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Information Delivery, Ecological Rationality, and Expected Utility: An Experimental Study

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Information abundance is atypical in most everyday decisions. Scholars in psychology suggest that, even when only limited information is available, the use of simple heuristics may lead individuals to unexpectedly high performance. We then ask, when information is abundant, do individuals perform as well as when information is limited but delivered in a customary manner? In a sequential decision context, we investigate whether individuals use simple heuristics likely to result in information waste. We present theoretical and empirical analyses that compare individuals' performance in terms of expected utilities in four different information treatments. In a laboratory experiment, each respondent selected a time at which to enter a market based on information on product development funding. Respondents who were administered limited information and had to make a decision on a per-period basis performed as well as those who were administered all information before making a final decision. We offer statistical evidence for the use of a heuristic that only detects local optima, which is consistent with ecological rationality whereby individuals adapt to an environment of limited information that can only allow them to search for such optima. A discussion of research limitations and their potential for future research completes this article.

Keywords: Information Delivery, Ecological Rationality, Expected Utility, Decision Making, Economics Experiment.

1. Introduction

"People follow rules without being able to articulate them, but they can be discovered."
– *Vernon L. Smith* (2003: 470)

Individuals are boundedly rational and, as a result, most do not formally optimize. Instead, they use simple heuristics or rules of thumb that are typically adapted to humans' environment and can be successful in delivering rewards close to optimality (e.g. Kleinmuntz 1985, Simon 1990, Gigerenzer and Goldstein 1996, Gigerenzer et al. 1999, Goldstein and Gigerenzer 1999, Todd 1999, Dudey and Todd 2001). Gigerenzer et al. (1999) suggest that "[a] heuristic is ecologically rational to the degree that it is adapted to the structure of an environment [...]. Thus, simple heuristics and environmental structure can both work hand in hand to provide a realistic alternative to the ideal of optimization" (p. 13). Dudey and Todd (2001) refer to ecological rationality as the "decision mechanisms that are matched (that is, adapted) to the particular structure of information in the environments in which they are applied" (p. 197). From the perspective of ecological rationality, we wish to study how the amount and delivery method of information affect individuals' decisions.

The question of how individuals cope with information in their decision process is central to all sequential decision situations. Examples include buying a house, selling a used car, selecting a candidate for a job, or selecting a time for product introduction to market. In these examples, we argue, acquiring costly information may often be inefficient. Indeed, from ecological rationality, individuals lack appropriate heuristics to be used in environments that offer an abundance of information because such environments are rarely encountered and, as a result, the heuristics they possess to make decisions are expected to only perform well in environments of limited information.[1] Therefore, in this paper, our key hypothesis is that individuals are likely to perform as well when surrounded by limited information, but this information is delivered in a customary manner, as compared to when information is abundant, which is atypical in most everyday decisions.

This hypothesis is theoretically and experimentally investigated in an uncertain context where an individual must select a time at which to enter a market with a new product and information is acquired over time on the amounts of potential funding for product development. We conduct a laboratory experiment where we compare individual performances, in terms of expected utilities, among four distinct information treatments differentiated by the completeness of information, the manner in which this information is administered, and the point in time at which a decision must be made. In this experiment, we use real incentives (performance-dependent payments) and measure each respondent's risk propensity.

Gigerenzer and Goldstein (1996) demonstrate via simulations that using simple heuristics to process information may lead to stunning performance. According to Gigerenzer et al. (1999), individuals possess an adaptive toolbox that contains "fast and frugal" heuristics that are well-adapted to the decision situation at hand. These heuristics require little information and minimal cognitive effort. This view on heuristics seems, however, in contrast with Tversky and Kahneman (1974) who concentrate on the mistakes individuals make when applying simple heuristics. Our findings allow us to reconcile these differing views on heuristics for two determinants of heuristic performance, namely the amount and delivery method of information. Specifically, we find that respondents who were administered large amounts of information perform neither worse nor better than those who were administered less information and had to make a time-to-market decision on a per-period basis. In fact, our respondents appear to have used a simple heuristic that can only detect local optima. We offer evidence for the use of a similar heuristic for treatments where either information is limited or abundant, but this heuristic does not perform well for the latter treatment. Consequently, in Gigerenzer et al. (1999) terms, the toolbox containing fast and frugal heuristics is well-equipped for decisions with limited information. However, because of their unfamiliarity with treatments that offer an abundance of information, individuals appear to lack appropriate tools to handle these treatments.

Our work also complements previous experimental work on sequential choice behavior. Rapoport and Tversky (1970) compared normative predictions for different search tasks where each intensively studied respondent had to select to stop or continue the search. Their normative and experimental decision frameworks were based on search with and without recall (i.e. respondents cannot go back to a previously encountered alternative). They observed that respondents' reactions were often in tune with normative expectations, and when respondents deviated they were likely to stop the search too early. More recently, Seale and Rapoport (1997) conducted a study on sequential decision making where sequential information to respondents was limited to the rank of the various alternatives. They, as we, also observed a tendency for the search to stop too early. We choose to alter the decision framework of Rapoport and Tversky (1970) by suggesting a different payoff function that reflects our time-to-market context. This allows us to make a stronger case for information processing difficulties by offering a sequential decision context that approaches the complexities of reality. As a result, we are able to offer a step toward external validity testing by verifying the applicability of their findings on other decision situations. Moreover, we transform our respondents' payoffs into utilities in order to accommodate for the effect of risk preference.

The next section presents the time-to-market context used for the theoretical and experimental analyses and, as a result, used to evaluate expected utilities. Then, we articulate the four information treatments and our key hypothesis based on an ecological rationality perspective. Section §4 expounds the design of the experiment. Section §5 spells out the findings which allow us to test our key hypothesis, offers an interpretation of these findings, and offers insights on the respondents' selection process. Section §6 presents a discussion of research limitations and suggests directions for extending this line of research.

2. Decisional Context and Expected Utilities

As a basis for our experimental investigation, imagine an individual with an innovative idea for a product who aims at making profit in the process of starting a new firm based on this product. The new firm's expected total revenue depends on product quality and market development – measured by the level of competition – once the product is released. Product quality changes as a result of funding invested in product development, where the higher the funding, the better the product quality and the larger the expected total revenue. We note that higher quality may lead to lower expected total revenue, as the demand for the product may diminish due to higher pricing. However, for the benefit of experimental analysis where complexity has to be limited, we abstract from the demand function in our decision framework.

The relationship between level of competition and expected total revenue for the new firm is such that the higher the former, the smaller the latter. The firm must thus compare over time the gain from further developing the product at a cost – and so achieve a better product quality – to the loss from an increase in competition. It is assumed that the product does not deteriorate over time, and so each dollar invested in development will have a non-negative effect on product quality. Although in most product development activities there is uncertainty in both the outcome from a given amount of investment and the amount of investment available in a given period, we keep our model tractable and limit the complexity of experimental instructions by representing the effect of investment on product quality by a fixed parameter but financing by a random variable.

On any given time period, the state of the new firm is measured by product quality achieved so far, level of competition, and funding to date. Product quality, denoted q_t at time period t, changes as a result of funding available in each period. Formally, $q_{t+1} = q_t + b Z_{t+1}$ or, equivalently, $q_{t+1} = q_0 + b \sum_{i=1}^{t+1} Z_i$. Initial product quality, q_0, is known and may correspond to the quality reached once the new firm's owner has invested all personal savings in developing the product. b is the incremental quality per dollar invested. Z_i is the random input of funding at period $t=i$. Z_is are independent identically distributed random variables with a normal probability distribution function F_Z of positive mean m_Z and variance s_Z^2.

The state of the new firm also depends on its level of competition, denoted C_t at period t. C_t is a random variable with a normal probability distribution function F_t of positive mean m_t and variance s_t^2, where the mean increases with t at an increasing rate while the variance decreases with t at a decreasing rate (m_t and s_t^2 are convex in t). Whereas expected competition increases at an increasing rate mirroring the fact that pioneers try to erect market entry barriers with certain market segments that are eventually not accessible for others, variance on competition decreases at a decreasing rate mirroring the fact that a more saturated market is just less subject to variation in competition as one becomes better at predicting the specific market situation and learn to react better. Under these conditions, the level of competition can diminish due, for instance, to firm failures. However, as its variance diminishes over time, that level is unlikely to drastically fall down – and firms are less likely to fail – as the industry matures. Competition variables C_ts are independent of investment variables Z_ts.

As the firm continues its product development activity at period t, a random amount of dollars Z_t is allocated to this activity and product quality q_t is expected to improve. The firm receives revenue $R(q_t,C_t)$ if it chooses to stop development at t, where $R(q_t,C_t)$ is the total revenue associated with quality q_t and competition C_t. Marginal revenue increases with increased quality while it decreases with increased competition: $a = dR/dq_t > 0$ and $-b = dR/dC_t < 0$, respectively. Total non-discounted net profit if product development is terminated at t, P_t, is modeled as total revenue associated with quality q_t and competition C_t minus accumulated funding up until t, where total revenue is separable in its two components (no discounting is a reasonable assumption for products of relatively short lifecycle). Formally,

$$P_t = aq_t - bC_t - \sum_{i=1}^{t} Z_i = aq_0 + (ab-1)\sum_{i=1}^{t} Z_i - bC_t \,,$$

which is normally distributed at any time period t, as P_t is a linear combination of independent normally distributed random variables.

According to Freund (1956), two assumptions are sufficient to equate expected utility maximization with selecting the maximum of $E(P_t) - (a/2)Var(P_t)$, where a (> 0) reflects the risk aversion level of an individual, $E(\cdot)$ is the expectation and $Var(\cdot)$ the variance operators. The first assumption requires that risky outcome P_t (profit) be normally distributed, whereas the second assumption requires that decision makers exhibit constant absolute risk aversion and obey a global exponential utility function $U(P_t) = -e^{-a P_t}$. It is straightforward to verify that Freund's approach can be extended to risk-loving behavior where $a < 0$.[2] An individual's risk propensity a can be calculated from a lottery comparison, which was part of our experiment.[3]

Optimal times-to-market and resulting expected utilities are derived for various information treatments, which are differentiated by: the completeness of information on product development funding, which can be in the form of a realization (full) or a probability distribution (partial); the manner in which this information is administered, which can be upfront or sequential; and the point in time at which a time-to-market decision is made, which can be sequential or at the final time period (which represents, e.g., the length of the window of opportunity). For each information treatment we construct a decision rule to be applied by a rational individual. These decision rules are characterized in Appendix A. Because it allows us to complement the experimental literature on sequential decision making, the information treatment where respondents are provided with funding information on a per-period basis and where they must decide each period whether or not to enter a market is of most interest. In this case, a rational respondent is forced to use a simplified decision rule with a myopic property that compares conditional expected utilities from entering now or waiting an additional period.

3. Information Treatments and Key Hypothesis

In the remaining, we focus our attention to the four information treatments that correspond in Table 1 to partial-sequential information (*PSI*) as just described, partial-initial information administered upfront (*PII-U*), full-initial information administered upfront (*FII-U*), and full-initial information administered sequentially (*FII-S*). For all treatments but *PSI*, a time-to-market is selected after all information is known. For *PII-U* basic information on the probability distribution of product development funding is administered. This distribution is given upfront for each time period. For *PSI*, *FII-U* and *FII-S* (simulated) information on an actual outcome of product development funding is provided; these treatments only differ in the presentation and timing at which the information is made available, and on the timing of the decision itself. For *PSI* information on an amount of funding available for additional product development is solely provided for the current period, whereas for the next period only the probability distribution of this amount is known. No information is provided after the next period. For *FII-U* information on funding is available upfront for all possible entry time periods, whereas for *FII-S* that information is presented sequentially for one additional period at a time. We note that basic information on the probability distribution on the level of competition is also given to keep uncertain the decision environment. Appendix A offers our optimization calculus for each information treatment.[4]

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(Insert Table 1 about here)
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Our main experimental manipulation is to force a group of respondents (treatment *PSI*) to decide at each new time period whether or not to enter the market with a new product whilst only having information on the current period funding for product development and expectations on that funding for the next period. A rational individual compares expected benefits from entering the market at the current period to that of entering it next period. Waiting one more period is the option to choose when expected benefits from entering in the next period are higher (regardless of what might happen in any subsequent period). Note that, in our experiment, once an individual chooses to enter the market, she cannot pull out of the market and select another period to enter. Also, if this individual chooses not to enter, her time-to-market can only happen at a later period as there is no coming back. We consider this partial-sequential information treatment to be closest to the actual decision environment faced by most individuals. Indeed, individuals possess information about the past and the present, but only expectations about the near future. Furthermore, most products experience a one-shot trial to enter the market and one cannot go back in time. Therefore, ecological rationality suggests that, under *PSI*, respondents select their time-to-market based on the use of well-performing (in the sense of expected utilities) heuristics.

As a mean of comparison, another group of respondents is considered which corresponds to those under treatment *FII-U*, where, instead, the time-to-market is selected at the final period and a realization of product development funding is given upfront for each time period. Since individuals are unfamiliar with dealing with such a plethora of information, we hypothesize that, under this treatment, individuals do not obtain higher expected utilities. This discussion leads to our key hypothesis.

HYPOTHESIS: *Those forced to sequentially decide on whether or not to enter the market and informed on current realization of product development funding, but only given an expectation* *for next period, perform as well, in terms of expected utilities, as those who know upfront each and every realization of product development funding and wait at the final time period to select a time-to-market.*

We further discriminate between our ecological rationality hypothesis and a possible simplistic competing hypothesis whereby individuals become overwhelmed by large amounts of information and prefer to receive that information on a per-period basis (i.e. sequentially), everything else being the same. Figuratively speaking, "spoon-feeding" information may help to "swallow" it. We therefore manipulate the manner in which information is administered, upfront versus sequential, and analyze a group of respondents under treatment *FII-S*, where the time-to-market is selected at the final period and a realization of product development funding is given sequentially but still for each time period.

We complete our analysis by considering a group of respondents under treatment *PII-U*, where, instead, a probability distribution on product development funding is given upfront for each period. We show in Appendix A that, everything else being the same, an individual consistent with normative theory is expected to choose the same time-to-market for treatments *PSI* and *PII-U*. The intuition is that, under these treatments, incremental expected utilities are identical, although absolute utilities are not. Therefore, even if the amount and delivery method of information are quite distinct for these two treatments, we argue that their comparison is likely to provide an understanding of heuristic performance. As the *PII-U* treatment is the only one where respondents possess no exact information, the use of simple decision heuristics that rely on exact information may not perform well and those who are administered this information treatment are likely to use different heuristics.

4. Experimental Design

Each respondent was confronted with only one information treatment. Respondents registered through the online recruitment system ORSEE (Greiner 2003). They consisted of a similar proportion of males and females. Most were students in fields of study including business, economics, law, education, and sociology. We ran 16 sessions. For each session, two respondents were allocated to each of the four information treatments. We invited ten participants so as to minimize the effects of no-shows. On arrival, excess participants were paid a show up fee of 2.50€ and they were released. A total of 128 respondents took part in the whole experiment, with a total of 32 respondents per treatment. Each session took approximately one hour.

The realizations of funding for product development were drawn in each session by a pseudo random number generator integrated in the experimental program. Within each session, the same random numbers were applied to all respondents and thereby to all treatments, but these numbers were drawn afresh for each session. Playing each of the four treatments with two participants in each session, and applying the same random numbers to all participants in that session, controlled for a potential influence of the realization of random numbers on the treatments. We tested the random number generator with all 192 (16 sessions times 12 periods) realizations of the funding variable Z_t and found no evidence for a rejection of the hypothesis that Z_t was normally distributed.[5]

The information treatment was carefully explained upfront to respondents. Details appeared on each respondent's computer screen and on a handout (that also explained truncated normal distributions) kept by the respondent throughout the experiment. Average payment for each respondent was distributed in an incentive compatible manner and hence dependent on the actual payoff of the time-to-market selected by that respondent. Respondents did not receive upfront compensation, but could earn money from their market entry decision, which ranged between 0.71€ and 21.41€ with a mean earning of 10.35€. This experiment cost a total of 1,324.80€ and was programmed for a computer laboratory and conducted with the software *z-Tree* (Fischbacher 1999). Appendix B offers a portion of the translated instructions.[6]

We selected a decision horizon of 12 time periods, which is sufficiently long to allow for variations in the times-to-market whilst meeting our financial constraints for the experiment. Table 2 offers a description of each model parameter, their numerical value for the experiment and the unit of measurement, as well as expected values for the random variables. Maximal expected financing is 39.60€ by period 12, which results in a maximal average quality for the product of 44.2 units, a maximal average revenue from quality of 87.88€, and a gross profit of 48.28€. Since 100% competition costs 50€ it would represent 103.6% (50/48.28) of the market size, implying a slightly negative average return from participation in such a market. But the maximal expected competition in the experiment only reaches 79.3%, and thus maximal expected loss from competition is 39.63€ (by period 12).

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Insert Table 2 about here
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Our approach is experimental. This approach is most appropriate because it allows us to obtain a measurement of the time-to-market selected by a respondent and that respondent's risk propensity, which are necessary to test our behavioral hypothesis. Moreover, an incentive-compatible experiment provides monetary incentives encouraging respondents to better concentrate on the details of the decision scenarios. Jamal and Sunder (1991) comment that "rewards increase the reliability and reproducibility of laboratory results and, therefore, constitute a valuable, albeit expensive, research tool" (p. 151). An overview of studies also shows "a tendency for the error variance of the observations around predicted optimal level to decline with increased monetary reward" (Smith and Walker 1993: 259).

5. Empirical Findings and Interpretations

We use our empirical findings to test our key hypothesis and offer insights on the respondents' selection process. Specifically, we report on a pattern suggesting that our respondents may have locally optimized. This local optimization appears to be the result of the use of similar decision heuristics across all experimental treatments in which realizations of product development funding was given, thus excluding the *PII-U* treatment. Unless stated differently, all reported significant effects are at a p-level of .000.

5.1. Key Hypothesis Testing

5.1.1 General Effects

Under our key hypothesis we claim that performance, as accounted for by (observed) expected utilities, should not be significantly different between treatments *PSI* and *FII-U*, despite the significant differences in the amounts and delivery methods of information. We begin testing with a repeated-measure ANOVA (henceforth RMANOVA). Predicted and observed (expected) utilities are two dependent within-subjects variables. Observed utility is calculated by substituting a respondent's time-to-market, along with her risk propensity, in the utility formulas of Appendix A. Information treatment is a factor and risk propensity a covariate.

First, we find a significant difference between observed and predicted utilities. This utility difference indicates that respondents had a tendency to select a sub-optimal time-to-market and, as a result, forego maximal utility. We also find a significant interaction effect between this difference and the treatment. This finding is important because it highlights the fact that whether or not a respondent's observed utility comes close to optimality depends on the completeness of information, the manner in which this information is administered, and the point in time at which a time-to-market decision has been made, as reflected by the four treatments.

We also find significant main effects of both risk propensity and information treatment. However, there is a non-significant interaction effect between risk propensity and the difference between predicted and observed utilities (p-level at .270). As a result, risk propensity has no influence on how close our respondents come to optimality, and respondents do not need to be separated based on their risk propensity for further analyses. We note that risk propensity exhibits a main effect on the utilities because risk propensity is part of the calculation of both predicted and observed utilities.

Figure 1 reveals that the ordering of observed utilities between the information treatments is as expected. Specifically, the lowest predicted utility is for *PII-U*, where the least specific information is administered, yet this information is given upfront and the decision is made once all this partial information has been given. However, on average, the respondents almost reach the predicted utility in this decision scenario. For *FII-U* and *FII-S*, respondents are expected to be associated with large utilities because they are administered large amounts of information. However, their observed utilities fall short of these expectations. Our findings for *PSI* are also surprising. As hypothesized, the respondents appear to perform as well as for *FII-U*, or even *FII-S*, but most unexpectedly those under the *PSI* treatment outperform on average their predicted utility. We will later propose the use of local optimization as a justification for this finding.

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(Insert Figure 1 about here)
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5.1.2 Treatment Effects

Within the RMANOVA we further analyze treatment effects by estimating the parameters of each treatment (where *FII-S* corresponds to a redundant parameter). Parameter estimates are obtained separately for predicted and observed utilities. For predicted utilities, significant estimates were obtained for *PII-U* and *PSI.* In accordance with expectations (because less information is administered), we observe that predicted utilities are smaller under these two decision scenarios. More interestingly, for observed utilities only *PII-U* is significant and leads to the smallest observed utilities, whereas the three other information treatments do not differ significantly from each other.

We also ran two univariate ANOVAs with, as the respective dependent variables calculated for each respondent, observed utilities (UNIANOVA I) and utility differences between predicted and observed values (UNIANOVA II). We use the same factor and covariate variables as in the RMANOVA, but make the necessary pairwise comparisons between the *PSI* and the three other treatments via contrasts. In UNIANOVA I, risk propensity and treatment are significant (p-level at .043 for the latter). The contrasts reveal that only the difference between *PSI* and *PII-U* is significant (p-level at .026, one-sided test). With respect to observed utilities, differences between *PSI* and *FII-U* or *PSI* and *FII-S* are non-significant (p-level at .715 and .513, respectively). In UNIANOVA II, the utility difference is significantly affected by the treatment but not by risk propensity (p-level at .270 for the latter). The contrasts also reveal that *PSI* significantly outperforms both *FII-U* and *FII-S*, thus providing additional support for our key hypothesis. However, the difference between *PSI* and *PII-U* in terms of differences between predicted and observed utilities only approaches marginal significance (p-level at .109, one-sided test).

5.2. Local Optimization and Anchoring-and-Adjustment

We also show in Appendix A that the decision rule underlying the *PSI* treatment requires a look into the near future, and as such is myopic. As an objective comparison, we first compare this treatment to the *PII-U* treatment which, according to normative theory, is expected to provide the same time-to-market (Appendix A) although the amount and delivery method of information are quite distinct for these two treatments. For *PII-U*, basic information on the probability distribution of product development funding is presented upfront for each time period. Instead, for *PSI*, a realization of product development funding is solely provided for the current period, whereas for the next period only the probability distribution of this amount is known. No information is provided after the next period. Therefore, under the *PSI* treatment, we would normatively expect that our respondents look forward just one step in their time-to-market decision and *disregard* funding realized in the potential entry period and in the past (because that funding is received regardless of whether or not they stop or continue the decision process).

To validate this claim we look at the rank of the observed time-to-market as per the ranking scale of the predicted time-to-market. These ranks are reported in Table 3 for each treatment. We observe that, under *PSI*, our respondents appear to perform worst in terms of their market entry rank. Predicted time-to-market and observed time-to-market exhibit a (Pearson) correlation coefficient of -.307 (p-level at .093), yielding a tendency to a late time-to-market when this time should be early, and vice versa. Therefore, respondents under *PSI* have a marginally significant tendency to do just the opposite of what is recommended by a forward-looking, myopic decision rule. Then, from Figure 1, how can these individuals perform surprisingly well with an average expected utility for observed time-to-market that is higher than the average expected utility had the optimal time-to-market been selected?[7] We argue that the answer lies in ecological rationality and address it next through the use of a constructed example.

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An individual is to find the highest point of a country road with her eyes covered. She is able to recognize the ups and downs of the road. In addition, someone is constantly whispering in her ear what she can expect for the next foot step. Under ecological rationality, we argue, she would walk along the road and look for the end of a steep ascent. If she is not allowed to walk back (or to try anything else), then she would focus on looking for such an ascent and select the next step as the highest point. However, if she is allowed to walk back, then she would look for both a steep ascent and a steep descent. In this case, she would select a place just after the steep ascent and just before the steep descent as the highest point. But when walking back is prohibited, the ascent must last longer to arrive at a similar accuracy.

We argue that our respondents were faced with a similar paradigm and, as a result, used a similar local-optimization heuristic. Specifically, respondents under the *PSI* treatment, where there was no way back, looked at their current product development funding and that of the previous period, whereas those under treatment *FII-U* or *FII-S* looked at the current product development funding and that of one period ahead. Consequently, for *PSI* past and current realizations of product development funding should be high, whereas for *FII-U* or *FII-S* the current realization should be especially high but the future one low. Table 4 shows that this is exactly what we observe. Those under *PSI* had a tendency to enter the market when product development funding had been above average in the round before and at the potential entry period. Instead, those under *FII-U* or *FII-S* entered when funding was above average in the potential entry period and below average in the subsequent period. We note that this search heuristic does not take into account the increase in the level of competition over time because there is symmetry among the treatments on how competition behaves over time. We also note that this heuristic appears to perform well for the *PSI* treatment because a limited amount of information is displayed. However, this heuristic is too simple to take advantage of the abundant amount of information provided under *FII-U* or *FII-S*, which, arguably, are less realistically encountered treatments.

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(Insert Table 4 about here)
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Respondents who were administered treatment *PII-U* appeared to have made good market entry choices. However, using the local-optimization heuristic was impossible since exact amounts of product development funding were unknown to these respondents. Instead, we speculate, the *PII-U* treatment might have been proper to the use of an anchoring-and-adjustment heuristic (Tversky and Kahneman 1974), where each respondent selects an anchor (e.g. period 6 because it is half way) and asks herself whether to enter the market somewhat earlier or later. This mental adjustment process is likely to be effective in the *PII-U* treatment because, although information is limited (as compared to that of the full-initial information treatments), by basing the evaluation of times-to-market on expected values (since there is no realization delivered in this treatment but only probability distributions), small deviations from the predicted (optimal) entry time only provides small deviations from the predicted expected utility. In Gigerenzer et al. (1999) terms, the adaptive toolbox may contain the appropriate tool for the *PII-U* treatment which also offers limited information.

5.3. Relation to Prior Evidence

Our findings appear consistent with other experimental studies. First, in our experiment, the ratio of the percentage of respondents with early market entry to the percentage of those with late market entry is 58:28, 58:28, 52:19, and 77:10 for, respectively, treatments *PSI*, *FII-U*, *FII-S* and *PII-U*. We are therefore able to confirm a behavioral tendency detected by Rapoport and Tversky (1970) and Seale and Rapoport (1997). That is, respondents had a tendency to select too early rather than too late of a time-to-market. We further note that our utility computations are accounting for the effects of risk propensity and, as a result, risk propensity is precluded as a potential explanation for this behavior.

Second, Corbin et al. (1975) conducted an experiment with sixteen subjects who repeatedly performed a seeking task for which the maximum number had to be selected in a stack of five cards. They offer evidence for a heuristic where individuals took into account the magnitude of the current observation, the magnitude of the current observation relative to previous observations in the same stack of cards, and the trend exhibited in previous observations in the stack. We would like to offer our analysis as additional evidence for the use of a similar heuristic in sequential decisions that are made in a context that approaches the complexities of reality.

6. Conclusion

6.1. Summary of Findings

We offer this research as an attempt to better understand whether individuals use simple heuristics likely to result in information waste when information is abundant. In the context of selecting a time-to-market, we experimentally manipulated the amount and delivery method of information on product development funding and compared predicted and observed (expected) utilities between four information treatments. Our findings complement the applied decision theory and bounded rationality literature by highlighting ecologically rational decision rules likely to have been used in our time-to-market context.

When selecting a time-to-market, our respondents may have locally, as opposed to globally, optimized. As a result, they may have compared, on a per-period basis, the amount of product development funding, taking into account the uncertain competitive nature of their environment. In an information treatment where the exact amount of funding was available for the present time period, but a probability distribution on this amount was given for the next period (treatment *PSI*), respondents appeared to have focused on information from the current and one earlier period only. When product development funding at one, or at both of these periods, was higher than expectation, respondents were likely to enter the market. However, when they were faced with an information treatment where the exact amount of product development funding for every period was delivered to them upfront (treatments *FII-U* and *FII-S*), their decision rule appears to slightly differ. They were likely to look at funding in the current and one period ahead and enter if current funding was clearly above, but funding in the subsequent period below, expectation. Using the entire set of information (for all time periods ahead and, as a result, globally optimize) to select a time-to-market appeared unlikely.

We believe that our findings have an implication for (sequential) everyday decisions. Investing in costly information can be an ineffective strategy when an individual's adaptive toolbox does not contain the appropriate heuristics to handle the provided information. Instead, this individual may be best advised to acquire no information. But if that individual insists on acquiring information, then we would advise that she also invest in decision-aid software and/or consultancy services in an attempt to more efficiently process the acquired information. The decision of whether to acquire no or costly information, with or without decision supports, is clearly based on the tradeoffs between costs and benefits, but most importantly, we argue, on whether or not the individual possesses the appropriate heuristic for processing information.

6.2. Limitations and Future Research

The implication just described has its limitation because it may be perceived as impossible to judge whether or not an individual possesses an appropriate heuristic for a given decisional context (and some individuals may even be unable to describe the heuristic they use). We think, however, that this difficulty can be overcome by providing individuals with a list of criteria that can identify whether or not appropriate heuristics are available to them. Such criteria may include the level of novelty of the decisional context, as it is more likely for an individual to possess the appropriate heuristics when facing a customary decision. Another criterion is the level of complexity in evaluating tradeoffs, as complex tradeoffs may prevent an individual from using simple heuristics such as anchoring-and-adjustment.

Another limitation lies in the fact that we did not investigate other types of heuristics that may have been used by our respondents and led to the behaviors we identified. In our statistical analysis, instead, we concentrated on the most plausible behaviors, namely detection of local optima for the *FII-U*, *FII-S*, and *PSI* treatments. Verbal protocols could provide a way to obtain detailed information on the heuristics individuals use in an experiment. Respondents are asked to think aloud, enabling the researcher to better understand a respondent's decision process. However, whether or not this approach provides a realistic reflection of what actually are the drivers of individual decisions is currently under debate. For instance, it has been shown that when the task entails a high cognitive load, or when information cannot be easily verbalized, concurrent verbal protocols have caused problems (e.g. Biemiller and Meichenbaum 1992, Meichenbaum and Biemiller 1998).

For the time-to-market context analyzed in our experiment, we acknowledge that the parallel use of students, marketing managers, and firm owners would have provided a more complete picture. Information processing is expected to differ between students, managers, and entrepreneurs (Barnett and Koslowski 2002). Indeed, students who received formal training may be better optimizers, but their limited experience may result in a lack of appropriate heuristics in their adaptive toolbox. However, experimental economists often judge it advantageous to experiment with students as "[t]he use of professionals in laboratory experiments may solve problems but create others" (Friedman and Sunder 1994: 40). In Burns (1985), which compares the behavior of professionals and student subjects in the trading of wool, the professionals reacted to incentives present in situations in which they were familiar as opposed to those of the experiment. "If the object of an experiment is therefore to measure reactions to the experimental conditions and objectives, it is unproductive to choose as subjects those whose prior experience is contrary to the current design requirements, for they will have difficulty in adjusting to a new frame of reference" (p. 152).

This article is a small but important step towards gaining a more systematic view on what are the decisional contexts for which individuals possess the appropriate tools in their adaptive toolbox to cope with information processing. The necessity, efficiency, and impact of decision aids may become more predictable from building on the current research, and decision aids could be sought by those who lack the appropriate heuristics (e.g. van Bruggen et al. 1998). Scholars focusing on the display of information furthermore argue that an individual's decision-making process can be improved "by making the environment more conducive to effective decision making" (Kleinmuntz and Schkade 1993: 221). Interactions may exist between the amount of information, delivery method of information, and information display, thus influencing the efficiency of the heuristics used. We believe that, combined with this article, these additional research endeavors would provide a clearer picture of how individuals make, and can improve, their decisions.

Appendix A: Predicted Times-to-Market and Predicted Expected Utilities

For the full-initial information (administered upfront or sequentially) treatment, the respondent knows upfront the value stream of product development financing, i.e. the set $\{ Z_t \}_{t=1,2,3,\ldots t}$ is known where t is the lifecycle horizon for the product. Also, the respondent knows the probability distributions for the competition variables for each time period t in $\{1,2,\ldots,t\}$. Hence, a rational individual would select a time-to-market that maximizes the expected utility equivalent $E(P_t) - (a/2)Var(P_t)$, which corresponds in these treatments to

$$\Phi_{FII-U/S}(t) \,|\, Z_1, Z_2,\ldots, Z_t, F_1, F_2,\ldots, F_t = aq_0 + [ab-1]\sum_{i=1}^{t} Z_i - bm_t - \frac{a}{2} b^2 s_t^2 .$$

Expected utilities are, respectively, for the partial-initial information (administered upfront or sequentially), partial-sequential information, and full-sequential information treatments

$$\Phi_{PII-U/S}(t) \,|\, F_Z, F_1, F_2,\ldots, F_t = aq_0 + [ab-1]\cdot tm_Z - bm_t - \frac{a}{2}\left\{[ab-1]^2 \cdot ts_Z^2 + b^2 s_t^2\right\},$$

$$\Phi_{PSI}(t) \,|\, Z_1, Z_2,\ldots, Z_{t-1}, F_Z, F_t = aq_0 + [ab-1]\sum_{i=1}^{t-1} Z_i + [ab-1]\cdot m_Z - bm_t - \frac{a}{2}\left\{[ab-1]^2 s_Z^2 + b^2 s_t^2\right\},$$

and $$\Phi_{FSI}(t) \,|\, Z_1, Z_2,\ldots, Z_t, F_Z = aq_0 + [ab-1]\sum_{i=1}^{t} Z_i - bm_t - \frac{a}{2} b^2 s_t^2 .$$

We note, however, that for the partial- and full-sequential information treatments, the characterization of the predicted time-to-market must be done differently. As per our experimental analysis, we focus on the partial-sequential information treatment, where a respondent only receives partial information on product development financing and competition. Moreover, this information is received on a per-period basis. Therefore, to derive the predicted time-to-market we utilize an approach based on conditional expected utilities which is similar in spirit to that of optimal stopping, as offered in the dynamic programming literature. We thus offer a condition based on our model parameters that characterizes the predicted time-to-market. Specifically, if the respondent chooses to enter at period t, then expected utility $\Phi_{PSI}(t)$, given the financing up until period t is known and the probability distributions of product development financing and competition variables are known up until period t+1, is

$$\Phi_{PSI}(t) \,|\, Z_1, Z_2,\ldots, Z_t, F_Z, F_1, F_2,\ldots, F_{t+1} = aq_0 + (ab-1)\sum_{i=1}^{t} Z_i - bm_t - \frac{a}{2} b^2 s_t^2 .$$

The expected utility at t+1, given the financing up until period t is known and the probability distributions of product development financing and competition variables are known up until period t+1, is

$$\Phi_{PSI}(t+1) \,|\, Z_1,\ldots, Z_t, F_Z, F_1,\ldots, F_{t+1} = aq_0 + (ab-1)\sum_{i=1}^{t} Z_i + (ab-1)m_Z - bm_{t+1} - \frac{a}{2}\left\{(ab-1)^2 s_Z^2 + b^2 s_{t+1}^2\right\} .$$

From these last two equations, the conditional incremental expected utility (the increase in expected utility, looking one period ahead in time) is

$$\Phi_{PSI}(t+1) - \Phi_{PSI}(t) \mid Z_1, Z_2, \ldots, Z_t, F_Z, F_1, F_2, \ldots, F_{t+1}$$
$$= \left\{[ab-1]m_Z - [ab-1]^2 \frac{a}{2} s_Z^2\right\} - \left\{b[m_{t+1} - m_t] - \frac{a}{2} b^2 [s_t^2 - s_{t+1}^2]\right\}.$$

Given that the expected competition m_t increases at an increasing rate with t and the variance on competition s_t^2 decreases at a decreasing rate with t, conditional incremental expected utility decreases with t. Thus, to maximize expected utility, market entry should occur in period T where T is the smallest t for which $\Phi_{PSI}(t+1) - \Phi_{PSI}(t) \mid Z_1, Z_2, \ldots, Z_t, F_Z, F_1, F_2, \ldots, F_{t+1} \leq 0$. This optimal condition expresses the fact that market entry should occur when the reduction in expected utility from an increase in competition as market entry is delayed one more period exceeds the increase in expected utility from additional funding. In essence, one can maximize expected utility by delaying entry just as long as the incremental expected utility of the next period is positive, and enter the market just before it becomes negative. Thus one can be assured that it never makes sense to delay market entry when incremental expected utility is decreasing in the hope that the situation will turn around and become more profitable later. If $\Phi_{PSI}(t+1) - \Phi_{PSI}(t) \mid Z_1, Z_2, \ldots, Z_t, F_Z, F_1, F_2, \ldots, F_{t+1} \geq 0$ for all t (i.e. if in every period it appears preferable to delay entry for another period), then $T = t$, implying that market entry should never occur.

We further use conditional incremental utility functions to compare predicted (optimal) times-to-market. These functions for the three remaining treatments are

$$\Phi_{PII}(t+1) - \Phi_{PII}(t) \mid F_Z, F_1, F_2, \ldots, F_{t+1} = [ab-1]m_Z - b[m_{t+1} - m_t] - \frac{a}{2}\left\{[ab-1]^2 s_Z^2 + b^2[s_{t+1}^2 - s_t^2]\right\},$$

$$\Phi_{FII}(t+1) - \Phi_{FII}(t) \mid Z_1, Z_2, \ldots, Z_{t+1}, F_Z, F_1, F_2, \ldots, F_{t+1} = [ab-1]Z_{t+1} - b[m_{t+1} - m_t] - \frac{a}{2}\left\{b^2[s_{t+1}^2 - s_t^2]\right\},$$

and $$\Phi_{FSI}(t+1) - \Phi_{FSI}(t) \mid Z_1, Z_2, \ldots, Z_{t+1}, F_Z, F_1, F_2, \ldots, F_{t+1} = [ab-1]Z_{t+1} - b[m_{t+1} - m_t] - \frac{a}{2}\left\{b^2[s_{t+1}^2 - s_t^2]\right\}.$$

For any time period t it follows that

$$\Phi_{PII}(t+1) - \Phi_{PII}(t) \mid F_Z, F_1, F_2, \ldots, F_{t+1} = \Phi_{PSI}(t+1) - \Phi_{PSI}(t) \mid Z_1, Z_2, \ldots, Z_t, F_Z, F_1, F_2, \ldots, F_{t+1}$$
$$< E\left[\Phi_{FII}(t+1) - \Phi_{FII}(t) \mid Z_1, Z_2, \ldots, Z_{t+1}, F_Z, F_1, F_2, \ldots, F_{t+1}\right]$$
$$= E\left[\Phi_{FSI}(t+1) - \Phi_{FSI}(t) \mid Z_1, Z_2, \ldots, Z_{t+1}, F_Z, F_1, F_2, \ldots, F_{t+1}\right],$$

where the expectation is taken according to the probability distribution of Z_{t+1}. Since smaller conditional incremental utilities lead to a quicker crossing with the horizontal axis (the t axis), it is expected that predicted (optimal) times-to-market be ordered as follows: $t_{PII}^* = t_{PSI}^* < t_{FII}^* = t_{FSI}^*$.

Appendix B: Description of the *FII-U* Treatment in the Computerized Experiment

Imagine you are an entrepreneur with a new product idea. You must decide on when to enter a market in one of 12 time periods. Periods in the following tables will refer to the corresponding point in time of your potential time-to-market. Once you choose to enter the market, all values associated with later entry times become irrelevant and your profit only depends on the product quality and the competition at this time-to-market. Product quality and competition are measured in independent units.

Over time competition potentially increases, diminishing your chances of making profits. For each unit of competition that is realized at the point in time when you enter the market, your profit decreases by 0.50€. Please be aware that only the realized level of competition at the time of entry affects your profits negatively. Competition levels of later periods are irrelevant.

Meanwhile, product quality increases as a result of your product development expenditures. The higher these expenditures, the higher your product quality and, as a result, the higher your profits will be. Having invested your private savings, you can provide the basic quality which achieves 10.5 units on the product quality scale. For quality improvement you depend on external investors. These investors provide you with funds fully invested in product development. For each € invested, your product quality rises by 0.85 units. For each unit your product achieves on the quality scale your revenue increases of 1.99€. Naturally, you must pay back the invested funding (interest-free) to your external investors. Please be aware that the cumulated product development expenditures increase your product quality and your product development activities use up this accumulated funding up to the period in which you enter the market.

The longer you delay your time-to-market, the higher your product development expenditures will be and, as a result, the higher your product quality but also the higher the expected level of competition. You do not receive additional funds after you have entered the market. Your time-to-market will determine the expected level of competition and product quality. Among the 12 time periods available, you must decide when to stop pursuing product development activities and introduce your product to the market. Only your time-to-market decision (and no other decisions) results in payments.

Please be aware that the level of competition is normally distributed. That is, its realization is random and follows a bell curve with an expected value m and a standard deviation s. For a representation of a normal probability distribution, please refer to the handout in front of you.

The level of competition lies between 0 and 100. The expected level of competition increases from period to period. However, the variation in the level of competition goes down. Consequently, as you postpone your time-to-market decision, the level of competition will most likely be higher and less risky. Levels of competition located three standard deviations from the expected value are truncated to these extreme limits.

At each period you will be informed on potential funding and its accumulation so far. Please note that you do not save any time if you make you decision quicker. All participants must reach a certain stage before the experiment continues. You will have 30 to 40 minutes for your time-to-market decision. Therefore, it is worth thinking carefully about your decisions.

The following table offers the expected levels of competition and standard deviations for each possible entry time. As mentioned earlier, the level of competition is random and follows a normal probability distribution. For instance, if you decide to enter in period 1 the level of competition is expected to be 29.54 and the probability that this level lies between 30 and 40 is 37.44%.

Period	Mean	Standard deviation	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
1	29.54	8.29	0.92	11.57	39.72	37.44	9.67	0.68	0	0	0	0
2	33.66	8.09	0.17	4.39	27.98	45.81	19.48	2.16	0	0	0	0
3	37.86	7.89	0	1.18	14.77	44.75	33.12	5.93	0.25	0	0	0
4	42.14	7.69	0	0.20	5.52	33.32	45.62	14.33	1.01	0	0	0
5	46.50	7.50	0	0	1.39	17.92	48.65	28.44	3.60	0	0	0
6	50.94	7.32	0	0	0.20	6.53	38.15	44.33	10.32	0.46	0	0
7	55.46	7.14	0	0	0	1.51	20.69	51.56	24.15	2.08	0	0
8	60.06	6.96	0	0	0	0.20	7.22	42.24	42.68	7.45	0.21	0
9	64.74	6.79	0	0	0	0	1.49	22.75	53.83	20.69	1.23	0
10	69.50	6.62	0	0	0	0	0.16	7.40	45.45	41.35	5.55	0
11	74.34	6.46	0	0	0	0	0	1.32	23.76	55.89	18.27	0.76
12	79.26	6.30	0	0	0	0	0	0	7.07	47.61	40.92	4.40

This table shows potential funding per period if you delay your market entry from the previous to the stated period. [*values are examples from session* 16]

Period	Investment
1	3,02
2	1,15
3	6,60
4	3,58
5	0,00
6	2,63
7	5,41
8	2,36
9	4,59
10	4,60
11	4,18
12	1,55

This table shows, for each possible entry time, the accumulated funding you can spend on product development so as to enhance your product quality. [*values are examples from session* 16]

Period	Sum of Investments
1	3,02
2	4,17
3	10,77
4	14,34
5	14,34
6	16,97
7	22,38
8	24,74
9	29,33
10	33,94
11	38,12
12	39,67

Please decide now in which period you wish to enter the market.

References

Allais, M. 1953. Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiome de l'ecole Americaine. *Econometrica* **21** 503-546.

Barnett, S.M., B. Koslowski. 2002. Adaptive expertise: Effects of type of experience and the level of theoretical understanding it generates. *Thinking & Reasoning* **8**(4) 237-267.

Biemiller, A., D. Meichenbaum. 1992. The nature and nurture of the self-directed learner. *Educational Leadership* 50(2) 75-80.

Burns, P. 1985. Experience and decision making: A comparison of students and businessman in a simulated progressive auction. In V.L. Smith (Ed.), *Research in Experimental Economics*, Vol. 3 (pp. 139-157). JAI Press, Greenwich, CT.

Corbin, R.M., C.L. Olson, M. Abbondanza. 1975. Contexts effects in optional stopping decisions. *Organization Behavior and Human Performance* **14** 207-216.

Dudey, T., P.M. Todd. 2001. Making good decisions with minimal information: Simultaneous and sequential choice. *Journal of Bioeconomics* **3**(2-3) 195-215.

Fischbacher, U. 1999. z-Tree - Zurich toolbox for readymade economic experiments - experimenter's manual. Working Paper #21, Institute for Empirical Research in Economics, University of Zurich.

Freund, R. 1956. The introduction of risk into a programming model. *Econometrica* **24** 253-263.

Friedman, D., S. Sunder. 1994. *Experimental Methods: A Primer for Economists*. Cambridge University Press, Cambridge, UK.

Gigerenzer, G., D.G. Goldstein. 1996. Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review* **103**(4) 650-669.

_____, P.M. Todd, ABC Research Group. 1999. *Simple Heuristics that Make Us Smart.* Oxford University Press, New York, NY.

Goldstein, D. G., G. Gigerenzer. (1999). The recognition heuristic: How ignorance makes us smart. In G. Gigerenzer, P.M. Todd, (Eds.), *Simple Heuristics that Make Us Smart*, pp. 37-58. Oxford University Press, New York, NY.

Greiner, B. 2003. The Online recruitment system ORSEE – A guide for the organization of experiments in economics. Working Paper. Max Planck Institute for Research into Economic Systems, strategic Interaction Group. Kahlaische Strasse 10, D-07745 Jena, Germany.

Hammond, P.J. 1998. Objective expected utility. In S. Barberá, P.J. Hammond, C. Seidl (Eds.), *Handbook of Utility Theory*, Vol. 1 (pp. 143-212). Kluwer, Boston, MA.

Jacoby, J., D.E. Speller, C.A. Kohn. 1974a. Brand choice behavior as a function of information load. *Journal of Marketing Research* **11** 63-69.

____, ____, C.A. Kohn-Berning. 1974b. Brand choice behavior as a function of information load: Replication and extension. *Journal of Consumer Research* **1** 33-42.

Jamal, K., S. Sunder. 1991. Money vs gaming: Effects of salient monetary payments in double oral auctions. *Organizational Behavior and Human Decision Processes* **49** 151-166.

Kahneman, D., A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* **47**(2) 263-291.

Kleinmuntz, D.N. 1985. Cognitive heuristics and feedback in a dynamic decision environment. *Management Science* **31**(6) 680-702.

____, D.A. Schkade. 2003. Information displays and decision processes. *Psychological Science* **4**(4) 221-227.

McCord, M., R. de Neufville. 1986. “Lottery equivalents”: Reduction of the certainty effect problem in utility assessment. *Management Science* **32**(1) 56-60.

Meichenbaum, D., A. Biemiller. 1998. *Nurturing Independent Learners: Helping Students Take Charge of their Learning*. Brookline Books, Cambridge, MA.

Rapoport, A., A. Tversky. 1970. Choice behavior in an optional stopping task. *Organizational Behavior and Human Performance* **5** 105-120.

Seale, D.A., A. Rapoport. 1997. Sequential decision making with relative ranks: An experimental investigation of the “secretary problem”. *Organization Behavior and Human Decision Processes* **69**(3) 221-236.

Simon, H. A. 1990. Invariants of human behavior. *Annual Review of Psychology* **41** 1-19.

Smith, V.L. 2003. Constructivist and ecological rationality in economics. *The American Economic Review* **93**(3) 465-508.

____, J.M. Walker. 1993. Monetary rewards and decision cost in experimental economics. *Economic Inquiry* **31** 245-261.

Todd, P.M. 1999. Simple inference heuristics versus complex decision machines. *Minds and Machines* **9** 461-477.

Tversky, A., D. Kahneman. 1974. Judgment under uncertainty: Heuristics and biases. *Science* **185** 1124-1131.

van Bruggen, G.H., A. Smidts, B. Wierenga. 1998. Improving decision making by means of a marketing decision support system. *Management Science* **44**(5) 645-658.

Figure 1 Means of Predicted Expected Utilities, Observed Expected Utilities, and their Differences

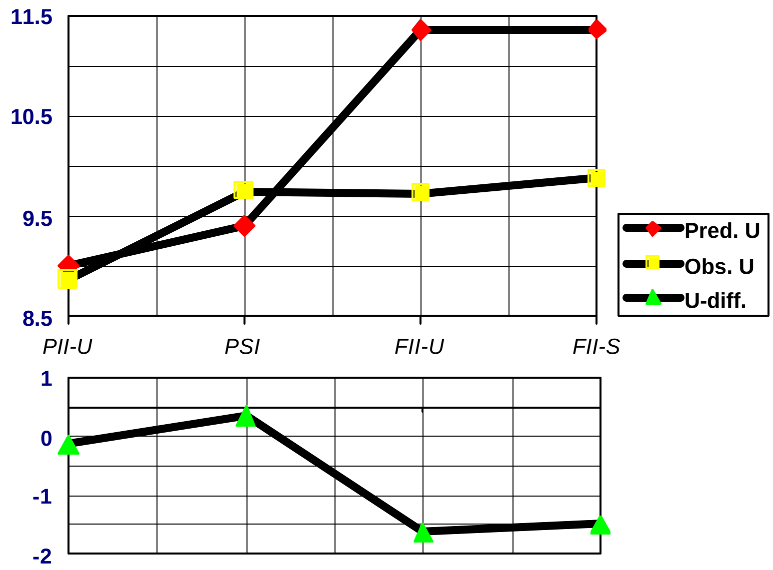

Table 1 Information Treatments for Theory Development and Experiments (bolded cells are experimentally analyzed)

<table>
<tr><td colspan="3" rowspan="2"></td><td colspan="2">Precision of information on funding</td></tr>
<tr><td>Partial (probability distribution)</td><td>Full (realization)</td></tr>
<tr><td rowspan="3">Time of decision</td><td rowspan="2">Final time period</td><td>Information administered upfront</td><td>· give probability distribution for C_t, t = 1,2,…,t

· give probability distribution for Z_t, t = 1,2,…,t (they are identical)

partial-initial information: PII-U</td><td>· give probability distribution for C_t, t = 1,2,…,t

· give numerical value for Z_t, t = 1,2,…,t

full-initial information: FII-U</td></tr>
<tr><td>Information administered sequentially</td><td>• give probability distribution for C_i, i = 1,2,…,t

• give probability distribution for Z_i, i = 1,2,…,t

partial-initial information: PII-S</td><td>· give probability distribution for C_i, i = 1,2,…,t

· give numerical value for Z_i, i = 1,2,…,t

full-initial information: FII-S</td></tr>
<tr><td colspan="2">Sequential</td><td>· give probability distribution for C_i, i = 1,2,…,t+1

· give numerical value for Z_i, i = 1,2,…,t

· give probability distribution for Z_{t+1}

partial-sequential information: PSI</td><td>• give probability distribution for C_i, i = 1,2,…,t+1

• give numerical value for Z_i, i = 1,2,…,t+1

full-sequential information: FSI</td></tr>
</table>

Table 2 Numerical Values Used in the Experiment

Parameter description	**Symbol**	**Value**	**Units**
planning horizon	t	12	week/month/quarter/year
initial quality	q_0	10.50	quality units (dimensionless)
incremental quality per $ of funding	b	0.85	quality units (dimensionless)
funding mean	m_Z	3.30	€
funding variance	s_Z^2	2.7225	€^{2}
marginal revenue from quality	A	1.99	€
marginal loss in revenue from competition	B	0.50	€
risk propensity	a	-0.35 to 0.40	in $-e^{-ax}$
initial competition mean	m_0	25.5	% in $t=0$
initial competition variance	s_0^2	72.25	%^{2} in t=0

(a) time-independent parameters

Parameter description	**Symbol**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
competition mean: (increasing convex) $m_t = 0.04t^2 + 4t + m_0$	m_t	29.54	33.66	37.86	42.14	46.50	50.94	55.46	60.06	64.74	69.50	74.34	79.26
change in competition mean: $\Delta m = m_t - m_{t-1}$	Δm	4.04	4.12	4.20	4.28	4.36	4.44	4.52	4.60	4.68	4.76	4.84	4.92
competition variance: (decreasing convex) $s_t^2 = s_0^2 e^{-0.05t}$	s_t^2	68.72	65.37	62.19	59.15	56.27	53.52	50.91	48.43	46.07	43.82	41.68	39.65
change in competition variance: $\Delta s_t^2 = s_t^2 - s_{t-1}^2$	Δs_t^2	-3.52	-3.35	-3.19	-3.03	-2.88	-2.74	-2.61	-2.48	-2.36	-2.25	-2.14	-2.03

(b) time-dependent parameters

Expected values for	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
total expected funding	3,30	6,60	9,90	13,20	16,50	19,80	23,10	26,40	29,70	33,00	36,30	39,60
incremental quality	2,81	5,61	8,42	11,22	14,03	16,83	19,64	22,44	25,25	28,05	30,86	33,66
total quality	13,31	16,11	18,92	21,72	24,53	27,33	30,14	32,94	35,75	38,55	41,36	44,16
expected competition	29,54	33,66	37,86	42,14	46,50	50,94	55,46	60,06	64,74	69,50	74,34	79,26
revenues from quality	26,48	32,06	37,64	43,22	48,80	54,39	59,97	65,55	71,13	76,71	82,30	87,88
funding reimbursed	-3,30	-6,60	-9,90	-13,20	-16,50	-19,80	-23,10	-26,40	-29,70	-33,00	-36,30	-39,60
loss from competition	-14,77	-16,83	-18,93	-21,07	-23,25	-25,47	-27,73	-30,03	-32,37	-34,75	-37,17	-39,63
total expected profit	8,41	8,63	8,81	8,95	9,05	9,12	9,14	9,12	9,06	8,96	8,83	8,65

(c) random variables

Table 3 Mean and Median of Observed and Predicted Market Entry Times and their Rank Differentials*

	Treatment			
	Partial-initial information administered upfront (*PII-U*)	Partial-sequential information administered sequentially (*PSI*)	Full-initial information administered upfront (*FII-U*)	Full-initial information administered sequentially (*FII-S*)
Observed time-to-market	Mean 5.22 Median 5	Mean 5.19 Median 4.5	Mean 7.09 Median 7	Mean 5.56 Median 6
Predicted time-to-market	Mean 6.9 Median 7	Mean 6.97 Median 7	Mean 7.97 Median 9	Mean 7.84 Median 8
Market entry rank	Mean 3.94 Median 4	Mean 5.48 Median 6	Mean 4.06 Median 4	Mean 4 Median 4

* In each decision scenario 1 respondent out of 32 reported an erroneous value in the lottery comparison and was discarded.

Table 4 Mean Funding in Periods near the Time-to-Market and Significance Level of Deviation from an Expected Value of 3.30€

	Mean funding at	Funding at $t_{\bullet}$ < 3.30€	Funding at $t_{\bullet}$ > 3.30€
PSI	$t_{\text{entry}-2}$	3.02€ 0.423	—
	$t_{\text{entry}-1}$	—	4.04€ 0.022
	t_{entry}	—	3.81€ 0.029
	$t_{\text{entry}+1}$	not applicable	not applicable
	$t_{\text{entry}+2}$	not applicable	not applicable
FII-U	$t_{\text{entry}-2}$	2.96€ 0.245	—
	$t_{\text{entry}-1}$	—	3.55€ 0.276
	t_{entry}	—	4.43€ 0.000
	$t_{\text{entry}+1}$	2.86€ 0.054	—
	$t_{\text{entry}+2}$	2.84€ 0.106	—
FII-S	$t_{\text{entry}-2}$	—	3.36€ 0.832
	$t_{\text{entry}-1}$	—	3.86€ 0.085
	t_{entry}	—	4.23€ 0.000
	$t_{\text{entry}+1}$	2.56€ 0.002	—
	$t_{\text{entry}+2}$	3.06€ 0.422	—

Endnotes

[1] Consumer researchers would look at this phenomenon from a different perspective. According to the consumer behavior literature, individuals are only able to process up to a certain amount of information. This information overload phenomenon was first demonstrated in Jacoby et al. (1974a, b). Information overload is less relevant for our study because we show that the similarity in performance under the different information treatments stems from the similarity in the heuristics used.

[2] Extending Freund's (1956) approach, we assume that individuals exhibit constant absolute risk aversion and obey the utility function $u(x) = -sign(a) \cdot e^{-ax}$, where $sign(a)$ equals 1 if a is positive, -1 if a is negative, and 0 if a is 0. For risk-averse decision makers (a > 0), it can be shown that expected utility for normally distributed risks is

$$E(u, N_{m,s}) = \int_{-\infty}^{\infty} -e^{-ax} \cdot \frac{1}{\sqrt{2p}\,s} e^{-\frac{[x-m]^2}{2s^2}} dx = -e^{-a\left[m-\frac{a}{2}s^2\right]}.$$

For risk-lovers (a < 0),

$$E(m, N_{m,s}) = \int_{-\infty}^{\infty} e^{ax} \cdot \frac{1}{\sqrt{2p}\,s} e^{-\frac{[x-m]^2}{2s^2}} dx = \frac{1}{\sqrt{2p}\,s} \int_{-\infty}^{\infty} e^{\frac{2axs^2-[x-m]^2}{2s^2}} dx \cdot$$

Since $2axs^2 - x^2 + 2xm - m^2 = -\{[x - (m + as^2)]^2 - 2mas^2 - a^2s^4\}$, we obtain

$$E(u, N_{m,s}) = \frac{1}{\sqrt{2p}\,s} \int_{-\infty}^{\infty} e^{\frac{-[x-(m+2s^2)]^2}{2s^2}+a\left[m+\frac{a}{2}s^2\right]} dx \;=\; e^{a\left[m+\frac{a}{2}s^2\right]}.$$

Therefore, when a < 0, expected utility is maximized if and only if $m + (a/2)s^2$ is maximized.

[3] The decision situation used for our lottery comparison is available upon request to the first author. We extract a by assuming rational individuals in the sense of Hammond (1998), whose system of axioms contains conditions of ordering, independence, and continuity and represents the weakest requirements on rationality as compared to other methods. From his findings (Lemma 4.3), it is possible to derive a lottery comparison method for 2 lotteries

$$L_A = [\tilde{p}, X_{\min} + a(X_{\max} - X_{\min}); 1-\tilde{p}, X_{\min}] \text{ and } L_B = [p_a, X_{\max}; 1-p_a, X_{\min}],$$

where individuals must report a probability p_a for two given risky outcomes $X_{\min} < X_{\max}$, a given parameter $a \in (0,1)$ and a probability $\tilde{p}$ so that they are indifferent between lottery L_A and L_B. This indifference condition leads to

$$\tilde{p} \cdot u(X_{\min} + a(X_{\max} - X_{\min})) + (1-\tilde{p}) \cdot u(X_{\min}) = p_a \cdot u(X_{\max}) + (1-p_a) \cdot u(X_{\min}),$$

and for an exponential risk averse utility function $u(x) = -e^{-ax}$ one has to compute the (unique) solution $\alpha > 0$ of

$$-\tilde{p}(e^{-a(X_{\min}+a(X_{\max}-X_{\min}))}) - (p_a - \tilde{p})(e^{-aX_{\min}}) + p_a \cdot (e^{-aX_{\max}}) = 0.$$

Compared to other forms of eliciting risk preferences such as certainty-equivalent-based methods, lottery comparisons possess an advantage (McCord and de Neufville 1986) in that no certainty effect is distorting findings since none of the alternatives included in the questionnaire is certain (the certainty effect has already been demonstrated in Allais' [1953] paradox and has been treated in prospect theory [Kahneman and Tversky 1979]).

[4] In Table 1, the treatments described by partial-initial information administered sequentially (*PII-S*) and full-sequential information (*FSI*) are less informative for our current focus and are not tested.

[5] The normal distribution was cut at ±2 standard deviations. Whenever values beyond the cutoff points occurred, they were treated as if the cutoff points had occurred. This reduced the standard deviation and made the distribution slightly different from a normal.

[6] We did not perform manipulation checks because we did not manipulate emotions or perceptions but implemented a purely economic context. From pretests and discussions with the respondents, it appears that the experimental instructions were clear.

[7] For the *PSI* treatment, a respondent's observed utility can be higher than that respondent's utility had the predicted (normative) time-to-market been selected. The reason lies in the fact that, in the normative analysis, a conservative decision rule is derived that ignores future potential funding.