



Paper to be presented at the DRUID 2011

on

INNOVATION, STRATEGY, and STRUCTURE -
Organizations, Institutions, Systems and Regions

at

Copenhagen Business School, Denmark, June 15-17, 2011

Early impressions and performance feedback in entrepreneurial search: An experimental study

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Abstract

This paper reports the preliminary findings from an experiment of entrepreneurial search in complex opportunity spaces. The results support behavioural accounts of entrepreneurial risk taking by showing that performance feedback influences entrepreneurial search behaviour. We find that performance feedback influences where and for how long human subjects search in the opportunity space. Importantly, early performance feedback is critical, since it establishes the frame of reference with which later feedback is processed and evaluated. Early impressions create heterogeneity in experiences and this initial heterogeneity imprints the dynamics of entrepreneurial search. Our results also point to an interesting puzzle: Initial positive feedback leads to an earlier stopping of entrepreneurial search, while at the same time

promoting the exploration of more distant alternatives in the opportunity space. We conclude that feedback variables may be used not only to manipulate entrepreneurial status quo biases, but also to foster entrepreneurial search and to balance the exploration-exploitation tradeoff.

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Keywords: Entrepreneurial search, opportunity discovery, variable risk preference, laboratory experiment

Introduction

The discovery and exploration of new business opportunities through the recombination of resources lies at the heart of the entrepreneurial process (Schumpeter 1934; Kirzner 1973). Researchers have characterized the recombination of resources as an entrepreneurial search process (Minniti & Bygave 2001; Denrell et al. 2003; Lippman & Rumelt 2003; Auerswald 2008). A main challenge of entrepreneurial search is that most recombinations prove to be a failure, making entrepreneurial search inherently risky. Research has pointed to a higher risk preference (Knight 1921) or to a systematic misrepresentation of risk (Busenitz & Barney 1997; Simon et al. 1999) to explain individual differences in opportunity discovery and exploration. In contrast, psychological and behavioural accounts of risk behaviour claim that risk preference is sensitive to performance feedback and the influence of performance feedback on entrepreneurial search has been relatively neglected in the entrepreneurship literature.

In our research, we study the role of performance feedback for entrepreneurial search in a laboratory experiment. Based on prior literature, we hypothesize that ongoing performance feedback influences for how long and where entrepreneurs search for new recombinations. We also argue that early feedback is especially important for entrepreneurial search, since it imprints the frame of reference with which later feedback is processed and evaluated.

Our preliminary results generally confirm prior studies of variable risk preference and show that various types of performance feedback are significant predictors for entrepreneurial search. We find that performance feedback influences where and for how long human subjects search in the opportunity space. Broadly, negative performance

feedback leads to more sustained entrepreneurial search and more exploration of the opportunity space, even though the relationship is more nuanced than expected. Importantly, early performance feedback is critical, since it establishes the frame of reference with which later feedback is processed and evaluated. Early impressions create heterogeneity in experiences and this initial heterogeneity imprints the dynamics of entrepreneurial search. Our results also point to an interesting puzzle: Initial positive feedback leads to an earlier stopping of entrepreneurial search, while at the same time promoting the exploration of more distant alternatives in the opportunity space. We also find that early performance feedback, i.e. success or failure in the early stages of the entrepreneurial search process, stimulates behaviours that are suited for achieving performance improvements in the long run.

Our results point towards important underpinnings of the ‘status quo bias’ (Burmeister and Schade 2007; Sandri et al 2010), as they suggest that entrepreneurial activity can be fostered, for instance, by reducing the opportunity costs of entrepreneurial search. Moreover, we find that sustained entrepreneurial search activity can be found for only few subjects. These individuals, however, not only maintain their search but even broaden their search over time despite negative performance implications.

This research contributes to research in entrepreneurship as it shows the importance of early performance feedback on entrepreneurial search. This imprinting effect has important implications for search behaviour and performance, and it might explain who becomes an entrepreneur, regardless of other traits. Moreover, our findings highlight that exploration-exploitation tradeoffs (March 1991) have nuanced implications and heavily depend on which specific feedback variable is examined.

The rest of the paper is structured as follows. In the next section, we briefly review prior literature on entrepreneurial search, risk taking, and performance and develop a set of hypotheses. In section 3, we explain the motivation and setup of our laboratory experiment. Section 4 presents the results from the experiment. Section 5 discusses the contributions and limitations of our research.

Theoretical motivation

Prior research on entrepreneurship has evolved around three core research questions, namely why, when, and how 1) entrepreneurial opportunities arise, 2) certain individuals and firms and not others discover and exploit opportunities, and 3) different modes of action are used to exploit these opportunities (Shane & Venkataram, 2000). Hence, many scholars in the entrepreneurship field have argued that entrepreneurship studies should embrace the discovery of opportunities as the main construct and unit of analysis of entrepreneurship research (Shane, 2000; Shane & Venkataraman, 2000; McMullen & Sheperd, 2006; McMullen, Plummer & Acs, 2007). The notion of opportunity discovery may be further specified as an entrepreneurial search process (Minniti & Bygrave, 2001). According to prior literature, entrepreneurs search for new combinations of existing resources to create new business opportunities (Denrell et al. 2003; Lippman & Rumelt 2003). A central question is then how entrepreneurs structure and manage the search for new opportunities (Sommer et al 2009).

Entrepreneurial search is challenged by the fact that most recombinations prove to be a failure (Nelson & Winter 1982; Sarasvathy 2004; Miller 2007). In other words, entrepreneurial search is inherently risky. Early research in entrepreneurship therefore

has pointed to a higher risk preference as a main trait of entrepreneurs (Knight 1921).

Entrepreneurs are more risk seeking and thereby are more likely to engage and be more persistent in the search for new opportunities.

However, psychological and behavioral accounts of risk behavior claim that risk-taking systematically responds to performance feedback. Decision-makers use a subjective aspiration level to evaluate performance feedback and adjust risk-taking accordingly. When performance exceeds aspirations, they adjust their risk preference downward. The theory is based on psychological processes of risk perception and risk preference (Kahnemann & Tversky 1979) and organizational processes of search (Cyert & March 1963). Viewed from this perspective, the risk preference is not an ingrained trait, but rather depends on the context in which the individual is situated. Individuals are said to be more risk seeking facing losses, and more risk averse when facing gains. This has important ramifications for entrepreneurial search. Positive performance feedback triggers a reduction of risky actions and to a curbing of entrepreneurial search. Negative performance feedback, on the hand, leads to more risk seeking and makes entrepreneurial search more intense. For example, Wennberg and Holmquist (2008) find support for these relationship between entrepreneurial risk taking and performance feedback in their study of international entrepreneurship

Two aspects of entrepreneurial search appear to be important in this context. First, an aspiring entrepreneur may decide when to engage in the search for new combinations (Lippman and Rumelt 2003). Simon (1955) has argued that individuals search for new alternatives if existing alternatives do not satisfy the aspiration of a

decision-maker. Thus, the idea is that negative performance feedback prompts and prolongs entrepreneurial search for new opportunities. This is our first hypothesis:

H1: Negative performance feedback prolongs entrepreneurial search.

The second aspect relates to where to search for new opportunities. Entrepreneurs may search in the neighborhood of existing experiences and competencies (exploitation) or they may explore more distant alternatives (March 1991). Since wandering away from existing competencies increases the risk of failure, seeking out and exploring more distant alternatives is more risky. We therefore hypothesize that negative feedback elicits the search for more distant alternatives:

H2: Negative performance feedback leads to more distant (explorative) entrepreneurial search.

Search behavior adapts to performance feedback, but individuals may also respond to performance feedback by adapting aspiration levels (March 1988; Levinthal & March, 1993). Positive performance feedback might lead to an upward adjustment of aspiration levels and a larger gap between performance and aspirations. The dynamics of aspiration level adaptation may critically depend on first impressions from performance feedback. Initial positive feedback may stipulate confidence in the searcher's abilities and the munificence of the environment (March & Shapira 1992; Camerer & Lovallo 1999; Simon et al. 1999; Gatewood et al. 2002), leading to entrepreneurial search that is both more sustained and more distant. Thus, the long-term dynamics of entrepreneurial search may be heavily imprinted by early impressions. The early impressions of searchers might create heterogeneity in experiences in a population of searchers and this initial heterogeneity could be magnified by subsequent experiences. Thus, two individuals may

differently interpret performance feedback in the later stages of search depending on their initial performance. We therefore propose that initial positive performance feedback promotes entrepreneurial search and tends to a) prolong the search for opportunities and b) motivates an individual to explore more distant alternatives. In contrast, early negative feedback frustrates aspiring entrepreneurs, leads to an earlier break-off of search, and tends to constrain search to the neighborhood of prior experience:

H3a: Early negative performance feedback leads to an earlier stopping of entrepreneurial search.

H3b: Early negative performance feedback leads to less distant (explorative) search.

Methods

Experimental design

Our research uses an experiment for testing the above hypothesis. An experiment is particularly suited for such a purpose because it allows to (a) clearly define and alter variables of interest, (b) control the setting from external influences, and (c) develop experimental designs that explicitly considers formal developments in the field. Our experimental design deliberately uses average students as subjects. We made these choices in order to minimize selection bias and concentrate on baseline entrepreneurial behavior. For the latter we also deliberately chose not to use entrepreneurs or non-entrepreneurs because we were interested in general human behavior and how it reveals facets of entrepreneurial behavior.

Experimental framing

The purpose of this experiment is to study the influence of performance feedback on entrepreneurial search. To remove any possible influence of prior knowledge, we confront subjects with an opportunity that is completely new to them. In other words, subjects should not be able to draw on existing mental maps to guide the search of the opportunity space (e.g. Gavetti and Levinthal 2000). To create such a framing for the experiment, we developed a fictional account, the “alien game”, in which the subjects are requested to design products for aliens. The subjects are not aware of the tastes or preferences of the aliens. Instead they only know that aliens like ten basic geometric shapes, representing $N=10$, which can be combined in various configurations. The payoff for each configuration is initially unknown. The task is to create combinations of these shapes, receive performance feedback on a single combination, and iteratively search for the combination that produces the highest payoff. Subjects were initially placed at the lowest-performing configuration (unknown to them) and receive information on the payoff of each new combination as they make trials. The subjects were not informed about key parameters like the degree of complexity of the landscape (K), the average performance or peak performance (global optimum) of the opportunity space, and the performance of other players. Hence, players can only infer the nature of the opportunity space based on the performance feedback. With this “alien game”, we intended to limit the role of prior mental maps of the search space and eliminate potential reference points that could provide individuals with an understanding of which configurations lead to good or bad performance.

Experimental setup

The simulation software was specifically written for the experiment. It displays a window with 10 geometric attributes, arranged one in each row, which individuals can freely select or deselect, thereby making a binary choice for each attribute. As a result, there are $2^{10}=1024$ combinations; each associated with a distinct payoff. The payoffs were generated by the standard NK algorithm (Kauffman 1993), a model widely used in the literature on search (Levinthal 1997) and on entrepreneurship (Denrell et al. 2003; Auerswald 2008) to create opportunity spaces in theoretical models. The main attraction for our research is that the K parameter of the NK model allows us to manipulate the ruggedness of the opportunity space. If $K = 0$, attributes are independent, and there is only one local (& global) maximum payoff in the space. As K increases, more and more attributes of a configuration become interdependent, with $K = N - 1$ ($K = 9$ in our case) being the case of full interdependence among all attributes. The number of interdependencies given by K determines the payoff surface of the opportunity space. With higher values of K, there are more local peaks and performance differences among neighboring configurations, differing only in a single attribute, become relatively more pronounced (Kauffman 1993; Rivkin 2000). The K parameter of the model serves as an indicator for the complexity of the opportunity space (Simon 1962; Levinthal 1997). The higher K, the more challenging is the recombination and the more rugged the opportunity space.

Each game has 25 rounds. In the first round, the subjects were informed about the initial configuration and the associated payoff. This configuration represented the lowest-performing configuration in the landscape (though the subjects did not know this).

Subjects then had 24 trials (rounds) to select configurations of features. Subjects received feedback in the form of a payoff for each combination of geometric shapes they selected.¹

Every subject played the simulation three times (games 1-3). While the number of features remained the same (i.e. constant $N = 10$), we varied (a) the complexity of the landscape in which individuals searched ($K = [0, 5, 9]$; with different individuals seeing these in different sequences to control for possible confounding effects. In each game, the subjects had the goal of maximizing the accumulated payoffs over all 25 rounds. We thereby made searching the opportunity space risky: the payoff of a new configuration could be less than the payoff of the prior configuration, thus decreasing their total accumulated performance in comparison to simply repeating their previous feature combination. The experimental design thereby captures the exploration-exploitation tradeoff (March 1991).

The simulation software supports and monitors all of the above functions in detail. It allows individuals to select/deselect attributes, and, when satisfied, submit a specific configuration of attributes to learn the associated payoff, thus completing one of the 24 trials in each game. It displays all previous choices that individuals made in each game. It automatically stops the game after 24 trials and starts the next game. The interface proved to be very intuitive and all students were comfortable with the software after a brief introduction. The software records the attributes every individual selected as well as the performance that each individual achieved in every round for all games (~1000 data points for each individual).

¹ The payoff that is associated with each configuration was obtained from three distinctive NK landscapes randomly generated before the experiment based on the standard NK algorithm with random interaction patterns. All landscapes were normalized, so that the highest performing configurations had a uniform payoff. To hide the mean and the maximum performance of a landscape and to prevent the learning of reference points across games, the raw NK payoff was multiplied with a game-dependent payoff factor.

70 subjects, almost all students majoring in some management area, participated in the experiment. They were randomly allocated to the two main treatment groups. All subjects played three successive games in which we systematically altered the complexity of the landscape ($K = 0, 5$ or 9). In total, this setup added up to 210 games (70 subjects x 3 games each) that were distributed across three different experimental sessions. For each session we ensured that we had more than 60 games, out of which at least 20 were played by subjects' who were facing the particular setup (landscape complexity and goal) as their first game; the subjects' second and third game was then a result of systematic alteration. This approach ensured that we control for potential learning effects across games while having a high sample size for each experimental session.

The experiment took place in a university computer laboratory. Each individual had a PC and an open view of a large screen that was used to explain the experiment (we presented the "alien game" cover story, and informed subjects of the number of trials and games, and standard rules for behavioral experiments). At the beginning of every game, the supervising instructor also pointed out that students are confronted with a new alien from a new planet; hence, making clear that knowledge acquired in prior games was not applicable in the new game. The latter was also reinforced by scaling the payoffs with different factors for each game.

In the room were two to four instructors to ensure that students were not distracted. Moreover, every student received 7.50 USD (as a voucher) for participation. The students were split into five groups (with roughly 20 students in each). The three students with the best overall performance within a group received substantial cash prizes (1st prize: 100 USD; 2nd prize: 50 USD; 3rd prize: 20 USD). The cash prizes were

announced at the beginning of the experiment to motivate competitive search behavior and to prevent students from collaborating (which was also prevented by the instructors in the room). Before the experiment, students had to individually sign-up and were randomly assigned to the experimental treatments and sessions. In addition, students conducted an online survey before and after the experiment.

Results

In the experiment, the subject's objective was to maximize accumulated performance at the end of the entrepreneurial search process. We therefore focus on the role of performance feedback in entrepreneurial search.

A general overview of the attained performance is reported in Figure 1a and 1b. Figure 1a shows the average highest performance that subjects have identified in each round. It reveals that subjects quickly realize their initial 'bad positioning' (at the lowest point of the search space) and manage to quickly increase their performance during the first rounds. However, the magnitude of performance improvements, i.e. the difference between current and the previous round's performance, reduces over time and performance only slightly improves in the late rounds (Fig. 1a). As expected, more complex task environments make entrepreneurial search more difficult: Subjects have more problems finding attractive positions in complex opportunity spaces (i.e. $K = 5; 9$), as compared to the smooth $K = 0$ landscape (Figure 1). The highest performance shows no significant difference between $K = 5$ and $K = 9$ landscapes in the 25th round (Mann-Whitney Test; $p=0.432$).

Figure 1b reports that subjects on average increase their wealth to over time. Again, the performance difference between $K = 5$ and $K = 9$ landscapes in the 25th round is not significant (Mann-Whitney Test; $p=0.225$).

Please insert Figure 1a and 1b here

Other variables that are important for the analysis can be found in Table 1, which also provides definitions and the basic descriptions.

Please insert Table 1 here

Several of the variables capture feedback conditions. Prior payoff reflects performance values in the previous round. Wealth (accumulated payoffs) reflects performance values in all previous rounds. Highest payoff is the maximum payoff that a subject has so far achieved in a given round and ‘rounds since highest payoff’ counts the number of rounds since the maximum payoff was achieved. This variable is particularly interesting as it shows the number of rounds in which a subject has received a negative performance feedback. This is illustrated in Figure 2, which, again, indicates that (a) negative feedback is generally increasing over time, and (b) search in complex landscapes is more difficult in later rounds.

Please insert Figure 2 here

In the following, we use several regressions to test the hypotheses and explore the relationships between the central variables in more detail. As a starting point, a Cox regression allows us to assess the likelihood of the stopping of search, i.e. the probability with which subjects stop searching rather than continuing the exploration of the opportunity space. Next, a Poisson regression provides insights into search distance, that is, where in the opportunity space subjects are searching. Finally, OLS regressions allow us to examine how the search performance can be explained.

What drives the stopping of entrepreneurial search?

Search behavior is influenced by the opportunity costs of search. Exploring a new opportunity (configuration) comes at the cost of not choosing the best configuration identified so far. This makes search in the experiment risky, since the performance of a new configuration may be less than the payoff from a prior configuration.

Figure 3 clearly indicates that subjects are inclined to stop searching which results in a decreasing share of active searchers over time. Only 18.7% of all subjects remain active searchers in the final round.

Please insert Figure 3 here

We use a Cox regression to estimate the likelihood of stopping to search in the opportunity space. The regression uses the set of feedback variables and examines their effect on the likelihood of breaking off entrepreneurial search (see Table 2). In the theory section, we hypothesized that negative performance feedback generally prolongs

entrepreneurial search (H1), while early negative feedback leads to an earlier stopping of search (H3a). We run two models, one with the basic parameters of the experimental treatment, and the other with feedback conditions that are unique for each subject and emerge during the search process.

Model 1 does not yield any significant result. Model 2 shows that the highest payoff that subjects has a major influence on the likelihood of search stop. The higher this payoff, the more probable is the stopping of search. Positive feedback thus leads to less risk taking and an earlier stopping of search. Interestingly, a different relationship is found for the feedback that subjects receive from search in prior rounds. Here we find for both wealth and prior payoff that higher values decrease the likelihood of stopping. This appears to contract our hypothesis on the relationship between performance feedback and entrepreneurial search. However, it appears that the subjects form subjective expectations about the prospects in an opportunity space. Positive feedback indicates that there are still potentially higher performing opportunities in the search space and this leads to more sustained entrepreneurial search. Thus, we can partly confirm our first hypothesis that positive feedback leads to a stopping of entrepreneurial search, while negative performance feedback prolongs search. Positive feedback has two effects: On the one hand, it raises the expectations about the opportunity space, on the other hand, it induces less risk taking.

Also remarkable is that ‘rounds since highest payoff’ is not significant, suggesting that subjects pay less attention to how far away their highest payoff is. In addition, imprint, i.e. the average accomplishments that subjects achieved in the first three rounds of their search, is highly significant for stopping behavior. Similar to the

highest payoff, subjects tend to stop earlier the higher the early performance feedback. This result confirms our conjecture that early impressions have an enduring on search dynamics by shaping the performance expectations of subjects. However, the sign of the effect is different from what we expected. This rejects hypothesis 3a.

Please insert Table 2 here

Where in the opportunity space do subjects search?

The second aspect of entrepreneurial search that we are interested in is where in the opportunity space subjects search. When do they search in the neighborhood of identified opportunities and when do they explore configurations that are more distant? We use a Poisson regression to examine the effects of performance feedback on the distance of search. Again, we ran two models (see Table 3); one model with the basic variables, the second model with our feedback variables. Model 1 essentially demonstrates the importance of complexity on search behavior. Model 2 offers deeper insights understanding by showing that higher complexity leads to a lower search distance. Hence, subject behavior is sensitive to the complexity of the landscape that she is searching in. In addition, subjects tend to broaden their search distance over time. This is quite remarkable as it shows that subjects either stop their search (see above) or opt to broaden search in the opportunity space.

Moreover, a higher prior payoff and a higher wealth in the previous round both lead to lower search distance, i.e. positive feedback narrows search, which is a clear indication for the hypothesized link between performance feedback and the distance of

entrepreneurial search. The highest payoff is insignificant. Rounds since highest payoff show a positive and significant relationship, i.e. subjects increase the search distance if they persistently fail to identify better-performing configuration. These findings thereby confirm hypothesis 2, as they show that both types of negative performance feedback, i.e. more rounds since highest payoff and perceived lower levels of higher payoff, lead to more explorative search. For imprint, we find that early negative feedback has once again a lasting effect on search dynamics. Initial negative feedback results in a lower search distance and less exploration of the opportunity space. This confirms hypothesis 3b.

Please insert Table 3 here

What explains the performance of subjects?

To support our analysis, we also examine the drivers of performance. The following OLS regressions examine the relationship between complexity, search behavior, and accumulated wealth, the dependent variable (see Table 4).

Please insert Table 4 here

The baseline results in model 1 are straightforward. The more complex a landscape the lower is the performance. Model 2 shows that the higher the average search distance the lower the performance; hence more explorative search does not pay off. This indicates that the prominent formal assumption of local search (Levinthal 1997), i.e. one bit flip per time step (translates in a search distance of one), warrants better performance than broader search (note that the mean search distance in the experiment is 2.35). At the

same time, a high imprint leads to high performance. Hence, imprint seems to stimulate entrepreneurial behavior suited to create performance improvements. We also find that average rounds since highest payoff is insignificant.

The OLS regressions reveal the importance of complexity, search distance and imprinting. While it is intuitive is that a low complexity landscape facilitates the achievement of high performance, it is remarkable that lower, rather than higher search distances lead to higher performance. Moreover, the role of imprint is important, as it seems to predetermine how subjects engage in later rounds of their search process. These basic results point to nuanced relationships between these variables.

Discussion

This paper examines features of the entrepreneurial search process that prior research has neglected. First, we selected an experiment to be able to focus and isolate on a few controllable variables of interest. These variables include feedback during the entrepreneurial search process (Cyert and March 1963; Gatewood et al 2002) and varying complexities of the search space (McKelvey 2004). Second, we developed an experimental framing that allowed for the exclusive examination of entrepreneurial search in an uncertain environment (cf. McMullen & Shepherd 2006). With the Alien Game, the role of prior knowledge is largely irrelevant for the search process. This allows us to concentrate on behaviour in a stylized entrepreneurial environment. Third, underlying our experimental design is the NK model (Levinthal 1997), which provides a formal conceptualization of the entrepreneurial search space. This is useful because results offer empirical insights for predictions that derive from prior formal work on

individual level search and decision making in management studies (Gavetti and Levinthal 2000, Gavetti 2005, Gavetti et al. 2005). Fourth, we chose an average student and examined her search behaviour with regards to entrepreneurial behaviour. This approach is dissimilar to prior entrepreneurship research, which typically pre-selects entrepreneurs, managers and/or non-entrepreneurs (e.g. Kaish and Gilad 1991, among many others) to examine the differences between different groups. We made all of the above choices to examine baseline entrepreneurial behaviour of human agents.

Our results show that subjects searching an opportunity space are heavily influenced by the feedback they receive during their search process. A first important insight is that imprint, i.e. the results from initial rounds of searching, predicts performance at the end of the search process. This is surprising because the NK landscapes, which subjects are searching in, are randomly generated and search heuristics only help in the non-complex (i.e. $K = 0$) landscape but not in the complex landscapes. Hence, the results show that initial performance feedback in early rounds influences search behaviour despite the randomness of the landscape. This is remarkable as it confirms prior conceptual work (Denrell and March 2001; March 2006) by showing that imprinting may pre-determine entrepreneurial behaviour among human beings simply based on the entrepreneur's initial luck.

Another important insight derives from subjects' stopping behaviour which we find to be highly relevant in our setting (see Figure 3). At the end of the search, most of our subjects have withdrawn from active search. They simply rely on the accumulation of the already achieved highest payoff. This points to an important aspect of search, namely the role of opportunity costs. In our experiment, subjects have realized that additional

search would compromise on existing performance. Withdrawing from entrepreneurial activity is therefore a possible, and in our case also quite reasonable solution. This finding is in line with work on the ‘status quo bias’ (Burmeister and Schade 2007), as it shows that individuals tend to stick to previously identified alternatives in the opportunity space. Moreover, our results highlight that waiting and optimal stopping (Sandri et al 2010) is crucial in entrepreneurial activity. We add to this stream of research by isolating two additional parameters, namely, (a) imprinting, i.e. the initial feedback in entrepreneurial search, and (b) opportunity costs, i.e. the cost related to deviating from an already identified opportunity. We find that both variables are important in entrepreneurial activity, as they may be used not only to manipulate status quo biases, but also to foster entrepreneurial search.

Feedback is also more generally of interest and our assessment the various variables reveal interesting artefacts. Both types of basic prior performance, i.e. performance in the preceding search attempt as well as the accumulated performance of all previous search attempts, are significant for determining both stopping and the breadth of search. While this confirms what one would expect, more interesting is the highest performance that subjects have achieved so far. This variable not only provide subjects with a benchmark for what is good and bad (our subjects do not have any other reference points), the frequency of the occurrence also offers insights regarding how often the subject receives negative performance and how well the search strategy works (see Figure 2). In particular this history of negative performance (rounds since highest payoff) is not significant for predicting stopping behaviour, but it does predict the breadth of search. We find that the longer the history of negative performance, the higher the search

distance. This finding holds among the active searchers whose share significantly decreases over time (with less than 20% at the end). Hence, we empirically find that only a few subjects are prepared to broaden search despite negative performance feedback. Broadly, this confirms studies of entrepreneurial task effort and search intensity (Cooper et al 1995; Gatewood et al 2002) and shows that the observation of how a general subject reacts to basic feedback conditions may allow for an early identification of entrepreneurial behaviour and traits.

The regressions clearly show important characteristics of entrepreneurial search behavior. Early feedback, measured as imprint, is significant and important for understanding behavior. However, our results on early performance feedback also present an interesting puzzle. Positive initial feedback induces search dynamics leading to an earlier stopping of search. This result contrasts with the influence of early performance feedback on search distance, where it substantially increases the proclivity to engage in more distant search. These findings point to the different meanings of exploration in the entrepreneurship and in the management literature. In the organizational search literature, exploration is usually associated with a higher distance of search. That is, agents engaging in exploration try out more distant alternatives by changing more than one attribute. Early performance feedback increases the proclivity to engage in more distant search. In the multi-arm bandit literature (e.g. March 1991), often considered as the canonical setting of the exploration-exploitation tradeoff, exploration relates to actively seeking out new information. This corresponds to the sustained search for new alternatives in the opportunity space. At least in the experiment, early performance feedback induces an earlier break-off of exploration in favor of exploiting a configuration

identified earlier. Disentangling these two effects of performance feedback on search behavior surely warrants further research.

Finally, our results provide empirical traction for formal work on the NK model in management. Our results not only confirm basic predictions of the NK model (see e.g. Figure 1a), the identified feedback variables also provide empirically based measures of what backward looking behaviors may consist of (Gavetti and Levinthal 2000). Moreover, the regression results offer predictions and causal mechanisms, which may be useful for future formal modeling.

Limitations and concluding remarks

Our study has certainly a number of limitations, including the abstract framing with the Alien Game (which is also part of our motivation). A more applied scenario may create different results. Another limitation is the statistical analysis, which could be more sophisticated. However, given the objective of this paper, we find that strong baseline results are a sufficient and important first step. We also suggest that all these limitations offer good opportunities for future research.

This paper is an attempt to distil baseline entrepreneurial behavior among average subjects. We think that our general, formal-based design is especially suited for this purpose and we are excited that we find significant and what we think are important results. We also think that research along these lines, i.e. the examination of fundamental entrepreneurial search activity is important for the development of entrepreneurial theories which are both empirically grounded and formally supported. We hope that our approach will encourage similar research.

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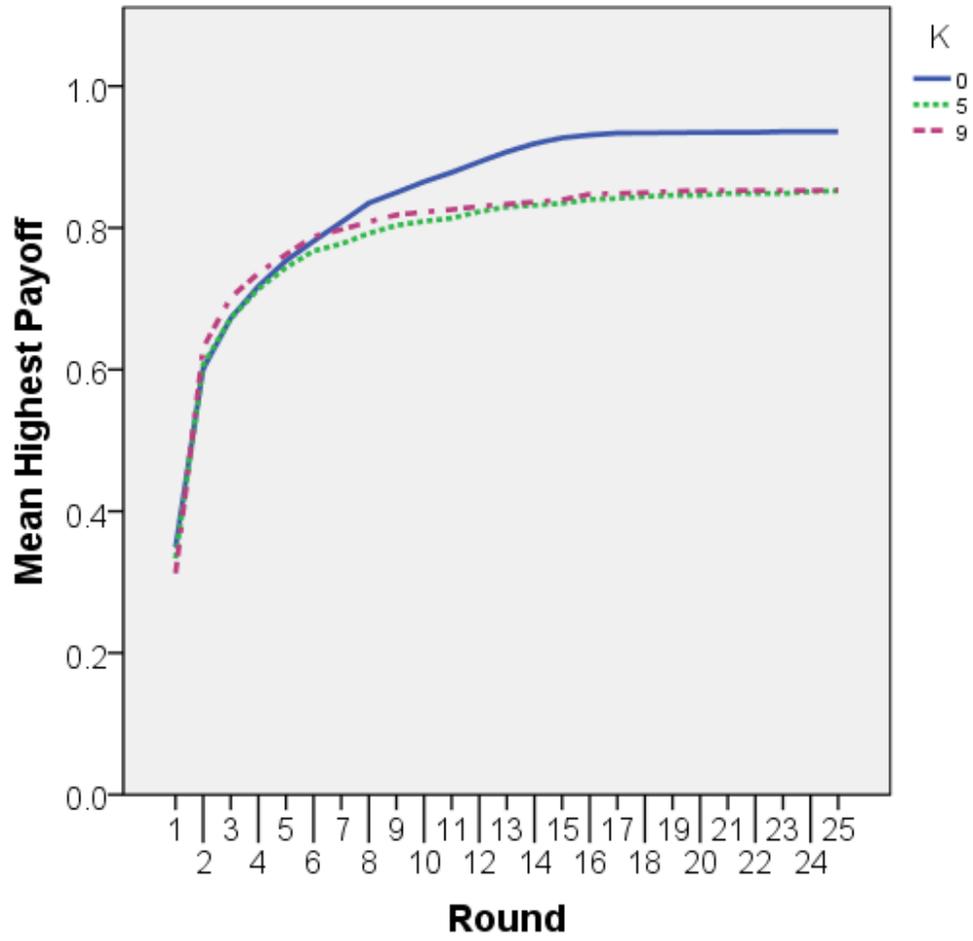


Figure 1a: Highest Payoff over time

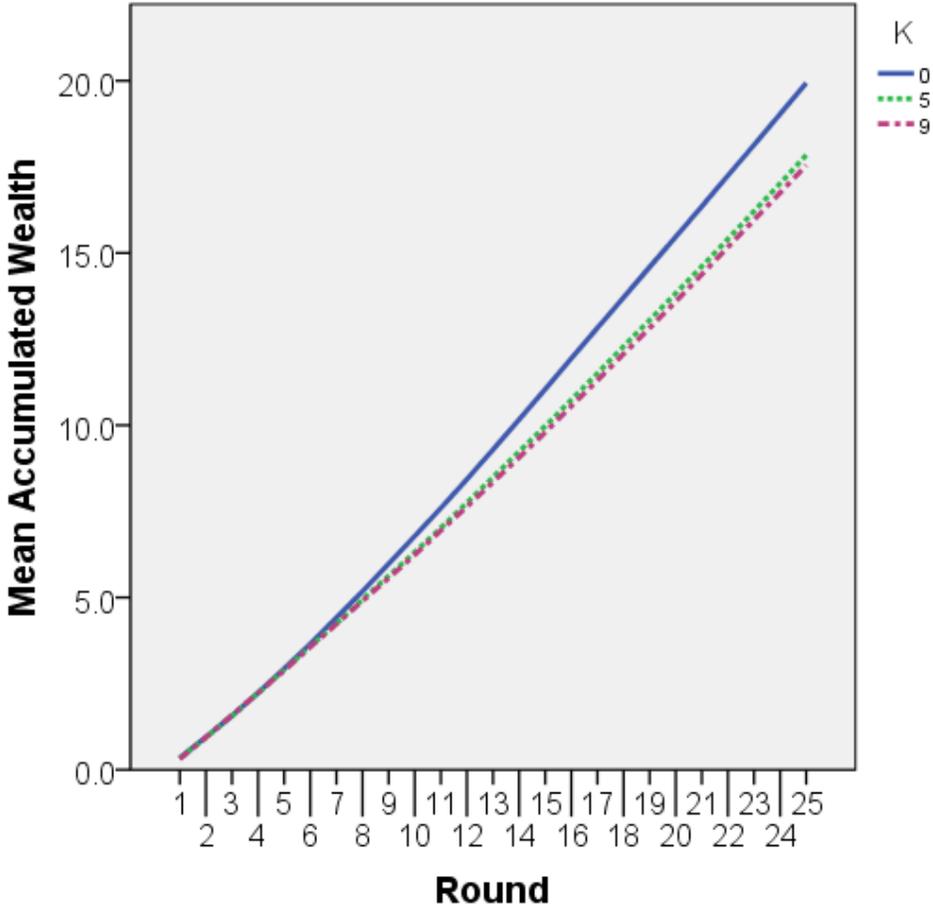


Figure 1b: Accumulated Wealth over time

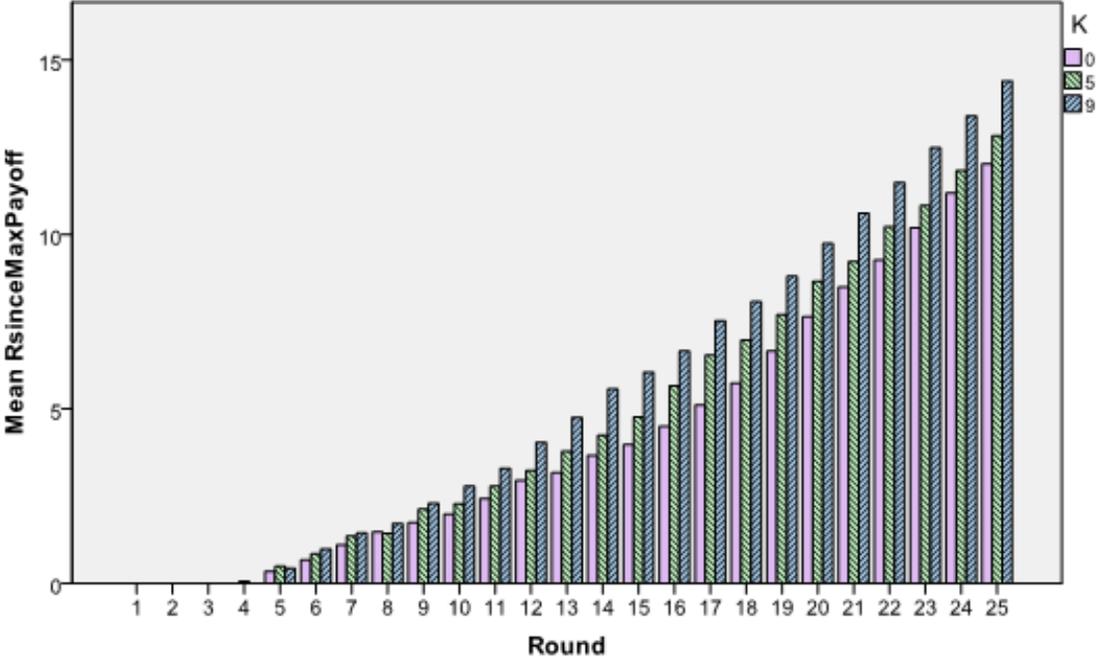


Figure 2: Evolution of negative performance feedback

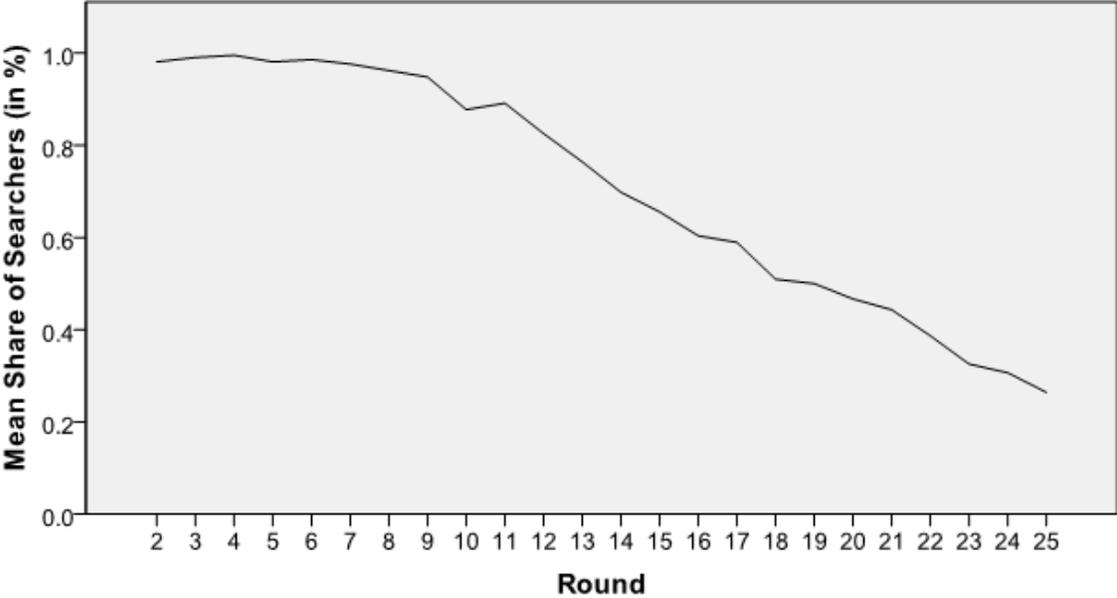


Figure 3: Subjects stop exploring the opportunity space

Table 1: Variables

Name	Type	Min	Max	Mean	Standard Deviation	Explanation
Average Rounds since Highest Payoff	discrete	0	9.63	1.85	2.00	Average 'Rounds since Highest Payoff' in round 25
Average Search Distance	scale	0	10	2.06	1.475	Average Hamming distance in round 25
Game position 1 / 2 / 3	discrete	1	3	-	-	Treatment (Ordering of landscapes)
Highest Payoff	scale	0.31	1	0.81	0.15	Highest payoff that subject has identified so far
Imprint	scale	1.12	2.23	1.58	0.19	Average performance after 3 rounds of search
K = 0/ K = 5/ K = 9	discrete	0	9	-	-	Complexity / ruggedness of landscape
PriorPayoff	scale	0	1	0.70	0.22	Performance in a previous round
Round	discrete	1	25	-	-	Number of rounds (trials) within game
Rounds since Highest Payoff	discrete	0	21	4.78	5.19	Number of trials since the subject has achieved the last maximum payoff
Search Distance	discrete	0	10	1.47 2.35	1.92 1.96	Hamming distance in - all rounds - active search rounds
Wealth	scale	0.31	23.43	8.96	5.60	Accumulated performance

Table 2: Stopping of search

	Model I	Model II
K = 5	-0.11 [0.188]	-0.339 [0.217]
K = 9	-0.066 [0.192]	-0.627 [0.216] **
Game Position 2	0.69 [0.195]	0.401 [0.201] *
Game Position 3	0.174 [0.191]	0.530 [0.196] *
Highest Payoff		10.291 [1.297] ***
Wealth		-3.696 [0.311] ***
Prior Payoff		-1.585 [0.628] *
Rounds since Highest Payoff		-0.034 [0.020]
Imprint		2.115 [0.485] ***
Time dependent covariate		0.130 [0.014] ***
-2 Log Likelihood	2426.996	1877.577
Chi-square	1.045	322.479
Number of games (events)	210 (167)	210 (167)

Cox regression with wealth as time-dependent covariate and search stop as dependent variable. Standard errors are reported in brackets.

* indicates significance at the $\rho < 0.05$ level, ** at $\rho < 0.005$ level, and *** at $\rho < 0.001$ level

Table 3: Search distance

	Model I	Model II
Complexity with K = 5	0.105 [0.0371] *	-0.100 [0.0372]*
Complexity with K = 9	0.149 [0.0379] ***	-0.106 [0.0395]*
Round	0.021 [0.0026] ***	0.132 [0.0162] ***
Prior Payoff		-0.883 [0.1400] ***
Wealth		-0.175 [0.0226] ***
Rounds since Highest Payoff		0.028 [0.0049] ***
Highest Payoff		0.030 [0.2201]
Imprint		0.740 [0.1000] ***
Game Position 2	0.004 [0.0369]	0.040 [0.0349]
Game Position 3	-0.057 [0.0373]	-0.048 [0.0357]
Scale	1.139	1.002
Deviance	3251.440	2854.433
Log-likelihood	-1241.689	-1043.185
Pseudo-R2	0.0364	0.1616
N	2861	2861

Poisson regression with robust estimators. Standard errors are reported in brackets. The sample (N = 2861) includes all search trials with a search distance greater than zero.

* indicates significance at the $\rho < 0.05$ level, ** at $\rho < 0.005$ level, and *** at $\rho < 0.001$ level.

Table 4: What explains the subjects' wealth in round 25?

	Model 1	Model 2
K	-0.272 [0.033] ***	-0.244 [0.026] ***
Game Position	-0.088 [0.148]	-0.081 [0.116]
Average search distance		-0.937 [0.86] ***
Average Imprint		4.256 [0.542] ***
Average Rounds since Highest Payoff		-0.080 [0.046]
R squared	0.251	0.576
N	210	210

Ordinary least-square regression (OLS).

* indicates significance at the $\rho < 0.05$ level, ** at $\rho < 0.005$ level, and *** at $\rho < 0.001$ level