



Quasi-Rational R&D Behavior in an Environment with Fundamental Uncertainty

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First Version: August 2012

Abstract:

The objective of our paper is to study R&D investments and pricing behavior in an environment with fundamental uncertainty. We designed a multi-period experiment in which each period consisted of two stages, an R&D phase and a pricing stage. Participants in the experiment had almost no information about the underlying functions, parameters, and probabilities. Subjects' behavior in the fundamentally uncertain environment of our experiment may best be characterized as some kind of procedural rationality which we call quasi-rationality. Pricing decisions are particularly close to equilibrium values. Although we do find some hints of the existence of behavioral effects in R&D decisions, only reinforcement effects are significant across both treatments and different model specifications. The introduction of patents has only a minor impact on R&D behavior. Overall, subjects learn to adapt remarkably well to a rather complex and fundamentally uncertain environment. (JEL: C90, D81, L10, O31)

Keywords: bounded rationality, duopoly, innovation, experiment, R&D competition

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[‡] We wish to thank Christian-Uwe Behrens and the participants of Hohenheimer Oberseminar for their helpful advice. Of course, all remaining errors are ours.

1. Introduction

By the beginning of the 16th century, geometry had already been studied for about 2,000 years. According to Alfred North Whitehead, however, “allowing for some minor qualifications, nothing had come from it except the intrinsic interest of the study. Then, as if a door had suddenly opened, Kepler produced the first important utilization of conic sections, the first among hundreds, Descartes and Desargues revolutionized the methods of the science, Newton wrote his Principia, and the modern period of civilization commenced. Apart from the capital of abstract ideas which had accumulated slowly during two thousand years, our modern life would have been impossible.” (Whitehead 1929, 74). This tiny insight from the history of science illustrates how difficult it is to measure the value of scientific results—even if the results are already known. It took almost 2,000 years to find major applications for geometry. How incredibly difficult, then, is anticipating the utility of research before results are available? Economic theory often simply assumes this problem away, as do many modern approaches to analyzing innovations.

Mainstream Industrial Organization theory analyzes R&D in terms of rational choice models. Competition in innovation is usually modeled as a stochastic noncooperative game with firms calculating their optimal levels of R&D investments (Reinganum 1989). The corresponding models cover the entire process of innovations: there are symmetric models of oligopolists competing on a level playing field (e.g. Loury 1979, Dasgupta and Stiglitz 1980, Lee & Wilde 1980); asymmetric models of an incumbent facing a potential newcomer (e.g., Gilbert and Newbery 1982, Katz and Shapiro 1987); models of licensing, adoption and diffusion of innovations (e.g., Kamien & Tauman 1984, 1986, Katz and Shapiro 1986); models with spillover effects and models without spillover effects; models that allow for R&D cooperation and models that do not (e.g., d’Aspremont and Jacquemin 1988, Kamien, Mueller and Zhang 1992); one-stage models (without) and multi-stage models with succeeding product market competition.

In each of these models, firms must be able to calculate the expected marginal profit of an increase in R&D spending ex-ante. These profits depend on the possible values of the targeted innovations and innovations basically consist of novel information. To assess the value of information, one has to know its content and the consequences that follow from the information. On one hand, if someone already knows the information, it is no longer novel. On the other hand, if one does not know the information, then one cannot calculate its value. This problem is known as the Arrows Information Paradox, and it also applies to innovations.

If one does not know the nature of an innovation and all of its characteristics, then one cannot derive its value. “[It] is hopeless to develop a model which will genuinely predict innovation: an innovation is something new, and if you know what will be in the future, you know it now” (Arrow 1991, 473). Furthermore, as R&D by its very nature is a search within an unknown terrain, researchers do not have reliable information about the probability distribution of different types of innovation. Consequently, researchers lack both prerequisites for calculating expected profits, including the possible contents of innovations and the probability of finding such innovations. If it is simply impossible to calculate returns on R&D investments, should there not be other determinants of investing than those that find their way into rational choice models? Our two-stage experiment tests this view.

We want to integrate two central aspects of competitive R&D into our project. The first is fundamental uncertainty (i.e., the impossibility of calculating expected profits from R&D ex-ante). Innovation in our experiment is characterized by a near total lack of quantitative knowledge by our participants about innovations’ values, the probability of finding specific innovations and about the consequences of innovations. The second aspect we aim to cover is the connection of the R&D process with competition in a market for final products. Again, subjects are not informed about the underlying functions (i.e., the demand functions). The succession of two basically competitive stages (R&D and selling products in a market) also serves to impede the emergence of collusive behavior, leading to the creation of an experimental environment with somewhat industry-like characteristics.

Our main research questions are as follows: How can R&D and pricing behavior best be explained? Is it best explained by measures of profitability or by behavioral variables? Can aspiration adaptation theory (e.g., Selten 1998) contribute to the explanation of behavior? Could reinforcement effects in the sense of successful R&D breeds further R&D play a larger role? Do patents make a difference?

Our main finding is that subjects learn to act in our complex and fundamentally uncertain environment remarkably well. This is true for pricing and for R&D behavior, which may be described best as “quasi-rational”.

Of course, there is a long tradition of empirical field studies on R&D that we cannot cover here. However, we believe it is fair to say that the results of these studies are, at best, mixed. There is no consensus about the impact of product market competition on R&D. Results range from a positive influence of competition on R&D (e.g., Beath et al. 1989, Geroski 1994, Nickel 1996) and an inverted-U-relation (e.g., Aghion et al. 2005) to a negative impact (e.g., Dasgupta and Stiglitz 1980). Furthermore, empirical literature suggests that

patents play only a minor role in determining R&D (Cohen et al. 2000). Patents seem to be important primarily in the pharmaceutical and chemical industries (Levin et al. 1987).

We are aware of only a few experimental papers on competitive R&D. Isaac and Reynolds (1988) and Hey and Reynolds (1991) present single-period patent races that are closely related to theoretical models of patent races and serve as theory tests. Both papers confirm Nash Equilibrium predictions and the impact of appropriability concerns. Isaac and Reynolds (1992) extend the experiment by adding a product market stage, showing that competition increases R&D. Sbriglia and Hey (1994) try to find some basic behavioral patterns within a search game in which subjects had to determine a particular combination of letters out of a given set of potential combinations. This particular combination can be interpreted as the content of a valuable patent. Zizzo (2002) conducts an experiment with close reference to Harris and Vickers (1987). In this multi-stage patent race, the patent is given to the competitor who first wins ten rounds of stochastic R&D competitions. It shows that experimental behavior deviates substantially from theoretical predictions. Sacco and Schmutzler (2007) present a two-stage game with R&D as a deterministic investment in cost reductions. They have different treatments for Bertrand and Cournot competition and find higher R&D investment in the case of Bertrand competition. Suetens (2008) analyzes the effect of R&D cooperation on product market collusion. In her experiment, R&D cooperation facilitates collusion. Breitmoser et al. (2008) study a dynamic indefinite horizon R&D race with uncertainty and multiple prizes. The subjects' behavior in different treatments is far less sensitive to treatments than theory predicts. In addition, investment is highest when rivals are close, i.e., when there is neck-to-neck competition).

The experiment that is most similar to ours is Cantner et al. (2007), in which R&D is also modeled as a highly complex search process. Subjects have to design a product in eight dimensions. The first subject to find the optimal value of a dimension gets the corresponding patent for four periods. Defining the intensity of competition by the closeness of rivals, they find that technology leaders (those who have the better product quality) invest more as the intensity of the competition decreases. This result is not compatible with neck-to-neck competition or with a U-shape of R&D intensity with respect to competition. In contrast to leaders, technology followers invest more in R&D as the gap between leader and follower decreases (i.e., as the competition intensity increases). Overall, Cantner et al. (2007) is still closer to Sbriglia and Hey (1994) than they are to our paper. First, Cantner et al. do not have a product market stage. Second, they do not allow for a non-disclosure of R&D contents. They automatically give a patent to the finder of an optimal component and inform rivals about the

optimal value of the component. In our experiment, innovators can keep their knowledge secret. Finally, and most importantly, Cantner et al. design a complex and uncertain environment. However, success probabilities can, in principle, be calculated. In our experiment, we design fundamental uncertainty by not giving subjects any information about the distribution of product qualities. We believe that a true innovation process is characterized by this lack of knowledge and that our design is therefore most similar to the real innovation problem.

The paper proceeds as follows. In section 2, we describe the experimental design. Our behavioral hypotheses are presented in section 3, and experimental results are discussed in section 4. Section 5 provides a conclusion.

2. Experimental Design

Our experiment consisted of two treatments: a Basic Treatment and a Patent Treatment. The Basic Treatment was composed of ten periods in a two-stage duopoly with differentiated products. Duopolists were randomly assigned to each other at the beginning of the experiment. Each pair was fixed for all ten periods of a session.

Each period consisted of two stages. In stage 1, both duopolists could conduct R&D, and in stage 2, they could choose their prices in a differentiated product market. R&D success determined the firms' product qualities z_i . A larger value of z_i increased the demand for firm i 's product and decreased firm j 's demand to a comparatively smaller degree.

The R&D process was designed as a search within a two-dimensional landscape (a,b) , $a \in [0,100]$ and $b \in [0,100]$, so that there were $101 \times 101 = 10,201$ combinations of a and b . Product quality is a function of these combinations, i.e., $z = z(a,b)$. More precisely, the quality function was defined as a flat lattice with 20 cones distributed on it. The flat part of the landscape quality is given by $z(a,b) = 0$. Quality is only above zero if subjects chose a combination on one of the cones. In these cases, quality is given by the height of the chosen (a,b) -combination. The cones differed by height and radius. The only information that was given to the subjects was that the maximum value of quality z was 100. Subjects did not receive any other information so that they viewed the landscape as a black box. They also did not know that there were any cones that determined z or anything else about the distribution of z -values. Figure 1 shows the R&D landscape.

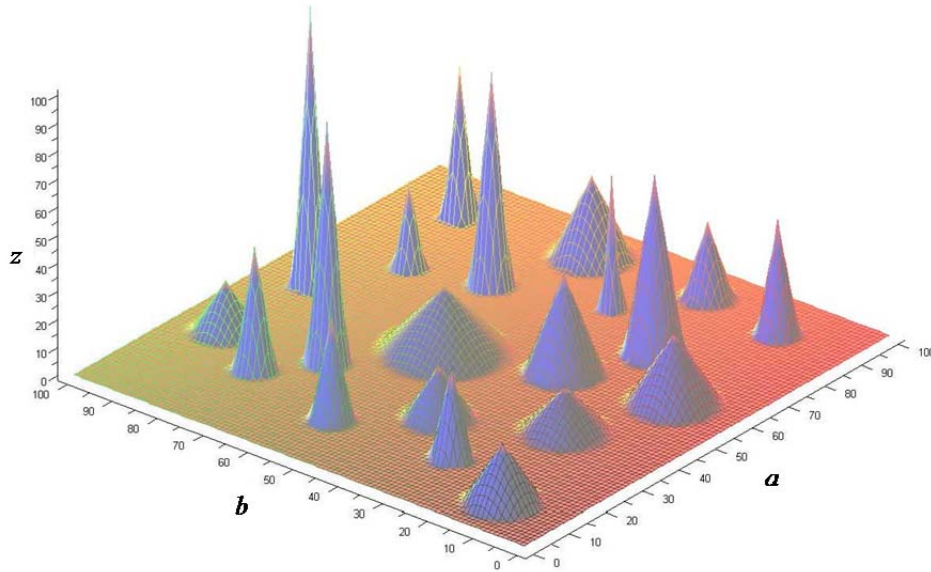


Figure 1: The R&D landscape

The R&D phase lasted for two minutes each period. Within this time, subjects could choose (a,b) -combinations in order to find high quality levels $z(a,b)$. Subjects could make as many trials as they wished. However, each trial cost 500 Experimental Points (EP). At the end of each R&D stage, each firm's quality was determined by the highest $z(a,b)$ value it had found during any of the previous R&D phases. Finally, both players were told their own R&D cost, their own quality level and their competitor's quality level. The coordinates (a,b) , however, remained private knowledge. Then the market phases began.

Each market phase lasted three minutes during which both duopolists had to choose their product price $p_i \in [0,600]$. Without having any production costs, product market profits (net of R&D cost) were given by the firms' revenues. However, subjects did not know their profit functions, so they had to determine prices by trial and error. To speed up this trial-and-error-process, we provided subjects with a revenue calculator. Subjects could enter their own hypothetical values and their competitor's price and were given the corresponding hypothetical revenues (of both players). Use of the revenue calculator was free, and subjects could enter as many trials as they wished. After choosing their prices, subjects were informed about the players' prices, quantities, and profits. Then a new period began.

The only difference between this Basic Treatment and the Patent Treatment was the possible introduction of the filing of a patent. Each player could file no more than one patent per period. A patent is granted for a particular (a,b) -combination. This combination and the other twelve nearest combinations around (a,b) were protected from the competitor's imitation. Subsequent to the R&D stage, the coordinates of the patent were given to the other duopolist. Patent protection started in period $t+1$ and lasted for a total of three periods, so that

in period $t+4$, access was opened to the innovator's rival. During the protection period, the patent holder has to pay 1,000 EP for each valid patent.

Demand for firm i 's product was given by

$$x_i = 100 + 2z_i - z_j - p_i + \frac{p_j}{2}, i = 1, 2 \text{ and } i \neq j. \quad (1)$$

Then profits of one period are given by

$$\pi_i = \left(100 + 2z_i - z_j - p_i + \frac{p_j}{2} \right) p_i - 500\sigma_i - 1000\phi_i \quad (2)$$

$i = 1, 2$ and $i \neq j$. Here σ_i denotes firm i 's number of R&D trials in the current period, and ϕ_i denotes its number of valid patents.

In April 2008, we conducted two sessions for each treatment at Clausthal University of Technology. We had 20 participants in each session.² All subjects were students at Clausthal University (Business Administration, Industrial Engineering and several other engineering programs). The sessions lasted for about two hours. Subjects earned about 20 Euros (28 US Dollar in April 2008) on average. The experiment was programmed and conducted in z-Tree (Fischbacher 2007).³

3. Hypotheses

The product market stage is designed similar to previous oligopoly experiments. However, the introduction of a competitive R&D stage before the market stage should lead to a more competitive atmosphere between the duopolists. Consequently, we hypothesized that participants would also behave competitively in the product market.

Hypothesis 1: *Price-setting behavior will be close to the competitive, subgame perfect Nash equilibrium of the stage game, i.e.,*

$$p_i^{NE} = \frac{200}{3} + \frac{14}{15}z_i - \frac{4}{15}z_j, \quad i = 1, 2 \text{ and } i \neq j.$$

Our design of the R&D phase is rather unique. Because subjects have almost no information about the R&D landscape, it is not easy to conjecture behavior ex-ante. As far as we know,

¹ Of course, we took care to inhibit negative quantities. If $x_i(p_i, p_j) < 0$, then p_i is changed to \hat{p}_i such that $x_i(\hat{p}_i, p_j) = 0$ and $x_j = x_j(\hat{p}_i, p_j)$.

² We had to exclude one subject (subject 14) in session 1 from our analysis. This person either completely misunderstood the rules of the experiment or tried to undermine it. He chose a prohibitive price of 600 in all periods and, consequently, never sold any products. His remaining partner thus could have, and did, behave like a monopolist.

³ Instructions for our experiment are available upon request.

there is no unique optimal search rule for such an unknown terrain. The cone structure of the landscape, however, helps to mitigate this in case a cone is hit, and local search routines are more efficient than pure random search. If we assume that subjects learn that the R&D landscape consists of some kind of cone structure, then they should apply some type of local search for local optima. In general, however, the non-existence of a clearly optimal behavior may strengthen the role of behavioral effects.

We organize our hypotheses with respect to R&D behavior into three groups of relevant factors. One group refers to factors of mere profitability, whereas the others refer to a subject's aspiration level and reinforcement effects. We start with our hypotheses with respect to profitability.

Hypothesis 2: *R&D efforts decrease in time.*

The logic behind this hypothesis is rather clear: in later periods, there are fewer periods of amortization left so that R&D productivity decreases over time. Accordingly, subjects should invest less in R&D.

Hypothesis 3: *R&D efforts decrease with increasing values of product quality z .*

The only information the subjects had with respect to the R&D landscape was that an upper bound of z existed. If subjects' z increases due to successful R&D attempts, the magnitude of potential improvements declines. Consequently, the expected value of further R&D also declines, so R&D is expected to decrease.

Aspiration level theory and aspiration adaptation theory have a long and successful tradition in behavioral economics (Simon 1955, Sauermann & Selten 1962, Cyert & March 1963, Selten 1998, Frey & Stutzer 2002) and constitute an important part on the theory of "bounded rationality." They are particularly important with regard to decision making in highly uncertain environments. We consider this to be sufficient for inclusion into our list of influence factors on R&D. There are two variables that are particularly relevant to the formation of aspiration levels and to influencing behavior: product quality and period profits, each compared to the competitor's level. Empirical innovation research has repeatedly espoused the existence of neck-to-neck competition effects (e.g., Ahn 2002, Aghion et al. 2005), meaning that two competitors close to each other are more intensively engaged in R&D than competitors with large differences in performance indicators. We believe that product quality z is the suitable variable for covering this neck-to-neck competition effect. If qualities are close, both players recognize that they may become (stay) quality leader. We assume that they indeed aspire to be the supplier with higher quality in such cases.

In accordance with aspiration level theory, aspiration levels should differ substantially between players in those cases where there are large profit differences. A subject with higher period profits will usually be satisfied with such profits and will invest less in further R&D. The other duopolist, however, who lags behind and realizes his rival is performing better, will usually have greater motivation to invest in R&D.

Hypothesis 4: *R&D efforts increase with the distance of current performance to subjects' aspiration levels, i.e., R&D increases with*

4.1 *neck-to-neck competition: the closer the qualities z_i and z_j are to each other, the more both will try to get in front*

4.2 *the lag in profits: if subject i lags behind (leads) in actual profits, he wishes to catch up to his competitor by investing more in R&D (is satisfied with the current status and invests less in R&D).*

Reinforcement learning is a plausible and successful concept in analyzing learning behavior. The basic idea is that behavioral strategies are reinforced by their previous payoffs (Camerer 2003, 268). Due to their lack of knowledge, the subjects in our experiment cannot optimize their R&D investments. Because previous success in R&D is their only source of new information, we apply the reinforcement concept to subjects' R&D learning behavior.

Hypothesis 5: *R&D efforts increase with previous success rates in R&D.*

Finally, we analyze whether there are treatment effects, i.e., whether patents have an influence on behavior and whether there are indicators for over- or underinvestment. Given that we cannot see a particular reason for over- or underinvestment to occur, we state hypothesis 6 as the following:

Hypothesis 6: *There will be neither over- nor underinvestment.*

Patents protect innovations from early imitations and are intended to induce an increase in R&D. If they operate in this way, then Hypothesis 7 should be confirmed.

Hypothesis 7: *The introduction of patents increases R&D and product quality for both duopolists and increases the patent holder's profits.*

4. Results

Our sample consists of 776 price decisions, 383 in the Basic Treatment and 393 in the Patent Treatment.⁴ Because equilibrium prices depend on both duopolists product qualities, it is useful to measure pricing behavior by its relative deviation from equilibrium prices. We define relative price deviations of subject i in period t (RPD_{it}) as

$$RPD_{it} = \frac{p_{it} - p^{NE}(z_{it}, z_{jt})}{p^{NE}(z_{it}, z_{jt})}$$

with p_{it} denoting i 's actual price in period t and $p^{NE}(z_{it}, z_{jt})$ denoting the corresponding equilibrium price. Figure 2 shows a box plot of RPD for different treatments and periods. We divided the ten periods into three groups: periods 1-3, 4-7 and 8-10.

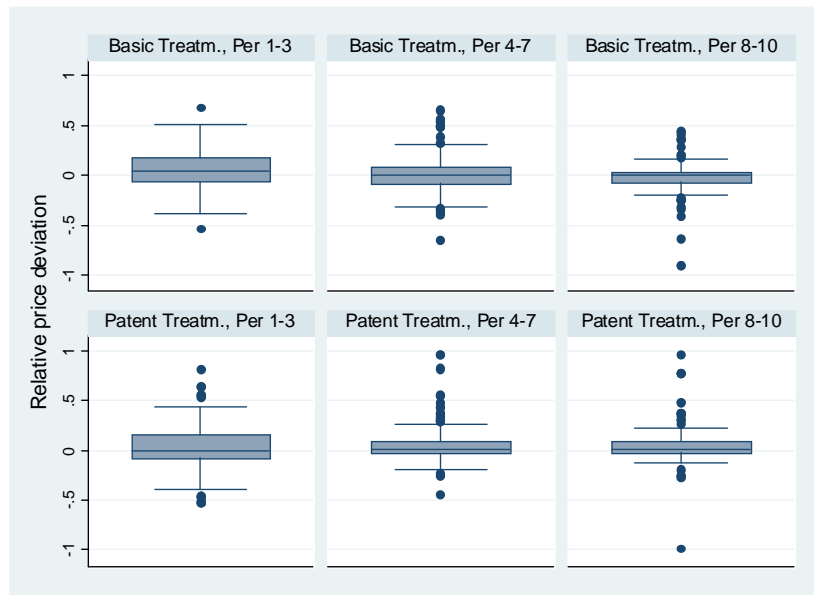


Figure 2: Relative price deviations over periods and treatments⁵

In both treatments and in all period groups, price deviations are clearly distributed near zero. This means that there is no visible over- or underpricing. Furthermore, the interquartile range decreases with time, i.e., prices are closer to their equilibrium values in later periods, outliers notwithstanding. According to the graphical exposition, equilibrium prices are a good predictor of actual prices. Table 1 shows the means and medians of RPD .

⁴ There are missing values in the data set, if one or both participants of a group don't choose a price within the given time or choose a price over the prohibitive price of the product market.

⁵ To provide better visibility of the price distribution, we omitted two outliers with a price deviation of more than +100 percent in Figure 2. Both occur in treatment 1, one during periods 1-3 and the other during periods 4-7.

Treatment	(Percentages)		
	Per 1-3	Per 4-7	Per 8-10
Basic Treatment	6.54 *	2.88	-2.09
	4.72 **	-0.03	-0,10
Patent Treatment	3.15	6.75 **	5.48
	0.21	1.55 *	0.54 **

Table 1: means (above) and medians of relative price deviations

** (*): significantly different from zero at a level of 1 percent (5 percent)
(Means: t-test; medians: sign-rank test; each test based on subjects' mean values)

Although price deviations are close to zero, it can be seen that some of the deviations are significantly different from zero. All significant deviations are positive, indicating that there is a slight tendency to choose prices above equilibrium values. In summary, we find

Result 1: *Price-setting behavior is close to Nash Equilibrium. Deviations from equilibrium are, however, biased towards higher prices.*

The remaining part of our analysis deals with R&D behavior. We previously explained that R&D activities in our experiment are costly search efforts in a totally unknown terrain. We implemented constant marginal cost of searching. R&D intensity is consequently measured by the number of participants' trials. We estimated several R&D Fixed Effects Regression models. One approach includes only those variables that indicate the profitability of R&D activities; the second approach covers aspiration level aspects; and the third model estimates the impact of reinforcement effects. Finally, we estimated a combined model. Each of these models is estimated separately for the Basic Treatment and for the Patent Treatment. We also carried out a joint estimation of the combined model. The results of our Fixed Effects regressions are presented in Table 2.

Result 2: *R&D efforts decrease with time.*

With increasing time (period numbers) fewer amortization periods remain so that the expected value of R&D expenditures decreases. The effect is highly significant in all estimations. Even the magnitude of the estimated parameter is quite robust. Hypothesis 2 is thus strongly confirmed.

Result 3: *R&D efforts decrease with product quality.*

Table 2 shows that the coefficient of lagged product quality ($max_z.L$) is negative in all estimations, in accordance with hypothesis 3. Note, however, that the impact of quality on R&D is significant only in estimations of the Patent Treatment.

Insert Table 2 about here.

Let us now turn to aspiration adaptation theory. To measure neck-to-neck competition, we have to define technological distance and technological leadership. We measure the technological distance of subject i by $\Delta z_i = z_i - z_j$. Subject i is the technology leader if his product quality z_i is greater than or equal to that of his competitor z_j , i.e., $\Delta z_i \geq 0$. Otherwise, subject i is the technology follower. Neck-to-neck competition then states that the technology leader's R&D should decrease with (lagged) Δz_i and that the technology follower's R&D should increase with (lagged) Δz_i .

Result 4: *The technology leader's R&D increases with the magnitude of his lead, Δz_i , whereas the technology follower's R&D increases with a decreasing quality gap.*

Table 2 shows that the coefficient for the leader's Δz_i is positive in all estimations. This means that a greater lead for the technology leader increases his motivation to conduct additional R&D. This result directly contradicts the neck-to-neck hypothesis (Hypothesis 4.1). Note, however, that coefficients are significant only in the Patent Treatment.⁶

All significant coefficients of follower's Δz_i correspond to estimations of the Patent Treatment and they are positive. This fits with the neck-to-neck hypothesis. The insignificant coefficients in case of the Basic Treatment, however, are negative. This contradicts Hypothesis 4.1. In summary, we find that the neck-to-neck competition hypothesis does not work well in our experiment.

Hypothesis 4.2 states that actual profit differences should impact R&D behavior. Let $\Delta \pi_i = \pi_i - \pi_j$ be the profit difference between subject i and j . We then define subject i to be the profit leader (profit follower) if $\Delta \pi_i \geq 0$ ($\Delta \pi_i < 0$). According to hypothesis 4.2, the corresponding (lagged) regression coefficients should be negative for both the profit leader and the profit follower.

Result 5: *The profit leader's R&D decreases with higher differences in (last period) profits ($\Delta profit_lead.L$). In contrast, the profit follower's R&D increases with increasing profit gaps.*

The coefficients of $\Delta profit_lead.L$ in Patent Treatment estimations are significantly negative. Coefficients for the Basic Treatment are smaller by a power of ten and are insignificantly positive.

⁶ We believe that this difference in behavior can be explained as follows: the Patent Treatment subjects were told that a patent protects the (a,b) -combination given by the subject as well as the twelve nearest other (a,b) -combinations. This additional information is a clear indication of the relevance proximity within the R&D landscape and may have influenced subjects' behavior.

In case of profit followers, all estimations show a negative coefficient for $\Delta profit_follow.L$, which is in accordance with Hypothesis 4.2. Again, however, only the estimated coefficients for the Patent Treatment are significantly different from zero. In summary, Hypothesis 4.2 is confirmed with respect to the impact of profit differences on R&D behavior.

Our third type of variable relates to arguments of reinforcement. Hypothesis 5 submits that successful R&D breeds further R&D. To quantify this thesis, we define

$$SR_{it} = \frac{\sum_{\tau=1}^{t-1} S_{i\tau}}{\sum_{\tau=1}^{t-1} Trials_{i\tau}} \quad \text{with } S_{i\tau} = \begin{cases} 0 & \text{if } z_{i\tau} = z_{i\tau-1} \\ 1 & \text{if } z_{i\tau} > z_{i\tau-1} \end{cases}$$

as the success rate of subject i up to (and including) period t . If there are reinforcement effects, R&D should increase with SR_{it} .

Result 6: *R&D efforts increase (at a decreasing rate) with previous R&D success rates.*

Table 2 shows that lagged SR_{it} (*Success rate.L*) is significantly positive whenever it is included in the regression equation. However, the relationship between SR_{it} and R&D is nonlinear, as the significantly negative coefficients for squared values of SR_{it} (SR_{it}^2 : *Success rate2.L*) show. Consequently, our data confirm Hypothesis 5.

One major motivation for the experiment was to determine whether there are any indicators for systematic over- or underinvestment in an innovation game with fundamental uncertainty. This, however, proved to be a difficult task because the subjects did not have any information that made it feasible for them to calculate the expected value of future R&D. Additionally, they did not know the distribution of product qualities within, and they did not have any information about the cone-structure of the two-dimensional search space. Assuming that the subjects learn that there is some systematic structure (a kind of landscape) of the quality distribution and that they develop some kind of feeling for the underlying function, we first have to define what a reasonable search behavior may look like. As far as we know, no optimal search routine exists in a completely unknown search space. Therefore, we defined a plausible search procedure that is presented in Figure 3. Having defined this routine, we calculated the probability of hitting upon a cone and, given the structure of the different cones, the average number of trials it takes to find the local quality maximum on each type of cone. Finally, we calculated the expected profit of continuing to search according to our search routine, given a player's actual product quality z_i . As long as expected profits are

above zero, the search should be sustained. Finally, we derived the critical product quality z_i^{crit} , providing the maximum value for which a sustained search is profitable.⁷

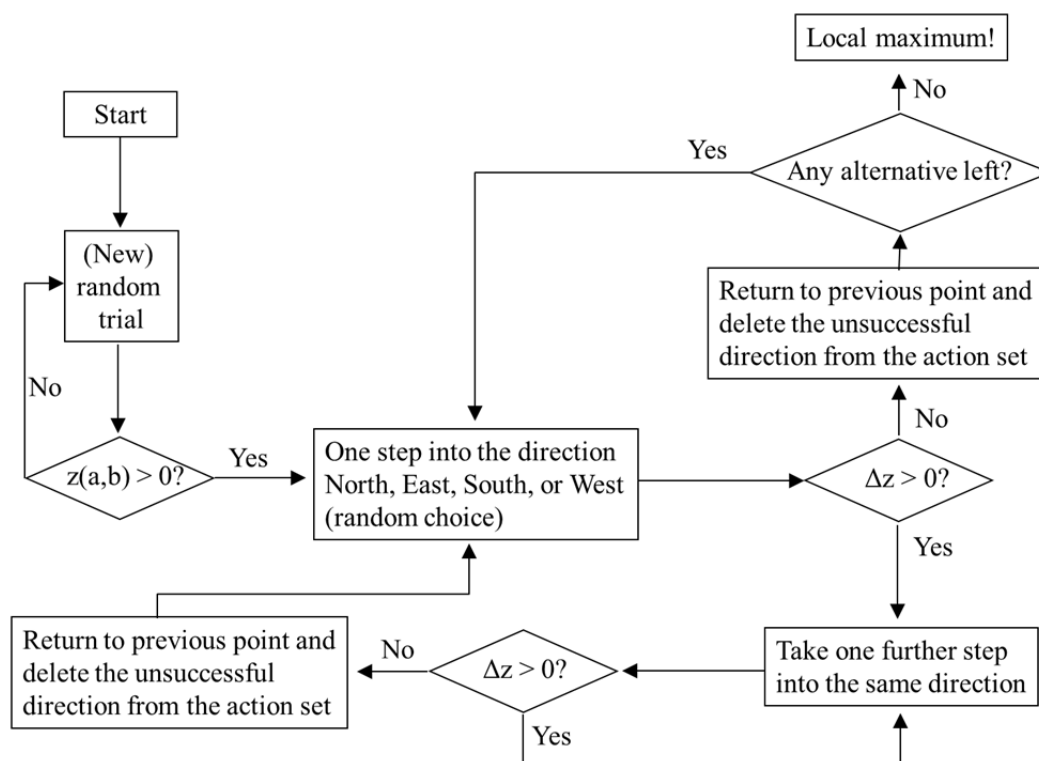


Figure 3: A simple search routine

Table 3 shows the critical values z_i^{crit} for periods 1 – 10, which indicate that continuing the search is profitable only if $z_i < z_{crit}$. As expected, z_i^{crit} decreases with time. It must be noted, however, that the decrease between periods 1 – 7 is rather small. Because the experiment ends after ten periods, z_i^{crit} declines sharply in periods 8 and 9.

<i>period</i>	1	2	3	4	5	6	7	8	9	10
z_{crit}	64	64	54	54	54	48	44	29	0	-

Table 3: Critical (maximum) values of quality z_i

We define R&D behavior to be quasi-rational if subjects search according to this stopping rule. Now we can compare the actual search to our prediction of quasi-rationality.

Result 7: *In periods 1 – 7, behavior is not significantly different from quasi-rational R&D. However, there is overinvestment within the final three periods.*

⁷ We also carried out a similar calculation for a purely random search. The calculation showed, however, that the performance of a purely random search is clearly inferior to the one used in our search routine.

Table 4 shows the corresponding data. On one hand, subjects seem to have developed a good feeling for when to stop searching. On the other hand, they do not seem to have understood the seriousness of the end-period problem, i.e., that further search is only worthwhile if they have a sufficient number of remaining periods for the amortization of R&D investments. One possible explanation for this overinvestment is that the experiment was framed in innovation terminology and that innovation in real life is not restricted by final periods. In contrast, firms often have a longer life-span than individuals and are not bound by human life expectancy. Consequently, overinvestment in the final periods may be due to our artificial construct of a finite time horizon.

Period	1	2	3	4	5	6	7	8	9	10	Total
Basic Treatment											
Underinvestment	0	2	1	3	5	5	7	5	0	0	28
Quasi-rational search	39	35	36	33	30	23	20	19	20	28	283
Overinvestment	0	2	2	3	4	11	12	15	19	11	79
Total	39	39	39	39	39	39	39	39	39	39	390
Patent Treatment											
Underinvestment	0	1	2	5	7	5	8	3	0	0	31
Quasi-rational search	40	37	32	32	30	23	18	21	19	21	273
Overinvestment	0	2	6	3	3	12	14	16	21	19	96
Total	40	40	40	40	40	40	40	40	40	40	400

Table 4: Under and overinvestment in R&D (frequencies)

In summary, we find that Hypothesis 6 does not work well in our experiment. Our last group of research questions refers to the impact of patents on behavior. Patents are generally understood as a means of increasing the value of innovation. The corresponding increase in profits is thought to stimulate R&D investments and, consequently, product quality. We also expected this to happen in our experiment (Hypothesis 7).

Result 8: *The introduction of patents increases R&D only in the first periods.*

Table 5 shows the number of R&D trials for different periods and treatments. In the first two periods, trials are clearly greater in the Patent Treatment, and this difference is significant at a level of 5 percent (U-test). However, the remaining differences are small and insignificant.

Period	Treatment	
	Basic	Patent
1	9.77	12.63
2	6.51	9.78
3	6.03	7.80
4	4.31	5.90
5	4.36	4.63
6	3.87	4.23
7	3.36	3.70
8	3.51	3.13
9	2.10	2.90
10	0.79	1.90
All Periods	4.46	5.66

Table 5: R&D trials (means)

Larger investments in R&D in the Patent Treatment should also result in higher levels of product quality. Table 6 shows the corresponding values of product qualities in different periods and treatments. Mean product quality in the Patent Treatment is higher in all periods. However, none of these differences is statistically significant.

Period	Treatment	
	Basic	Patent
1	29.01	33.02
2	36.32	39.72
3	39.14	42.37
4	40.06	44.43
5	42.06	46.87
6	43.66	48.58
7	46.26	48.57
8	47.56	49.77
9	47.87	51.07
10	48.49	52.10
All Periods	42.04	45.65

Table 6: Product quality (means)⁸

We conclude:

Result 9: *In all periods, product quality (z) is (insignificantly) higher in the Patent Treatment than in the Basic Treatment.*

Surprisingly, subjects earned (insignificantly) higher profits in the Basic Treatment (69,016.92 EP) than in the Patent Treatment (64,921.43 EP). This result may be due to the comparatively high patent fees of 1,000 EP per period of patent protection. To verify this, we

⁸ The decrease of product quality in period 7 is due to a new patent that decreases the competitor's product quality.

conducted an additional Patent Treatment with patent fees of 100 EP. The corresponding average profits (60,616.13 EP) are again lower than in Basic Treatment. Furthermore, the lower patent fees do not have a significant effect on the amount of patents. Hence, the patent costs cannot explain our results as they pertain to the effects of patents.

5. Conclusion

The main objective of our research endeavor is to study R&D and pricing behavior in an environment with fundamental uncertainty. We designed a multi-period experiment of conducting R&D and pricing one's own product. Each period consisted of two stages: an R&D phase and a pricing stage. Subjects had almost no information about the probabilities of R&D success, and they also did not know the demand function when determining their prices. We wanted to determine whether behavior in such an environment is close to equilibrium pricing and what determines R&D behavior.

We find that pricing behavior is surprisingly close to subgame perfect Nash Equilibrium in both treatments. The provision of little information regarding market data is thus no obstacle to near-equilibrium behavior.

With respect to R&D behavior, we distinguish three groups of determinants. Profitability is measured by the remaining number of periods for amortization of R&D investments and by the remaining potential for quality improvements. The later investments occur, the fewer periods for amortization remain. We therefore conjectured that R&D decreases with time. Subjects were told that the maximum product quality in our experiment was 100. The higher the current quality, the smaller the potential for further improvements, and as a result, R&D was expected to decrease with actual product quality. Both hypotheses with respect to profitability are strongly confirmed.

The second group of determinants refers to aspiration adaptation theory. We define a neck-to-neck competition hypothesis, arguing that the closer the duopolists' product qualities are to each other, the more intense the R&D competition will be. In the spirit of satisficing theory (Simon 1955), we also hypothesized that the profit leader (follower) will invest less (more) if the difference between the duopolists' profits increases. However, we found little evidence for the aspiration adaptation theory. The neck-to-neck hypothesis must be rejected completely, and the satisficing hypothesis works well only within the Patent Treatment.

The third group of determinants refers to reinforcement effects. Because subjects have hardly any information about the probabilities of finding higher product qualities, successes in

R&D may lead to a more optimistic assessment of R&D opportunities. In this sense, R&D success may breed additional R&D. Our data strongly confirm this hypothesis.

To find evidence for over- or underinvestment, we define the quasi-rational search behavior that corresponds to a particular search routine. Note that a precise definition of rational search behavior does not exist because subjects do not have any information about the R&D success probabilities. One of the major results of our paper is that subjects' R&D behavior fits quite well into our definition of quasi-rational behavior. Again, the nearly complete lack of information is no obstacle to sensible behavior. We only find significant deviations from our R&D benchmark in the final three periods of the experiment. Subjects seemingly underestimate the quantitative effects of the finiteness of the experimental time horizon.

Finally, the introduction of patents has only a minor impact on behavior. R&D spending differs significantly only during the first periods. All other conjectured effects appear to be insignificant. One possible explanation for this result is that patent fees of 1,000 EP per period of patent protection may be too high. To test this hypothesis, we conducted an additional Patent Treatment with patent fees of 100 EP and again found no significant effects of patents on behavior.

The main conclusion of our paper is that the subjects' behavior in the fundamentally uncertain environment of our experiment is reasonable. This is particularly true for the subjects' pricing decisions that were close to equilibrium value. Although we do find some hints of the existence of behavioral effects, only reinforcement effects are highly significant across both treatments and different model specifications. Given these results, our basic concern that rational choice models of innovation contradict the very nature of incalculable innovation must be qualified: subjects learn how to adapt to rather complex and highly uncertain environments remarkably well.

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Appendix

dependent variable: number of R&D trials												
Model	PA			AA			RL			CA		
	Basis	Patent		Basis	Patent		Basis	Patent		Basis	Patent	Both
Period	-.57 ^{***}	-.71 ^{***}		-.58 ^{***}	-.66 ^{***}		-.47 ^{***}	-.63 ^{***}		-.44 ^{***}	-.56 ^{***}	-.54 ^{***}
Success rate.L							29.68 ^{**}	51.56 ^{**}		38.61 ^{**}	66.47 ^{***}	41.38 ^{***}
Success rate2.L							-74.85 [*]	-198.5 ^{***}		-87.78 ^{**}	-227.2 ^{***}	-127.7 ^{***}
Δ profit–foll.L				-.0001	-.0002 ^{**}					-.0001 [*]	-.0002 ^{***}	-.0001 ^{***}
Δ profit–lead.L				.00004	-.0002 ^{***}					.00003	-.0003 ^{***}	-.0001 ^{***}
max–z.L	-.01	-.06 ^{***}		-.023	-.09 ^{***}		-.02	-.07 ^{***}		-.03	-.09 ^{***}	-.05 ^{***}
Δ z–foll.L				-.01	.09 ^{***}					-.02	.09 ^{***}	.03
Δ z–lead.L				.02	.06 ^{**}					.014	.06 ^{**}	.04 [*]
Patent.L		-.63			-.78 [*]						-.67	-.81 ^{**}
D–aggr–losses.L	1.23	1.22		1.05	.51		1.32	1.45 [*]		1.08	.72	.97
constant	7.64 ^{***}	11.85 ^{***}		7.74 ^{***}	13.68 ^{***}		5.60 ^{***}	10.18 ^{***}		4.77 ^{***}	10.91 ^{***}	7.91 ^{***}
n	351	360		351	360		351	360		351	360	711
R ² _{within}	.27	.32		.28	.37		.28	.33		.29	.40	.32
R ² _{between}	.27	.003		.19	.005		.02	.03		.01	.02	.09

PA – Profitability Approach AA – Aspiration Adaptation RL – Reinforcement Learning CA – Combined Approach
^{***} / ^{**} / ^{*}: significant at level of 1% / 5% / 10%

Table 2: Results of Fixed Effects Regressions

