underlying drift and a volatility of 500 points. In other words, the initial payoff of 1,000 points from period 0 could increase to a payoff of 1,500 points or decrease to a payoff of 500 points in period 1. Each of these events could happen with a probability of 50 percent. Assuming the participant reached a payoff of 1,500 points in period 1, her payoff in period 2 could increase to 2,000 points or fall to 1,000 points with the same probability of 50 percent (for a better understanding of the stopping problem, please refer to Figure 1 as well as the instructions and the binomial trees, in Figures A1 and A2 in the Appendix).

[8] The detailed instructions are provided in the Appendix. The instructions were provided to the respondents as hardcopies in order to improve the readability and to allow the respondents to review concepts as required. The first paragraph of the instructions, which describes the structure and rules of the experiment were additionally provided on the computer screen. Also, the actual experiment with payoff development, decisions on exit times etc., was fully computerized (see Figures A1 and A2 in the Appendix for sample screenshots).

In any period, a respondent could choose to continue the project, or to abandon it and receive the fixed termination revenue of 11,000 points. In the last period, period 10, termination of the project was compulsory (the 11,000 points were then added to the account in the last round). All revenues were subject to a risk-free interest rate of 10 percent, which was applied in every period. Participants were informed about all parameters and could observe the development of the binomial tree on their computer screens, whereby different colors and fonts indicated (1) the current payoff (marked red), (2) the future payoffs that could eventuate (marked black and bold), (3) the future payoffs that, based on the preceding development of the random mechanism, could not eventuate anymore (faded grey color) (see Figures A1 and A2 in the Appendix).

The final payoff from this part of the experiment was determined by randomly drawing one of the 20 rounds once this part of the experiment was completed. Due to this mechanism, where feedback information on the final payoffs was withheld until the end of this part of the experiment, participants could not employ reinforcement learning with respect to realized payoffs; the only situation in which a respondent would learn about her (here hypothetical) payoff was the trial period, which was intended. The experiment was neutrally framed as a problem of optimal stopping, in order to isolate participants' tendencies for project termination from other drivers of disinvestment or exit. The conversion rate was 3.500 points/1€.

Random mechanism

Each payoff development was uniquely determined, i.e., each round would typically lead to a different development, by means of a random mechanism deciding on the payoff development in the binomial tree. The increase or decrease of the payoff from period 1 to 10 was determined via a mix of real (RNG) and pseudo (PRNG) random mechanisms. The issue of randomization is, based on conceptual as well as methodological reasons, critical for this experiment (for a detailed discussion in this regard and the recommendation to combine RNG and PRNG mechanisms, please refer to Bem 2011). Generally, there are two ways to generate randomness in an experiment: (1) One can generate a random number table (or random function) which randomly assigns certain outcomes to the numbers generated (e.g. in our experiment a "1" would indicate an increase by 500 points, while a "0" would lead to a decrease by 500 points). Such mechanisms are often referred to as pseudo random number generator (PRNG). Based on the fact that it applies a mathematical algorithm to derive each subsequent number from the previous one, all numbers ultimately depend on the initial number generated.

Considering H_{CF} (the precognition hypothesis), by using exclusively a random number table in our experiment (as often done in psychological experiments), the issue of clairvoyance versus precognition arises, as the computer has already stored all the upcoming random numbers prior to the respondent making her actual decision. Thereby, solely applying a random number table does not allow us to exclude the possibility of respondents being "simply" aware of something that has been generated in the past which consequently causes issues regarding the interpretation of any positive 'non-classical' findings as precognition.

Another possibility of generating randomness is via a physical random number generator, exploiting, for example, an elementary quantum optics process. Such hardware based approaches are generally referred to as "true" or "real" random generators (RNG), despite the fact that even such a mechanism might not necessarily pass all mathematical tests of randomness (L'Ecuyer 2001). While such a device eliminates the possibility of clairvoyance, it does raise the possibility of psychokinetic interpretations, namely that respondents might influence rather than predict the RNG process, which consequently again raises issues regarding the interpretation of any positive findings as precognition.

In order to avoid such possible alternative interpretations, a coupled mechanism of PRNG and RNG was applied in this experiment. For the RNG the true random-number-generator hardware *quantis* was used, whereby photons – light particles – are sent one by one onto a semi-transparent mirror and detected. The exclusive events (reflection - transmission) are associated to "0" - "1" bit values. *Quantis* was also used to generate the sequence of numbers for the PRNG, which was pre-stored in the computer program z-Tree.[9] In every round of the experiment, each respondent would be allocated a random number from the PRNG mechanism and a value from the *quantis* mechanism. Thereby, the following number combinations determined whether an in-

[9] Note: Even though the PRNG was created with a true RNG, since the data generated is recorded, its sequence is determined, and as such qualifies as a PRNG. Quantis thereby generated 3500 bit values. These were consequently indexed to respondents' ID numbers (e.g. respondent 1 was allocated the first 200 numbers, respondent 2 the numbers 201-400 and so on).

crease or decrease would eventuate (each event has an equal probability of 50 percent): Should the PRNG and *quantis* generate equal values, the calculated random value would equal a “1”, and would consequently lead to an increase in the payoff. If the numbers of the PRNG and RNG are unequal, the calculated random value would be equal to a “0”, causing the payoff in the next period to decrease (see Table 1 below for a summary of this mechanism).

Pre-stored/ *quantis*	Real time/ *quantis*	Calculated random number	Resulting Payoff
0	0	1	up by 500 points
1	1	1	up by 500 points
0	1	0	down by 500 points
1	0	0	down by 500 points

Table 1: Generating the random sequence via pre-stored and real-time random numbers

Average earnings from the disinvestment task were 9.15 €, with a minimum of 4.10 € and a maximum of 20.10 €.

3.2. Holt and Laury lottery

The second section of the experiment included an incentive compatible measurement of risk attitudes via the Holt and Laury (2002) procedure. Respondents were confronted with 10 decision situations. In each situation, they could choose between lottery A (where payoffs were fixed at 2.00 € versus 1.60 €) and lottery B (which had a much larger range with payoffs fixed at 3.85 € versus 0.10 €), whereby throughout the 10 decision situations the probability of getting the larger payoff varied in each situation. This probability was continually increased from a value of 10% in situation 1, up to a value of 100% in situation 10. A risk loving participant would switch between option A and option B during decision situations 1 to 4, a risk neutral participant would switch to option B exactly during situation 5, while a risk averse respondent would do the switch later, during situations 6 to 10.

Once the Holt and Laury lottery was completed the computer again randomly picked one round from the lottery and each respondent was paid accordingly to her choice in that round; the lottery that was selected in that round was played out. Average earnings from the Holt and Laury lottery were 2.88 €, with a minimum of 0.10 and a maximum of 3.85 €.[10]

3.3. Demographics and sensation seeking

Demographics

In the third part of the experiment, respondents were asked to provide information regarding typical demographic characteristics (e.g., age, gender), and to indicate their prior experience with decision experiments in general as well as their current knowledge regarding real options theory. Additionally, respondents had to complete two personality questionnaires: One questionnaire tested their pattern of decision-making (by testing their traits of vigilance vs. buck-passing). However, for the sake of brevity, this data will not be further analyzed in this paper. The second questionnaire collected information regarding respondents' sensation seeking tendencies (Zuckerman 1979).

[10] Respondents finally were told their total payoff of the last two sections in Euro amounts.

Sensation seeking scale (SSS)

In Bem (2011), precognitive abilities were related to scores of sensation seeking in some of his experiments (see, however, the null results on the main effects in replications of some of his experiments as well as the non-existing relationship with sensation seeking in the study by Galak et al. 2012). Hence, our respondents had to answer the German version of Zuckerman's sensation seeking scale V (Beauducel et al. 2003). Thereby, respondents were presented with 39 questions, whereby each question contained two contradictory statements (e.g. "I prefer down to earth people as friends" (reverse scored) vs. "I would like to be friends with unconventional people, like artists and hippies"). Respondents were instructed to choose (via a click) the option they preferred / described them personally more accurately.

3.4. Premonition picture test

In the fourth section of the experiment, a novel extrasensory perception (ESP) or premonition test was run via the program e-prime (this procedure has been developed by Maier et al. 2010).[11] We were interested to see whether a potential, 'non-classical' ability to anticipate future developments in our RO experiment could be predicted by some other task potentially measuring a similar type of ability. Thereby, neutrally and negatively coded pictures from the International Affective Picture System (IAPS; Lang et al. 1993) were subliminally presented to the respondents. The IAPS picture set is a commonly used source in premonition studies (Bem 2011). In total 10 neutrally and 10

[11] We are grateful to Markus Maier, LMU Munich, for granting us access to his program and Vanessa Büchner, Anna Abratis, Olaf Menzel and Steffen Hering for helping us implementing and running it at our laboratory.

negatively coded pictures were selected.[12] Using the same type of random procedure as described under the real-options experiment (a combination of pre-recorded random numbers and real-time Quantis output), the computer consequently determined whether the respondent's pressing the "right" or "left" key on the computer's keyboard would result in the presentation of a negatively or neutrally coded picture.[13] The picture itself was shown for only 14 milliseconds (thus a subliminal presentation). The picture was masked; whereby the mask simply consisted of pixelated squares, which matched the color of the respective picture. The mask was presented 70 milliseconds before and after the presentation of the actual picture. The mechanism ensures that (1) no detectable patterns could cause participants' responses and that (2) clairvoyance and psychokinetic interpretation options (described in part 3.1) could be eliminated. It is important to note that the computer program did only determine whether a neutral or negative picture would appear (subliminally) on the screen once the key had been pressed (the pressing would activate the random mechanism).

The main hypothesis for this section of the experiment – and in fact the requirement for being able to actually use it as a predictor of potential precognition performance in the RO experiment was that participants would be able to identify (unconsciously choose) the neutrally coded pictures significantly more frequently than the negatively coded pictures (i.e., significantly more often than 50 percent of the time). However, neither a significant main effect nor any (nevertheless tried out) predictive success with the RO experiment was detected and this persisted even when the original

[12] It should be noted that only mildly negative pictures were chosen due to ethical reasons.
[13] Note that the respondents only unconsciously pressed the right or left button first since they were instructed to jointly press both buttons. The button that was effectively pressed first was processed.

picture set was analyzed and sorted for the most predictive pictures.[14] We consequently will not further analyze the results from this section of the experiment in this paper.

4. Experimental results

4.1 Characteristics of the sample and overview of analyses

In total, 100 students participated in the experiment, coming from 20 different fields of study. They were fairly young, with an average age of 27 years, a minimum of 21 years and a maximum of 38 years. The sample included 62 females and 38 males. On average, participants were quite risk averse. After excluding participants with inconsistent responses in the Holt and Laury (2002) procedure[15], we were left with 92 respondents who exhibited consistent risk attitudes. Similarly to the prevalent risk attitude among the general population, the large majority of 65 respondents turned out to be risk averse.[16]

In the following, we start the evaluation of our experimental findings with several descriptive statistics regarding exit times and payoffs (4.2.). Since each respondent delivers 20 different disinvestment times, and since exit times are censored at t = 10, we then analyze those observed times as dependent variable within several hierarchical Tobit panel regressions, using our theoretical predictions, i.e., real options approach, precognition (CF, for 'cognition future', in the following), heuristics, and

[14] Further information in this regard is available from the authors upon request.
[15] In the Holt and Laury (2002) task, individuals are supposed to switch from a low-risk to a high-risk lottery once (where the advantages of the high-risk lotteries increase stepwise). Switching back and forth leads to an uninterpretable response. Individuals doing that were classified as having a non-consistent response.
[16] The average Holt and Laury lottery value was 6.42.

several control variables (4.3.). The CF variable is the overall optimal (i.e., final payoff-maximizing) disinvestment time assuming that the respondent knew all future developments of the payoff variable (which was impossible by any 'classical' means).

We also analyze the payoffs from the games as dependent variable, predicting the actual payoff in the 20 games an individual plays employing hierarchical, regular random effects panel regressions, using the same predictors as for exit times, but leaving out the heuristics; since the heuristics are all payoff based, they would be highly endogenous with the dependent variable (4.4.).

An important additional step in our analysis is the *direct* analysis of the predictive performance of past- and future-based heuristics on exit choices, to be presented in 4.5.

4.2. Descriptive statistics

On average, theoretical exit times applying a real-options approach to the actual random developments of the payoffs on an individual-player individual-rounds basis, do not get very close to the empirically observed exit times: The theoretical prediction generates a value of 4.2 periods (standard deviation 3.8), while the actually observed average disinvestment time lies at 6.6 periods (standard deviation 3.3). The CF approach comes somewhat closer to this value, generating an average prediction of 5.1 periods (standard deviation 4.1). This replicates the findings on pronounced waiting tendencies (or psychological inertia) in this type of experiment by Sandri et al. (2010), Musshoff et al. (2013), and Schade and Snir (2012).

Figure 2 depicts the frequency distributions of the observed exit times, the exit times predicted by CF and those predicted by RO. The graphs include the complete set of 2,000 observations from all 100 respondents.

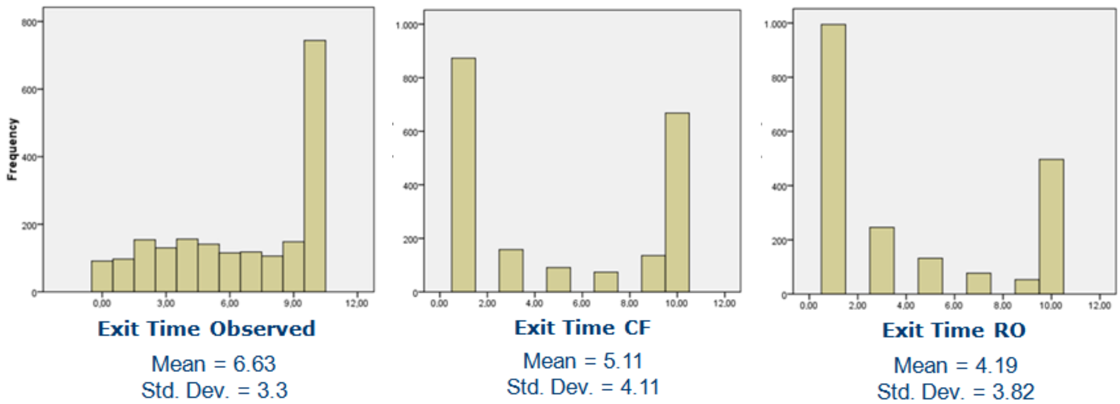

Figure 2: Theoretical (CF: precognition-based, RO: real-options based) and empirical distributions of exit times

Figure 3 now presents the distributions of payoffs from each round: observed payoffs, payoffs that would have been obtained via precognition (assuming a respondent was able to foresee the entire development of the random path from period 0), and payoffs that would have been obtained by applying the RO approach.

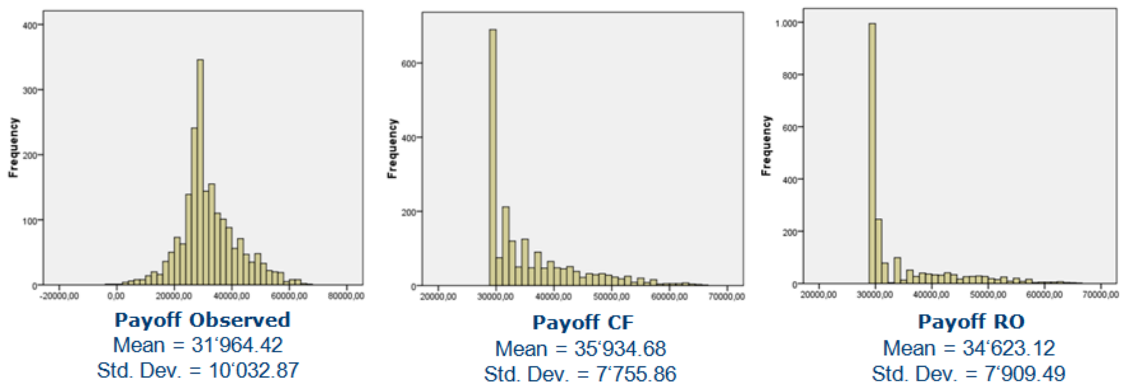

Figure 3: Theoretical (CF: precognition-based, RO: real-options based) and empirical distributions of payoffs

4.3. Hierarchical Regressions on Exit Times

We hierarchically built several Tobit random effects panel models in order to identify factors influencing the choice of exit time (we always specify t = 10 as the censoring point). The most important results are presented in the following Tables and commented below the respective tables. One additional model is reported in the Appendix – as specified in the text.[17] We first analyze the predictive power of three factors: the game played, varying from the first to the twentieth game (Period) to capture potential learning effects, the exit times in each of those games, predicted by precognition (exit time CF) and based on the outcome of the random walk in that specific game, and the exit times in each of those games, predicted by real options/optimal stopping (exit time RO) and based on the outcome of the random walk in that specific game.

tObserved	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Period	-.0340648	.0151671	-2.25	0.025	-.0637918	-.0043377
tRealOptions	.2173753	.0320332	6.79	0.000	.1545914	.2801591
tCF	.3365637	.0290766	11.58	0.000	.2795746	.3935527
_cons	5.570288	.3509467	15.87	0.000	4.882445	6.258131
/sigma_u	2.79664	.2284475	12.24	0.000	2.348891	3.244389
/sigma_e	3.605824	.0791062	45.58	0.000	3.450779	3.76087
rho	.3756008	.0389838			.3020716	.4539613

Table 2a: Tobit regression model including RO and CF as predictors

Table 2a reports on a regression model containing period, t_{RO} and t_{CF} as predictors, hence testing H_{RO} as well as H_{CF} (Table A1 in the Appendix shows that t_{RO} and t_{CF} are significantly correlated, but that there is no serious multi-collinearity problem present). As easy to see, later periods correspond with slightly earlier exit times, the

[17] Further models are available from the authors upon request.

RO approach delivers a highly significant prediction of individuals' exit times, but the strongest predictor appears to be CF, the optimal disinvestment times *if people had full knowledge of future developments*. Since the large z-value as well as the high significance level might indicate a 'non-classical' finding, one should look for potential alternative explanations (see also the discussion section). Statistically, there might only be one plausible alternative explanation: that the correlation between CF and actual exit times is a spurious one. Why could it be spurious? Means as well as distribution of empirical exit times are on average closer to CF rather than RO predictions since individuals exhibit a pronounced waiting tendency, on average (called 'psychological inertia', by Sandri et al. 2010), and t_{CF} overall predicts later exit times than t_{RO}.

In order to address this potential alternative explanation, we decided to calculate individual waiting indices. There are two ways of doing this, taking t_{RO} or t_{CF} as the benchmark. To be on the safe side, we did both. Thereby, the optimal exit times t_{RO} and t_{CF} were subtracted from the actually observed exit periods ($t_{observed}$) on an individual rounds basis per individual. We consequently obtained two different terms with each round and with each individual: one relating to the benchmark of real options theory ($t_{observed} - t_{RO}$) and one concerning precognition ($t_{observed} - t_{CF}$). An individual's average waiting tendency is calculated by averaging over the 20 rounds played, separately for each of those two terms. A resulting positive index value reflects the individual's average tendency to 'hold on for too long', a negative value, however, reflects the tendency to exit the investment 'too early' relative to the underlying theoretical model. Those indices are added to the regression model reported in Table 2a, leading to the two regression models reported in Tables 2b and 2c.

tObserved	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Period	-.0344864	.0149765	-2.30	0.021	-.0638398	-.0051329
tRealOptions	.2535594	.0316378	8.01	0.000	.1915505	.3155684
tCF	.3179161	.0284083	11.19	0.000	.2622368	.3735953
AveragedelayRO	1.271364	.0499407	25.46	0.000	1.173482	1.369246
_cons	2.342581	.2449724	9.56	0.000	1.862444	2.822718
/sigma_u	.4559426	.1655171	2.75	0.006	.131535	.7803501
/sigma_e	3.578604	.0776307	46.10	0.000	3.426451	3.730758
rho	.0159735	.0114936			.0033777	.0568839

Table 2b: Tobit regression model including RO and CF as predictors and individual waiting tendencies (RO Index) as control

tObserved	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Period	-.0346934	.0149283	-2.32	0.020	-.0639524	-.0054344
tRealOptions	.2025136	.0310727	6.52	0.000	.1416122	.263415
tCF	.3623438	.0286216	12.66	0.000	.3062464	.4184412
AveragedelayCF	1.289807	.0516723	24.96	0.000	1.188531	1.391083
_cons	3.470067	.2275877	15.25	0.000	3.024003	3.91613
/sigma_u	.5012587	.1523388	3.29	0.001	.2026802	.7998372
/sigma_e	3.567675	.0772576	46.18	0.000	3.416253	3.719097
rho	.0193581	.0116185			.0053751	.0566348

Table 2c: Tobit regression model including RO and CF as predictors and individual waiting tendencies (CF Index) as control

As easy to see, the delay indices become positive and highly significant in both regressions showing the individuals’ strong average tendency of ‘holding on for too long’, thus replicating Sandri el al. (2010), Musshoff et al. (2013), and Schade and Snir (2012). The indices based on t_{CF} and t_{RO} perform about equally well (generate similar z-values). More importantly, t_{CF} remains a highly significant predictor in both models indicating that the alternative explanation does not hold and our ‘non-classical’ findings are robust.

The regression model reported in Table 3 now includes the three heuristics proposed in the theory section as well as further control variables. To repeat, the heuristics are 'disinvest when the cash flow decreases for 2 consecutive periods' (Exit time 2decrease, testing H_{H3}), 'disinvest when the current cash flow reaches 0' (Exit time X gets 0; testing H_{H1}), and 'disinvest when the current cash flow becomes negative' (Exit time X gets neg; testing H_{H2}). Because the CF-based and RO-based indices turned out to perform about equally well, we arbitrarily chose to use the CF-based index. We added female, age, risk attitude, and sensation seeking as control variables. Because of missing values with the risk propensity variable, the number of observations is reduced to 92. An intermediate step of this hierarchical procedure (containing the heuristics but no further control variables) is reported in Table A2 in the Appendix.

According to this regression model, the heuristic to exit when the payoff gets negative is an important predictor of exit times, whereas the other two heuristics turn out to be either only marginally significant (payoff gets zero), or not significant at all (two decreases of the payoff in a row). The latter result is quite surprising, given the statement in Musshoff et al. (2013) concerning this matter. According to these authors, the heuristic "payoff down twice" turned out to be significant in the analysis of their experimental data (although no details are reported in their paper). In our regression model, the reason for this heuristic not being significant might be parallel multicollinearity problems with the other two heuristics and the RO prediction; in fact, two drops in payoffs quite frequently lead the decision maker either below its disinvestment trigger or to the zero or negative payoff points. Thus, the later analysis with respect to different past-based and future-based heuristics will also be clarifying in this regard (see 4.5). Although the effects of RO and CF are reduced via the integration of the heuristics (being consistent with the above explanation), they both remain strong and highly significant, nonetheless.

Random-effects tobit regression		Number of obs	=	1840
Group variable: Subject		Number of groups	=	92
Random effects u_i ~ Gaussian		Obs per group: min	=	20
		avg	=	20.0
		max	=	20
		Wald chi2(11)	=	985.95
Log likelihood	= -3581.4789	Prob > chi2	=	0.0000

tObserved	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Period	-.0346368	.0150957	-2.29	0.022	-.0642238	-.0050499
tRealOptions	.1423972	.0330837	4.30	0.000	.0775543	.2072402
tCF	.1876726	.0392349	4.78	0.000	.1107737	.2645716
AveragedelayCF	1.293094	.0580404	22.28	0.000	1.179337	1.406852
t2decrease	.0633873	.0532876	1.19	0.234	-.0410544	.167829
txgets0	.1014908	.0557401	1.82	0.069	-.0077578	.2107395
txgetsneg	.2471718	.0474716	5.21	0.000	.1541292	.3402144
Female	-.0712084	.2726993	-0.26	0.794	-.6056892	.4632723
Age	.0084616	.0288353	0.29	0.769	-.0480545	.0649777
Riskattitude	-.0007152	.0690516	-0.01	0.992	-.1360539	.1346235
Sensationseekingscale	-.0054499	.0203823	-0.27	0.789	-.0453984	.0344986
_cons	1.443418	1.123835	1.28	0.199	-.7592574	3.646094
/sigma_u	.6210342	.1405176	4.42	0.000	.3456247	.8964437
/sigma_e	3.459356	.0778874	44.41	0.000	3.306699	3.612012
rho	.0312223	.0138085			.0122899	.0696626

Table 3: Tobit regression model including variables t_{RO}, t_{CF}, individual waiting tendencies (CF-based Index), three heuristics, demographics, and personality variables (n = 92)

4.4. Analysis of payoffs

In the following, we replaced all of the exit time variables with the corresponding payoff variables. For example, we replaced the exit time choices according to precognition (t_{CF}) with the payoffs that would have been obtained if a hypothetical respondent had used precognition (payoff CF). We left out all heuristics as predictors because they are payoff based and would be highly endogenous with the dependent variable. We will later report on a regression involving additional control variables, however.

We are going to run regular random effect panel models. Tables 4 and 5 report the findings with payoff RO and payoff CF as predictors, respectively.

```
.
. xtreg PayoffObserved Period PayoffRealOptions, re

Random-effects GLS regression                   Number of obs      =      2000
Group variable: Subject                         Number of groups   =       100

R-sq:  within  = 0.6368                         Obs per group: min =        20
       between = 0.4200                                        avg =      20.0
       overall = 0.6181                                        max =        20

                                                Wald chi2(2)       =   3400.53
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------------
   PayoffObserved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
           Period |   46.86495   22.99481     2.04   0.042     1.795958    91.93394
PayoffRealOptions |   .9953528   .0170821    58.27   0.000     .9618725    1.028833
            _cons |  -2989.991    676.911    -4.42   0.000    -4316.712   -1663.269
------------------+-----------------------------------------------------------------
          sigma_u |  1838.9416
          sigma_e |  5931.1325
              rho |  .08769976   (fraction of variance due to u_i)
------------------------------------------------------------------------------------
```

Table 4: Payoff regression with observed payoffs as dependent and payoffs predicted by RO as independent variable

```
. xtreg PayoffObserved Period PayoffCF, re

Random-effects GLS regression                   Number of obs      =      2000
Group variable: Subject                         Number of groups   =       100

R-sq:  within  = 0.7665                         Obs per group: min =        20
       between = 0.4608                                        avg =      20.0
       overall = 0.7400                                        max =        20

                                                Wald chi2(2)       =   6317.30
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
PayoffObse~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      Period |   38.52014   18.43837     2.09   0.037     2.381606    74.65867
    PayoffCF |    1.11014   .0139764    79.43   0.000     1.082747    1.137533
       _cons |  -8332.609   579.3095   -14.38   0.000    -9468.035   -7197.183
-------------+----------------------------------------------------------------
     sigma_u |   1910.106
     sigma_e |  4755.5551
         rho |  .13891758   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table 5: Payoff regression with observed payoffs as dependent and payoffs predicted by CF as independent variable

Before integrating both predictors in one regression, we are going to demonstrate that we are facing considerable multi-collinearity problems here. Table 6 shows this via the correlations between the two payoff variables.

Pearson Correlation		Payoff_RO	Payoff_CF	Kendall's Tau		Payoff_RO	Payoff_CF
Payoff_RO	Correlation Coefficient	1	,930**	Payoff_RO	Correlation Coefficient	1	,782**
Payoff_CF	Correlation Coefficient	,930**	1	Payoff_CF	Correlation Coefficient	,782**	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 6: Correlations between payoff RO and payoff CF

The theoretical payoffs predicted via the application of either a real options approach or precognition are closely related. Analyzing both predictors simultaneously, as reported in Table 7, thus cannot be interpreted in terms of expecting efficient and unbiased parameter estimates. Rather, this regression model becomes a Litmus test of the relative dominance of those two concepts as a predictor of observed payoff values.

It is easy to see which of the two predictors is dominant. Whereas, in this direct 'competition' of predictors, the RO-based theoretical payoff actually becomes a predictor with a negative parameter value, the CF-based predictor performs extremely well with a z-value of still 32.97. This result remains robust when integrating additional control variables as demonstrated in Table 8.

```
. xtreg PayoffObserved Period PayoffRealOptions PayoffCF, re

Random-effects GLS regression                   Number of obs      =      2000
Group variable: Subject                         Number of groups   =       100

R-sq:  within  = 0.7686                         Obs per group: min =        20
       between = 0.4557                                        avg =      20.0
       overall = 0.7415                                        max =        20

                                                Wald chi2(3)       =   6385.26
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------------
     PayoffObserved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------------+---------------------------------------------------------------
             Period |   37.58338    18.3632     2.05   0.041     1.592181    73.57459
  PayoffRealOptions |   -.150828   .0373522    -4.04   0.000    -.2240369   -.0776192
           PayoffCF |   1.252904   .0379986    32.97   0.000     1.178428    1.327379
              _cons |  -8230.796   578.0729   -14.24   0.000    -9363.798   -7097.794
--------------------+---------------------------------------------------------------
            sigma_u |  1919.7435
            sigma_e |  4735.3243
                rho |  .14115654   (fraction of variance due to u_i)
------------------------------------------------------------------------------------
```

Table 7: Payoff regression with observed payoffs as dependent and payoffs predicted by CF as well as RO as independent variables

```
. xtreg PayoffObserved Period PayoffRealOptions PayoffCF Female Age Riskattitude

 Sensationseekingscale if Riskattitude > > 0, re

 Random-effects GLS regression                   Number of obs      =      1840
 Group variable: Subject                         Number of groups   =        92

 R-sq:  within  = 0.7665                         Obs per group: min =        20
        between = 0.4948                                        avg =      20.0
        overall = 0.7435                                        max =        20

                                                 Wald chi2(7)       =   5814.70
 corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

----------------------------------------------------------------------------------------
        PayoffObserved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------+----------------------------------------------------------------
                Period |    35.3955   18.99971     1.86   0.062    -1.843235    72.63424
     PayoffRealOptions |  -.1325536   .0385272    -3.44   0.001    -.2080656   -.0570416
              PayoffCF |   1.224657   .0392362    31.21   0.000     1.147755    1.301558
                Female |  -1211.297   532.3502    -2.28   0.023    -2254.684   -167.9096
                   Age |  -112.8413   56.70901    -1.99   0.047    -223.9889   -1.693676
          Riskattitude |   -7.25194   137.8936    -0.05   0.958    -277.5185    263.0146
 Sensationseekingscale |  -3.373429   40.77116    -0.08   0.934    -83.28344    76.53658
                 _cons |  -3845.011   2239.042    -1.72   0.086    -8233.452    543.4301
-----------------------+----------------------------------------------------------------
               sigma_u |  1831.5472
               sigma_e |  4700.3901
                   rho |  .13181918   (fraction of variance due to u_i)
----------------------------------------------------------------------------------------
```

Table 8: Payoff regression with observed payoffs as dependent and payoffs predicted by CF as well as RO as independent variables including control variables

Summing up, based on predicted payoffs we have indirect evidence that H_{CF} has higher predictive value than H_{RO}. Or - in other words - precognition appears to be a better model of individuals' exit choices than optimal stopping.

4.5. A direct test of past-based and future-based heuristics

Many people mistrust complex regression models (no matter how well specified they might be), and this mistrust might turn out to be especially strong when controversial claims such as having evidence for precognition are to be justified. Moreover, the most plausible past-based heuristic, the "payoff down twice" heuristic, turned out not to be significant in our regression model (see Table 3), most certainly because of simultaneous multi-collinearity with several other variables. We hence decided to enhance our statistical analysis by direct tests of the performance of two plausible past-based and two plausible future-based heuristics.

Specifically, the four heuristics that are looked at are:

- Payoff dropped in the last period (*t1negpast*),
- Payoff dropped in each of the last two periods (*t2negpast*),
- Payoff *will* drop in the next period (*t1negfuture*),
- Payoff *will* drop in each of the next two periods (*t2negfuture*).

With respect to each of the heuristics, the entire dataset was screened for the occurrence of the respective 'event' in each of the games. If it occurred twice in a game, only the first occurrence was evaluated since the second occurrence should not have been reached, anymore, if the individual indeed exited after the first occurrence.

With respect to this first occurrence, it was then tested whether or not the prediction based on this heuristic was correct. E.g., if the payoff dropped in two subsequent periods, it was tested whether the individual decided in favor of an exit in her next choice. Figure 4 displays the results of this exercise for all four heuristics together with the random benchmark.

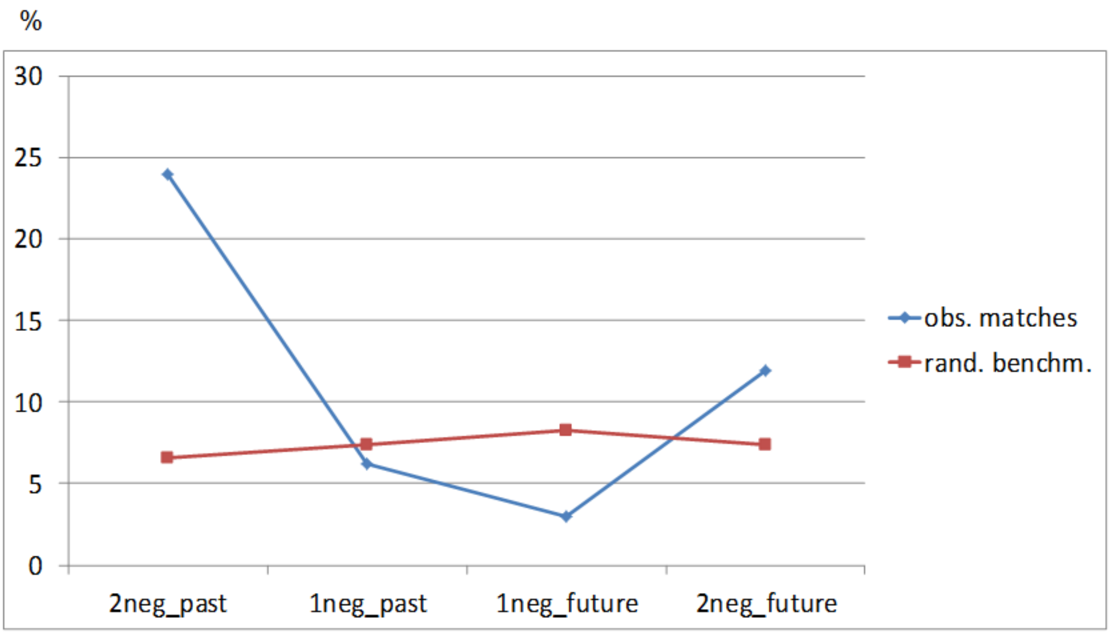

Figure 4: Observed matches of past- and future-heuristic based predictions with actual exits and random benchmark (standard errors for the respective distributions based on the means of the 100 individuals are, from left to right: .0160; .0111; .0091; .0085)

Regarding the random benchmark, it was calculated as an *overall probability* in the following way. First, it has to be taken into account that the heuristics work over a different interval. For the *t2negpast* heuristic to work, e.g., two random payoffs must have been revealed to the respondent. Therefore, this heuristic started to work only in round 2. The number of rounds where the heuristic could be applied divided by the total number of rounds where the respondent could exit generated a conditional probability. The probability of a random hit (1/11) was multiplied with this conditional probability for the respective heuristic. For the heuristic *t2negpast*, e.g., this is 8/11 *

1/11 = .0661.[18] Given the random errors reported in the legend to Figure 4, and comparing the respective percentages reported in the blue and red lines, it is easy to see that the empirical hits for the *t2negpast* and *t2negfuture* heuristics are significantly above the random benchmark whereas the empirical hits for the *t1negfuture* heuristic are significantly below it. This pattern is underlined by the, however, insignificant negative deviation of the *t1negpast* hits from the benchmark. The pattern, however, can be described quite simply. One drop in payoffs, no matter whether it occurs in the past or in the future, rather encourages the respondent to stay in the game than triggers her exit. Two drops, however, no matter whether they occur in the past or in the future, lead the respondent to exit.

5. Discussion, conclusion, limitations, and future research

The experimental findings contain two expected (replicative) and two novel aspects. One of the novel aspects is quite revolutionary.

One should not be surprised that the real options or optimal stopping approach performs quite well. Indeed, this has already been shown in previous research; and the experimental design was not radically different from that employed by Sandri et al (2010) and Musshoff et al. (2013). The pronounced waiting tendencies of an average individual, calculated only for the sake of robustness analysis of the precognition findings, here, is also a replication of what has already been documented by these authors.

[18] For t1negpast, the random benchmark is 9/11 * 1/11 = .0744. It is the same for t2negfuture. And it is 10/11 * 1/11 = .0826, for t1negfuture.

The contribution of this paper, however, lies in the two novel aspects of (a) an analysis of the predictive power of some plausible (past-based) decision heuristics and (b) in the specific test for precognition effects (or perhaps better: future-based heuristics).

With respect to (a), we have clear evidence for (past-based) heuristics being at work in disinvestment choices. In the regressions, the parameter of "payoff in a round falling below zero" becomes significant. This lends support to H_{H2} and hence indirectly to our theoretical reasoning on salience. This is also underlined by the fact that hypothesis H_{H1} turned out to be at least marginally significant in this regression; and this hypothesis contained the second heuristic we hypothesized as having at least secondary relevance to salience. Moreover, since some multi-collinearity is quite plausible to exist in this regression model (as discussed above) and the strong support for individuals using the stop-loss rule "payoff drops twice" in our analysis in 4.5, we also have support for H_{H3}.

Far more controversial are our findings on precognition (b), lending support to H_{CF} that we see as fairly robust, especially since the future-based heuristic "payoff will drop twice" (*t2negfuture*) turned out to be highly significant in our analysis presented in 4.5. But since "extraordinary claims require extraordinary evidence", an adage by US-astronomer Card Edward Sagan, we herewith invite comments, criticisms, and also replications of our findings. Specifically,

- Is there anything that might be improved in our statistical analysis, is there still the potential of artifacts? Are there any further analyses that should be carried out on our data? Are the theoretical benchmarks and the random benchmarks that we used plausible?

- Is there anything problematic with respect to our experimental design? Could it be improved in future research?
- And will our findings hold if the experiment is going to be replicated by others, in other laboratories, and with other respondents? Clearly, and this is a limitation of our study, 100 respondents are not few (especially since we present findings of a monetarily incentivized, economic experiment) and since we collected 20 observations with each of them, but also not many given the boldness of our claim to have evidence for precognition.

We would have been happy to present additional evidence for individuals' 'non-classical' predictive abilities via the subliminal picture task. Ideally, performance in this task would have been related to the strength of the predictive power of t_{CF} on the level of the individual or to the predictive power of *t2negfuture* in 4.5. We have not been successful with this part of our research since the picture task did not turn out to deliver any above-chance predictions.

We would like to argue, however, that our findings are strong and interesting enough to warrant attention in the scientific community, to warrant the above-invited discussions, further analyses, and replications. Since the potential implications of those findings, assuming their robustness, would be large, both for (psychological and physical) theory, as well as for the research and practice of decision making. Specifically, anecdotal evidence of some innovators, entrepreneurs, and stock brokers of 'just knowing when to disinvest' would then appear in new light.

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Appendix

Instructions

General information

Welcome to the experiment and thank you for your participation.

Please read these instructions carefully. If you have any questions during the experiment, please raise your hand and wait until one of the instructors attends to you. Everyone participating in this experiment received identical instructions.

The experiment will last about 120 minutes and consists of two parts and concludes with a questionnaire. At the end of each part you will receive instructions for the next part. Please read all instructions carefully as your earnings from the experiment will depend on your decisions.

At the end of the experiment you will receive your earnings in cash.

Feel free to use pen, scratch paper, and calculator available on your desk.

Please remain seated and do not communicate with other participants during the experiment.

First Part

The first part of the experiment consists of a trial game, followed by 20 repetitions of the same game. The trial game is played to make you familiar and more comfortable with the game. The trial won't be considered for payment.

Each game consists of 10 rounds.

In each game you should try to get as many points as possible as your earnings are proportional to the number of points you get during the experiment.

For each 3,500 points, you get 1 Euro.

At the end of the experiment, one of the 20 games will be randomly chosen by the computer and you will be paid according to your individual score (i.e., the number of points you have accumulated) in this selected game.

Introduction to the game

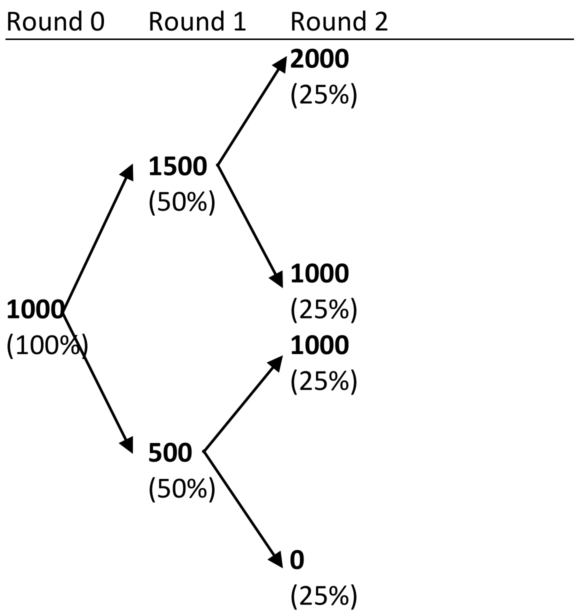
In each game you will start with a score of 1,000 points in Round 0. In the next round (Round 1) and in any subsequent round:

- Your points can either increase by 500 points with a probability of 50 %,
- Or they can decrease by 500 points, also with a probability of 50 %.

For example, from Round 0 to Round 1, in 50 % of the cases your points will increase to 1,500 points (1,000+500), or, in the remaining 50 % of the cases, they will decrease to 500 points (1,000-500).

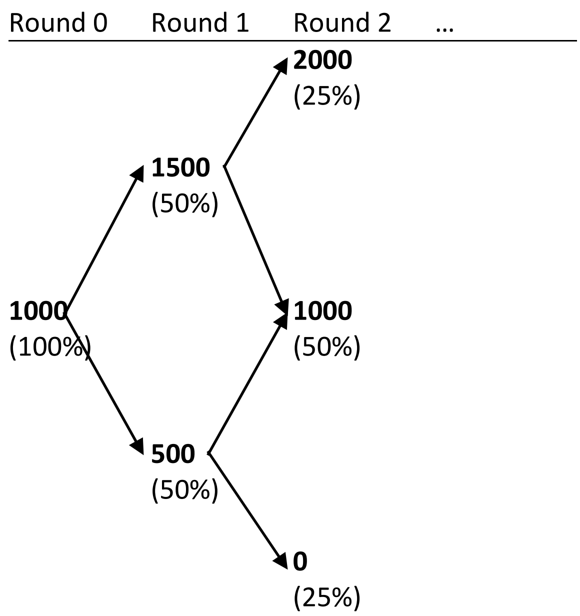
In the following diagram, you can see an example for this dynamics for three rounds:

The probability of occurrence of a certain score is written below the respective score in parentheses.



The situation can also be represented in a simpler form. The only difference is that for Round 2, the score of 1,000 appears just once and its probability of occurrence equals the sum of the probabilities that were separately listed in the diagram above.

In the following, we will use this form of representation throughout.



Your screen

You can see the potential developments of your points from round to round on your PC-screen. These developments will be represented in the following form:

Runde 0	Runde 1	Runde 2	Runde 3	Runde 4	Runde 5	Runde 6	Runde 7	Runde 8	Runde 9	Runde 10
1000	**1500**	**2000**	**2500**	**3000**	**3500**	**4000**	**4500**	**5000**	**5500**	**6000**
100,00%	50,00%	25,00%	12,50%	6,25%	3,13%	1,56%	0,78%	0,39%	0,20%	0,10%
	500	**1000**	**1500**	**2000**	**2500**	**3000**	**3500**	**4000**	**4500**	**5000**
	50,00%	50,00%	37,50%	25,00%	15,63%	9,38%	5,47%	3,13%	1,76%	0,98%
		0	**500**	**1000**	**1500**	**2000**	**2500**	**3000**	**3500**	**4000**
		25,00%	37,50%	37,50%	31,25%	23,44%	16,41%	10,94%	7,03%	4,39%
			-500	**0**	**500**	**1000**	**1500**	**2000**	**2500**	**3000**
			12,50%	25,00%	31,25%	31,25%	27,34%	21,88%	16,41%	11,72%
				-1000	**-500**	**0**	**500**	**1000**	**1500**	**2000**
				6,25%	15,63%	23,44%	27,34%	27,34%	24,61%	20,51%
					-1500	**-1000**	**-500**	**0**	**500**	**1000**
					3,13%	9,38%	16,41%	21,88%	24,61%	24,61%
						-2000	**-1500**	**-1000**	**-500**	**0**
						1,56%	5,47%	10,94%	16,41%	20,51%
							-2500	**-2000**	**-1500**	**-1000**
							0,78%	3,13%	7,03%	11,72%
								-3000	**-2500**	**-2000**
								0,39%	1,76%	4,39%
									-3500	**-3000**
									0,20%	0,98%
										-4000
										0,10%

This table can be interpreted as follows:

In the first round (Round 0) you receive **1,000** points (shown in red in the diagram). The points you may realize in the next rounds are written in **bold**. The probabilities of occurrence of the scores are listed under the respective score.

Assume that in Round 1, your score increased from 1,000 to 1,500 points. Then the scores that are written in **grey** are no longer possible, i.e., their probability of occurrence is 0.

In this case, your PC-screen will look the following way:

Runde 0	Runde 1	Runde 2	Runde 3	Runde 4	Runde 5	Runde 6	Runde 7	Runde 8	Runde 9	Runde 10
1000	1500	2000	2500	3000	3500	4000	4500	5000	5500	6000
0,00%	100,00%	50,00%	25,00%	12,50%	6,25%	3,13%	1,56%	0,78%	0,39%	0,20%
	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	0,00%	50,00%	50,00%	37,50%	25,00%	15,63%	9,38%	5,47%	3,13%	1,76%
		0	500	1000	1500	2000	2500	3000	3500	4000
		0,00%	25,00%	37,50%	37,50%	31,25%	23,44%	16,41%	10,94%	7,03%
			-500	0	500	1000	1500	2000	2500	3000
			0,00%	12,50%	25,00%	31,25%	31,25%	27,34%	21,88%	16,41%
				-1000	-500	0	500	1000	1500	2000
				0,00%	6,25%	15,63%	23,44%	27,34%	27,34%	24,61%
					-1500	-1000	-500	0	500	1000
					0,00%	3,13%	9,38%	16,41%	21,88%	24,61%
						-2000	-1500	-1000	-500	0
						0,00%	1,56%	5,47%	10,94%	16,41%
							-2500	-2000	-1500	-1000
							0,00%	0,78%	3,13%	7,03%
								-3000	-2500	-2000
								0,00%	0,39%	1,76%
									-3500	-3000
									0,00%	0,20%
										-4000
										0,00%

As you can see, the probabilities of occurrence of the scores have changed. In fact, they change in each round, i.e., they depend on the outcome(s) in the previous round(s).

Your decision and your profit

In each round you may:

- let your point score accumulate as described above (i.e., stay in the game)
- or terminate the game and accept a lump-sum payment of 11,000 points (eleven-thousand) (i.e., leave the game).

The *total* number of points you carry on to each subsequent round increases by **10 %** for each round left in the game (irrespective of whether you play all rounds or not), i.e., your total score will increase by one tenth and is then added to the points you will receive in the subsequent rounds. You can think of this increase as an interest payment.

The interest rate also applies to the lump-sum payment of 11,000 points, after you have left the game. It is added to the points you have collected until you decided to leave the game. Starting from the round in which you decide to terminate the game, this sum increases by 10 % for each of the remaining rounds.

Assume, you decided to terminate the game in Round X and receive 11,000 points.

Then your total score at the end of the game consists of:

- All points you have received before this round, increased by 10 % per round after you received them until round 10
- Plus 11,000 points you get because you have decided to leave the game. The 11,000 points also increase by 10 % for each of the remaining rounds (i.e., from Round X to Round 10).

If you stay in the game until the last round (i.e., play the entire game from Round 0 to Round 10), you automatically get 11,000 points at the end of the game (i.e., in Round 10).

Even once you have decided to terminate the game, you will still be able to observe the development of the points in the periods after your exit decision. However, these are only hypothetical payoffs and thus not payoff relevant (as you have already decided to exit the game).

While all this might sound quite complicated, the following example will illustrate, that it is actually quite straightforward.

Example

Imagine you received the points printed in **red**

Runde 0	Runde 1	Runde 2	Runde 3	...
1000	1500	2000	2500	
	500	**1000**	**1500**	
		0	500	
			-500	

In this case your total score is equal to:

- The 1,000 points you received in Round 0 increased by 10 % for each of the remaining 10 rounds of the game, i.e., $\underbrace{1000\cdot 1.1\cdot 1.1\cdot ...\cdot 1.1}_{10 times} = 1000\cdot 1.1^{10} = 2593.7$
- Plus the 500 points you received in Round 1 increased by 10 % for each of the remaining 9 rounds, i.e., $\underbrace{500\cdot 1.1\cdot 1.1\cdot ...\cdot 1.1}_{9 times} = 500\cdot 1.1^{9} = 1179$
- Plus the 1000 points of Round 2 increased by 10 % for each of the remaining 8 rounds, i.e., $\underbrace{1000\cdot 1.1\cdot 1.1\cdot ...\cdot 1.1}_{8 times} = 1000\cdot 1.1^{8} = 2143.6$
- Plus the 1500 points of Round 3 increased by 10 % for each of the remaining 7 rounds, i.e., $\underbrace{1500\cdot 1.1\cdot 1.1\cdot ...\cdot 1.1}_{7 times} = 1500\cdot 1.1^{7} = 2923.1$
- Plus the 11000 points you received in addition in Round 3 (because you decided to leave the game in this round) also increased by 10 % for each of the remaining 7 rounds, i.e., $\underbrace{11000\cdot 1.1\cdot 1.1\cdot ...\cdot 1.1}_{7 times} = 11000\cdot 1.1^{7} = 21435.9$

Therefore, your total score in this game equals to:

$2593.7 + 1179 + 2143.6 + 2923.1 + 21435.9 = 30275.3$ points

This means that you would have received 30275.3 points in this game.

Before the experiment starts we ask you to answer some comprehension questions in order to ensure that you understood the rules of the game.

We wish you a successful experiment!

Additional figures and tables

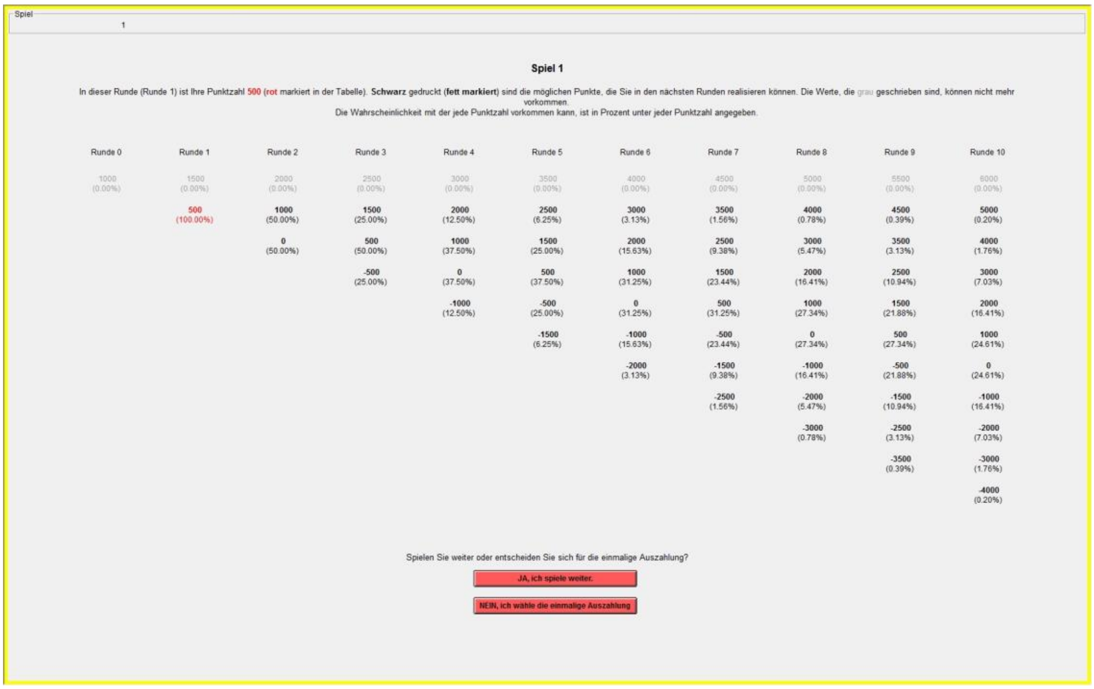


Figure A 1: Presentation of the stopping problem in the experiment – original screenshot (here respondent still decides whether to continue or abandon the investment)

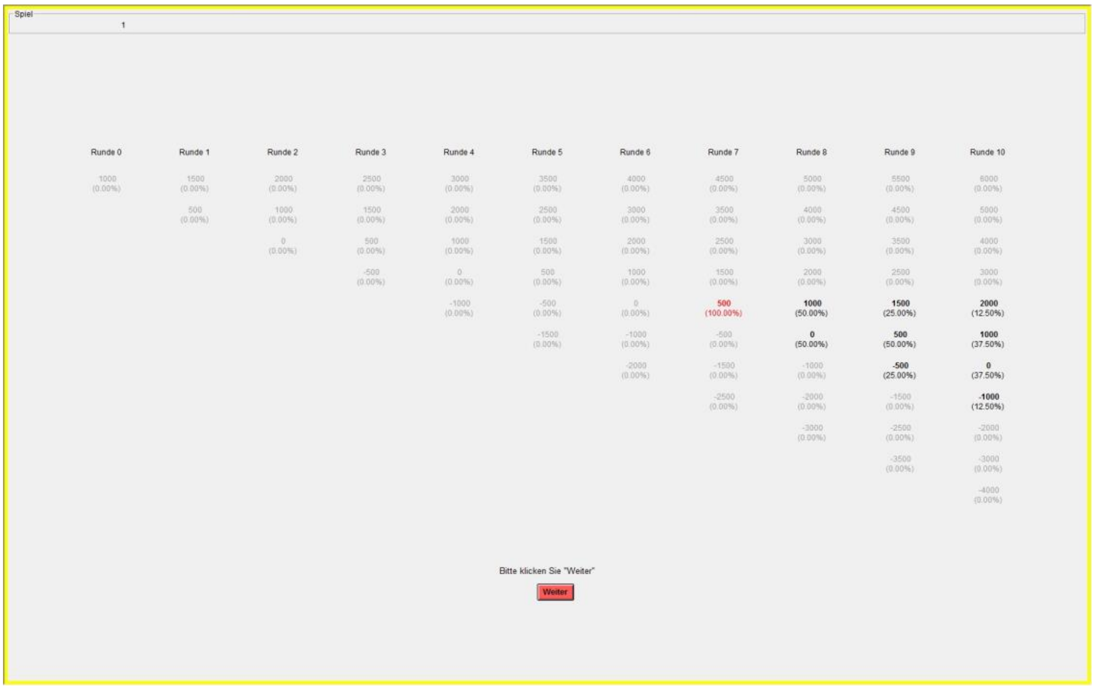


Figure A 2: Presentation of the stopping problem in the experiment – original screenshot (respondent already made her exit decision and only hypothetical outcomes are presented)

Pearson Correlation		t_RO	t_CF	Kendall's Tau		Payoff_RO	Payoff_CF
t_RO	Correlation Coefficient	1	,647**	t_RO	Correlation Coefficient	1	,556**
t_CF	Correlation Coefficient	,647**	1	t_CF	Correlation Coefficient	,556**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Table A1: Correlations between t_{RO} and t_{CF}

Random-effects tobit regression	Number of obs = 2000
Group variable: Subject	Number of groups = 100
Random effects u_i ~ Gaussian	Obs per group: min = 20
	avg = 20.0
	max = 20
	Wald chi2(7) = 1067.30
Log likelihood = -3881.3376	Prob > chi2 = 0.0000

tObserved	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Period	-.0333432	.0145657	-2.29	0.022	-.0618914	-.004795
tRealOptions	.1568654	.0317454	4.94	0.000	.0946455	.2190853
tCF	.1932441	.0376714	5.13	0.000	.1194096	.2670786
AveragedelayCF	1.286136	.0527327	24.39	0.000	1.182782	1.38949
t2decrease	.079935	.0512016	1.56	0.118	-.0204182	.1802882
txgets0	.0748078	.0538464	1.39	0.165	-.0307291	.1803448
txgetsneg	.2362114	.0460538	5.13	0.000	.1459476	.3264752
_cons	1.598372	.336855	4.74	0.000	.9381481	2.258595
/sigma_u	.573227	.1386366	4.13	0.000	.3015043	.8449497
/sigma_e	3.478072	.0753868	46.14	0.000	3.330316	3.625827
rho	.0264446	.0125567			.0097047	.0625054

Table A2: Tobit regression model including variables t_{RO}, t_{CF}, individual waiting tendencies (CF-based Index) and three heuristics (n = 92)