Oliver Baumann*

Search, Failure, and the Value of Moderate Patience**

Abstract

Conventional wisdom suggests that successful innovation in complex and novel environments requires patience – persistence despite failures – to ensure broad search for good solutions. Using an agent-based simulation model, I show that the link between patience and innovation is complex: Moderate levels of patience promote broad and effective search. High levels of patience, in contrast, can have unintended effects and even decrease performance despite increasing the degree of search. Furthermore, because translating the gains of patience into performance improvements requires time, low levels of patience are generally optimal for shorter time frames. My findings indicate that paying attention to how patience affects both the explorative and exploitative aspects of search can show when patience may effectively boost innovation.

JEL-Classification: C63, D83, O31.

Keywords: Agent-Based Simulation; Complexity; Experimentation; Moderate Patience; Search; Innovation.

1 Introduction

When firms need to solve complex and novel problems, they face a managerial dilemma. Because complexity results in high-dimensional solution spaces with numerous local optima, firms must search broadly for good solutions (Simon (1962); Levinthal (1997)). But if there is a genuinely new problem, then action-performance links are largely undefined, and firms cannot assess the usefulness of potential solutions through "offline" (cognitive) mechanisms such as calculations, thought experiments, or computer simulations. Instead, firms often can only evaluate candidate solutions through "online" exper-

* Oliver Baumann, Munich School of Management, Ludwig-Maximilians-Universität München, Ludwigstr. 28, 80539 München, Germany, phone: +49-89-2180-2982, fax: +49-89-218-99-2982, e-mail: baumann@lmu.de.

** For helpful comments on a prior version of this paper, I thank Shmuel Ellis, Donald Hatfield, Mu-Yen Hsu, Markus Lang, Dan Levinthal, Dirk Martignoni, Nils Stieglitz, the editors Dodo zu Knyphausen-Aufseß and Arnold Picot, two anonymous reviewers, and participants at the DRUID Summer Conference, the AOM Annual Meeting, the Israel Strategy Conference, and the Workshop of the Organization Section of the German Academic Association of Business Research. All remaining errors are mine.

iments, i.e., by implementing an alternative and observing its performance (Gavetti and Levinthal (2000)). However, although such experiential learning creates new knowledge, it entails a high risk of failures. Both conventional wisdom and various accounts in the academic (e.g., Fleming (2001); Thomke (2003); Cannon and Edmondson (2005)) and practitioner domains (Farson and Keyes (2002); Petroski (2006)) thus suggest that successful innovation requires patience, i.e., persistence despite failures[1].

For example, consider the anecdote of how Thomas A. Edison designed the first commercially useful incandescent light bulb (Israel (1998)). While searching for a high-performing configuration of the various interdependent design elements, which eventually included using a U-shaped carbon filament in an oxygen-free environment, Edison experimented with thousands of alternative design variants, appreciating the numerous failures he experienced ("I have not failed. I've just found 10,000 ways that won't work") and committing himself to being patient ("I am not discouraged, because every wrong attempt discarded is another step forward").

Hence, this line of reasoning suggests that patience is positively linked to innovation. Firms that continue to search despite experiencing failures will experiment with a higher number of alternatives and thus are more likely to identify innovative solutions. But is patience generally beneficial, and what performance trade-offs are associated with different levels of patience?

The issue of choosing a degree of patience relates to a broader class of problems that go beyond the challenge faced by firms that are experimenting with different design variants. Similar to complex technologies, firms as a whole have been conceptualized as systems of interdependent activities (Milgrom and Roberts (1995); Porter (1996); Siggelkow (2002); Gavetti and Rivkin (2007)). Firm managers are perceived as trying to find coherent and high-performing sets of activities, but when an environmental shock degrades their existing configuration, managers may have to experiment with completely new courses of action. How patient should firms be when searching for new activity configurations? A similar problem arises for new ventures. Start-up firms must engage in a range of activities before they can launch (Garud and Van De Ven (1992); Ravasi and Turati (2005)). But in emerging industries, business models and knowledge of successful practices are not yet established. Again, what are the implications of exhibiting different levels of patience when a firm is searching for a set of good activity choices?

To shed light on these issues, in this paper I draw from two related, but separate, areas of study. One stream of work generates insight into the role of failure and patience in innovation (e.g., Vincenti (1990); Petroski (1992); Thomke (1998); Lee et al. (2004)), but does not speak to how patience affects the search processes that lead to performance. The other stream models problem-solving search in new, complex environments (e.g., Levinthal (1997); Rivkin (2000); Winter, Cattani, and Dorsch (2007)), but largely assumes

1 The notion of "patience" comes with a number of (slightly) different connotations. In the course of this paper, I define it as persevering in an active search despite failures, rather than the passively waiting for an unpleasant situation to pass.

that firms can evaluate new alternatives through offline analyses. However, the notion of online trials has received little attention (for an exception, see, e.g., Gavetti and Levinthal (2000)). Hence, little is known about how search is affected by different levels of patience, and whether and how the value of patience is contingent upon the complexity and novelty of a problem.

In this paper I provide an initial integration of these two literatures by embedding in an agent-based simulation model stylized features of failure and patience in problem-solving search. The model comprises firms that face new, complex problems and search for better alternatives to their current solutions. By controlling how many failures firms are willing to tolerate, I systematically analyze how patience affects the dynamics of search and, ultimately, firm performance.

Even in this model set-up, counterintuitive effects can arise that show how patience and innovation interact in nontrivial ways. I find that moderate levels of patience – tolerating some degree of failure before abandoning a search path and starting over – promote broad and effective search. Also, the newer and more complex a problem is, the more distinct this benefit of moderate patience becomes. In contrast, high levels of patience can have unintended effects and even decrease performance despite further increasing the overall degree of exploration. This result arises because firms fail to confine the exploration that patience brings about, instead searching erratically and drifting away from potentially good solutions. Furthermore, since translating the gains of patience into performance improvements requires time, low levels of patience that result in more local search are generally optimal for shorter time frames.

The results of this paper relate to the trade-off between exploration and exploitation (Holland (1975); March (1991)). They suggest that to gain insight into the link between patience and innovation, paying attention to how patience translates into exploration is necessary but not sufficient. Rather, one must consider how patience affects the process by which the exploration of a new context will eventually be replaced by the exploitation of the newly identified opportunities. My findings also suggest that if managers seek to boost innovation, then trying to act on their organization's level of patience with respect to affecting this transition is more valuable than merely trying to increase the sheer amount of search.

The paper is structured as follows. The next section reviews prior research. Section 3 describes the model, while Section 4 presents the results of the simulation experiments. Section 5 discusses the findings. Section 6 concludes.

2 Prior Research and Propositions

2.1 Prior Research on Failure and Patience in Innovation

Given the costs and wasted effort that failed experiments entail, problem solvers may set limits on how many failures they are willing to tolerate. But what determines this level of patience? Clearly, one factor is personality. For example, the high degree of persistence that can often be observed among entrepreneurs or engineers (Garud and Van De Ven (1992); Forbes (2005); Lowe and Ziedonis (2006)) is typically attributed to behavioral traits such as overconfidence, optimism, passion, or foolishness (Kahneman, Slovic, and Tversky (1982); Baron (1988); March (2006)). In contrast, most other individuals tend to avoid courses of action that may result in failures (Thomke (1998); Lee et al. (2004)).

Another determinant is the experimentation environment that affects both the costs of failing and the costs and ease of reversing a failed experiment. The latter issue relates to the fact that the firm does not know the distribution of alternatives in advance, and that it usually encounters alternatives sequentially. Hence, if a decision maker hopes to find an even better alternative, he may discard his current solution despite the alternative being among the best available. If he is able to return to an option that has previously been passed over, he is said to "recall" the alternative, thus reversing the previous experiment(s) (Gigerenzer, Todd, and the ABC Research Group (1999)). For example, consider a software designer. If she finds that her recent experiments have degraded the performance of the project, she may easily revert to an old version that she knows has a satisfactory performance. In this case, the cost to recall will pertain only to the time invested in making and testing the eventually fruitless modifications. In contrast, a firm that is not satisfied with its performance after an acquisition can also return to a previous state. However, the degree of sunk costs and the time required to undo the investment will be different in magnitude. Thus, patience is typically higher in a lab environment, where experiments are frequently undertaken with the knowledge that they may fail, but in most organizations, there is heavy pressure to avoid failure (Denrell and March (2001); Thomke (2003); Lee et al. (2004)).

A third determinant relates to the time horizon. For example, in basic R&D, it is an accepted fact that to explore freely and broadly, problem solvers need sufficient time, allowing them to tolerate longer periods during which their search efforts may not bear fruit. On the other hand, consider product development in a fast-paced environment (Bourgeois and Eisenhardt (1988); Eisenhardt (1989); Fine (1998)). Here, decisions need to be made quickly, and product designers or managers will usually be given little time to demonstrate the feasibility of a concept and improve the performance of the initial prototypes. But by using techniques such as concurrent engineering or front-loading (Loch and Terwiesch (1998); Thomke and Fujimoto (2000); Loch, Terwiesch, and Thomke (2001)), firms try to speed up the search process and evaluate the potential of a product early on. In this context, product designers may not be able to have much patience for tinkering around with a concept. Instead, they may have to make the best out of a given idea and limited time, i.e., exploit a current concept as efficiently as possible.

But why, in the first place, should firms be patient at all? One major advantage of online experiments, despite the failures they may entail, is that when the paths of cause and effect are uncertain, tests generate knowledge (Allen (1977); Thomke (1998); Fleming (2001); Thomke (2003)). Hence, failures are appreciated, as they often denote an interim stage on a problem solver's journey of knowledge creation. Further, tolerating failures may be essential to accumulating a "sufficiently" large and focused body of knowledge (Popper (1959)). Vincenti (1990) gives detailed insights into the processes of knowledge creation in the early days of the aviation industry. As engineers faced the challenge of designing airfoils that had the desired lift and drag needed for a particular aircraft, they tested hundreds of different airfoils in actual trials. Only after experience had generated sufficient insight into what did or did not work and under which conditions, could they derive an aerodynamic theory that could then substitute for many online trials. In other words, they could evaluate further alternatives without the risk of failures. Petroski (1992; 1994; 2006) gives a different appreciation of failure in engineering design. He shows, for various cases from engineering history, how multiple failures often preceded the emergence of a successful design. In his view, by triggering further search that might lead to high-performing designs, designs which might not have been conceivable without taking the intermediate steps that were unsuccessful, failures can act as a stepping-stone toward important breakthrough solutions. Thus, these arguments suggest a positive relation between patience and performance:

Proposition 1a: *Higher levels of patience lead to broader search that will result in higher performance in the long run.*

However, some research also shows that the value of failure comes not only from creating knowledge or acting as a stepping-stone, but from the fact that it can trigger change. For instance, failures may convince problem solvers to abandon their current search path and try other routes instead (Petroski (1992)). For example, in the design process, "… the final version is [sometimes] closer to the first than any of the intervening versions" (Petroski (1992)). Hence, if a chosen search path is a dead end, a high degree of patience, which is often driven by an escalation of commitment, may translate into extensive search, but still result in the eventual failure of the particular project (Biyalogorsky, Bouldin, and Staelin (2006); Välikangas (2007)). Thus, understanding failures is important to improving performance (Thomke (2003)), because "… products are the result of as many failed experiments as successful ones [,] an innovation process … is at least partially based on 'accumulated failure' that has been carefully understood." In other words, failures need not only be endured, but the resulting knowledge must be utilized to correct actions (Mach (1905)). However, firms often possess no systematic culture and process for learning from failure, or fail to address this issue altogether (Tucker and Edmondson (2003); Baumard and Starbuck (2005); Cannon and Edmondson (2005)), "sweeping" failures "under the carpet". These considerations raise an alternative view:

Proposition 1b: *Higher levels of patience will not necessarily lead to higher organizational performance if the firm fails to learn from the increased level of search.*

The discussion above also suggests that when the level of patience is low, a firm will search less broadly and might explore only the neighborhood of its current solution, since it will not be willing to tolerate failures for an extended period of time. However, the local knowledge that is created enables the firm to take actions in this local context more quickly. Therefore:

Proposition 2: *Low levels of patience lead to local search and support the short-term improvement of a firm's current status.*

2.2 Prior research on Search in Complex and Novel Environments

Due to bounded rationality (Simon (1955; 1956)), firms need to search for new decision alternatives rather than optimize over a collectively known set of options, as assumed in neoclassical theory (March and Simon (1958); Cyert and March (1963)). But how do the complexity and newness of a problem affect the dynamics of search and the value of different degrees of patience? Following Simon (1962), I conceive of complex problems as systems that consist of a large number of elements that have many interactions. One property of such systems is that with a rising number of interactions between its elements, local peaks – internally consistent configurations of the system elements that cannot be improved through incremental changes – proliferate (Kauffman (1995); Levinthal (1997); Rivkin and Siggelkow (2007)). This property of complex problems increases the risk that constrained exploration will trap a firm on a low local peak, thus making broader exploration more beneficial. Furthermore, a higher number of system elements, ceteris paribus, makes problem-solving search more demanding, because it significantly increases the number of potential combinations of these elements, expanding the space in which problem solvers conduct their search for good solutions (Simon (1996)). Hence, to identify superior configurations, higher levels of search are critical. Concerning the complexity of a problem, this discussion suggests:

Proposition 3: *High interdependence between the system elements makes high levels of patience more valuable.*

Proposition 4: *A large number of system elements makes high levels of patience more valuable.*

However, it is important to determine how a firm knows whether a new alternative is satisfactory. Because prior modeling efforts have focused mainly on the discovery aspects of organizational search, the mechanisms by which new alternatives are evaluated have received less attention. Here, the dichotomy of offline and online evaluation (Lippman and McCall (1976); Levitt and March (1988); Gavetti and Levinthal (2000)) offers helpful assistance. The various mechanisms that fall into the offline domain are close to Freud's (1912) notion of thinking as internalized experimental action ("internalisiertes Probehandeln"). Hence, a firm will only adopt an alternative if offline reasoning has proven the superiority of the idea. Online (or experiential) evaluation is characterized by a strong "try-it-and see" aspect, requiring a firm to implement an alternative in order to learn about its value. Thus, online experiments are riskier than offline assessments, since they require departing from the status quo, and because the outcome of the trial is uncertain and may result in a failure. Hence, when a firm is faced with a problem but already has a certain degree of domain-specific knowledge, it can make a greater number of evaluations using an offline approach, thus decreasing the need to explore experientially. Because the firm can avoid adopting ideas that eventually turn out to be unproductive, it can efficiently build on its existing knowledge and quickly improve its performance. This behavior accords with March's (1991) notion of exploiting old certainties. In contrast, if the firm has only a little initial knowledge, it can only begin by exploring experientially, with higher levels of exploration proving more beneficial for generating wide knowledge.

With respect to the newness of a problem, this discussion suggests that:

Proposition 5: *High levels of initial knowledge in the domain of the search support the exploitation of a firm's current situation and correspond to low levels of patience.*

Proposition 6: *Low levels of initial knowledge in the domain of the search support the exploration of new alternatives and make high levels of patience more valuable.*

3 Model

To study the impact of different degrees of patience on the dynamics of search, I develop an agent-based simulation model. Computational models have gained broad popularity in studies of organizational search and learning (March (1991); Levinthal (1997); Gavetti and Levinthal (2000); Mihm, Loch, and Huchzermeier (2003); Winter, Cattani, and Dorsch (2007)) for a variety of reasons (Davis, Eisenhardt, and Bingham (2007); Harrison et al. (2007)). One is that they allow a more rigorous analysis than does verbal analysis, forcing the model's designer to make explicit all underlying assumptions. In contrast to algebraic approaches, computational models allow the researcher to incorporate a more complete set of features into the analysis. Although they cannot yield the "exact solutions" found in closed-form techniques, they do allow the researcher to model conditions of complex interactions under which algebraic approaches, such as the supermodularity framework for studying complementarities (Milgrom and Roberts (1990; 1995)), would be intractable. But most important, I am concerned with the question of how patience affects problem-solving search by decision makers who have only bounded rationality. Although exploring the underlying dynamics of search can be achieved with computational models, analytic models tend to be concerned with equilibria, not with the question of how, or whether, they will be attained.

The basic principle of agent-based simulation is straightforward (Macy and Willer (2002)): Decision-making agents such as firms, managers, or designers are confronted with controlled environments. They are equipped with heuristics that enable them to react to their environment, and the resulting behavior is recorded over time. By varying the behavior of the agents and the structure of the environment, I can systematically explore the impact and interdependence of the variables under consideration.

3.1 Complex Problems

I conceptualize firms as facing a set of interdependent decisions (Porter (1996); Levinthal (1997); Siggelkow (2002)). To explore and learn about this environment, a firm's managers or designers need to make many decisions. For instance, the designers of a jet engine might have to decide on the power of the engine or the materials that are used to manufacture it. Or a manager might have to decide on the firm's product variety or about the features of its production system. Furthermore, many of these decisions interact with one another. For example, the value of a powerful jet engine might depend on whether the structural properties of the materials from which it is made can endure the corresponding forces. Similarly, the value of flexible manufacturing capabilities will increase as a firm increases its product variety.

In the model, each firm must resolve N decisions $a_1, a_2, \ldots, a_N$. Without loss of generality, I assume that each decision is binary. For instance, a_1 might denote the decision to increase product variety $(a_1 = 1)$ or not $(a_1 = 0)$. Therefore, a firm faces 2^N possible configurations of choices, each of which can be represented by a binary vector $\boldsymbol{a} = (a_1, a_2, \ldots, a_N)$.

In computational studies of firms as complex adaptive systems, researchers often interpret the payoffs to configurations of interdependent choices as performance landscapes (Levinthal (1997); Rivkin (2000)). A performance landscape comprises N "horizontal" dimensions, the N decisions that the firm must make; and one "vertical" dimension that denotes the corresponding performance of each configuration. Thus, a performance landscape represents a mapping of each configuration $\boldsymbol{a}$ (each "point" on the landscape) to a performance value $V(\boldsymbol{a})$ (the "height" of the particular point).

I create performance landscapes with a variant of the NK model (Kauffman (1993; 1995)) – stochastically, yet in a well-controlled manner. The NK model has been developed in evolutionary biology and has recently been applied to a number of organizational issues (e.g., Levinthal (1997); Rivkin (2000); Ethiraj and Levinthal (2004); Lenox, Rockart, and Lewin (2006)). In the model, I assume that each decision a_i contributes c_i to the performance $V(\boldsymbol{a})$ that a firm receives from a particular configuration of choices $\boldsymbol{a}$. The contribution c_i of each decision a_i depends not only on how a_i is resolved (0 or 1), but also on the state of K other decisions $(\boldsymbol{a_{-i}})$ that interact with a_i. Hence, K controls the degree of interdependence between the decisions. When $K = 0$, all decisions are independent, and the performance contribution of each decision depends only on how the decision itself is resolved. In this case, the performance landscape is smooth and contains only a single peak. In contrast, if $K = N - 1$, then the value of each decision depends on how all other decisions are resolved. In this case, the landscape exhibits numerous local peaks. For each performance landscape I randomly determine the identity of the K decisions $\boldsymbol{a_{-i}}$ that influence the value of each decision a_i. Particular values for all possible c_i's are drawn from a uniform distribution over the unit interval, i.e., $c_i(a_i; \boldsymbol{a_{-i}}) \sim u[0;1]$. I calculate the value $V(\boldsymbol{a})$ of a given set of choices $\boldsymbol{a}$ as an average of its N performance contributions, i.e., $V(\boldsymbol{a}) = [c_1(a_1; \boldsymbol{a_{-1}}) + c_2(a_2; \boldsymbol{a_{-2}}) + \ldots + c_N(a_N; \boldsymbol{a_{-N}})]/N$. Thus, the parameters N and K make it possible to tune the complexity of a firm's environment in terms of size (N) and interdependence (K).

The landscape metaphor allows a natural representation of organizational search: Subject to its configuration of choices $\boldsymbol{a}$, a firm inhabits a particular point on the performance landscape. The firm searches for improvements to its current situation by identifying and evaluating alternative configurations. Its goal is to reach high points on the performance landscape, configurations of choices that create a high performance.

3.2 Problem-solving Search

In each period, each firm considers one alternative, $\tilde{a}$, that differs in only one decision from its status-quo set of choices a. Thus, if the firm is currently at 1000 (given $N = 4$), it has four alternatives available: 1001, 1010, 1100, and 0000. For instance, a jet engine designer might come up with an idea to modify the composite material that is currently being used. In a similar manner, a manager might think about modifying the firm's current production system by introducing new process-control software. Among the N possible local alternatives, each manager picks one at random. Hence, this procedure for generating alternatives that are similar to the existing configuration of choices represents a behavior of local search, a central feature in both theoretical (March and Simon (1958); Cyert and March (1963); Nelson and Winter (1982)) and empirical (Stuart and Podolny (1996); Rosenkopf and Almeida (2003)) accounts of organizational learning and adaptation. As noted earlier, cognitive bounds prevent managers from coming up with highly innovative ideas, i.e., with alternative configurations that differ in multiple dimensions from the status quo.

The evaluation of a newly identified alternative $\tilde{a}$ can proceed in either a cognitive (offline) or experiential (online) manner. If the firm needs to explore experientially, it must first adopt the new alternative by moving from point a to the nearby point $\tilde{a}$ on the landscape. Subsequent to the adoption of $\tilde{a}$, the firm learns whether the new alternative denotes an improvement over the previous configuration ($V(\tilde{a}) > V(a)$) or not ($V(\tilde{a}) < V(a)$). In the latter case, the firm has experienced a failure. However, independent from the exact performance of the new alternative, the firm has gained knowledge about the performance implications of a configuration that was then unknown. Should the firm encounter the same configuration again during the course of its further search, it could evaluate its relative attractiveness in an offline manner[2]. In the next period, the firm will generate another local alternative based on its new status quo set of choices.

The offline evaluation of a new alternative $\tilde{a}$ proceeds in the reverse order. Here, the firm can determine the value $V(\tilde{a})$ of the alternative without implementing the idea. If the firm finds that the alternative represents an improvement $(V(\tilde{a}) > V(a))$, then the firm will adopt the improvement and move from point a to the nearby point $\tilde{a}$ on the landscape[3]. In contrast, if the value of $\tilde{a}$ is lower than or equal to the value of the firm's current alternative ($V(\tilde{a}) \leq V(a)$), then the firm will discard the alternative and remain on its current point on the landscape, generating another local alternative in the next period.

Which alternatives a firm can assess offline is determined by the parameter $KNOW$ (with $0 \leq KNOW \leq 1$), which represents the firm's initial degree of knowledge in the domain of the new problem. Thus, $KNOW$ is an inverse measure for the fundamental novelty of

2 This property of the model assumes that a single evaluation act is sufficient to understand the (real) value of a new alternative. Issues such as search depth (Katila and Ahuja (2002)) or reinforcement learning (Sutton and Barto (1999)) are beyond the scope of this model. Also, I assume that there is no "organizational forgetting" during the search process.

3 To focus exclusively on the dynamics of patience and search, the model assumes that the firm always adopts the superior (offline) alternatives. Thus, it abstracts from many real-world intricacies involved in the adoption of innovations such as the role of promoters (Hauschildt and Gemünden (1999)).

the problem that the firm needs to explore. The value of $KNOW$ may be influenced by the fact that the firm has encountered similar problems before. It may also be actively shaped by investing in human capital or new technologies that increase the scope of the firm's offline evaluation capabilities. Hence, when $KNOW = 0$, the firm starts its exploratory search without any offline knowledge and initially needs to evaluate any alternative experientially. In contrast, if $KNOW = 1$, then the firm has the expertise to assess the value of any potential alternative offline. For all intermediate values of $KNOW$, the firm has the offline evaluation capabilities for the corresponding (randomly determined) fraction of all possible configurations.

Once a firm has implemented a configuration and knows that this alternative cannot be further improved by any local alternative, the search ends. In this case, the firm has reached a local peak on the landscape, which acts as a competency trap (Levinthal and March (1981); Levitt and March (1988)) and terminates a firm's exploratory search. A local peak is a configuration of choices $\boldsymbol{a}$ with $V(\boldsymbol{a}) > V(\tilde{\boldsymbol{a}})$ for all $\tilde{\boldsymbol{a}}$ that differ from $\boldsymbol{a}$ in one decision. However, a firm can only be sure it has reached a local peak when it has generated enough knowledge to determine by means of offline reasoning that all local alternatives would yield a worse performance than would its status-quo set of choices. If there remains only one local alternative that the firm cannot assess offline, then the firm cannot be sure that it has reached a local peak, because the unknown alternative might yield an even higher performance.

3.3 Different Levels of Patience

The uncertainty involved in an online evaluation poses the risk that the newly adopted alternative will yield a lower performance than the previous one[4]. But to explore uncharted areas on the landscape, firms may have to tolerate some degree of failure. To represent different approaches of how firms might deal with this issue, I introduce a patience parameter, PAT, that denotes the maximum number of periods that a firm is willing to tolerate, while exploring experientially, a performance that is below the performance of the best alternative thus far encountered[5]. Hence, the firm always "remembers" the present best alternative, and during its online evaluations, counts the number of periods in which it does not come up with an alternative that exceeds this benchmark[6]. If a firm finds a better alternative, it sets its "failure counter" back to zero and uses the newly found alternative as the new benchmark. In contrast, if the firm does not develop an alternative after PAT online trials, then it will discontinue its current path of exploration and re-implement the benchmark alternative. For instance, if $PAT = 1$, then the firm will be exploration-averse and make no more than one online evaluation that turns out to be a failure

4 In the model, I assume that firms have no assumptions about unknown alternatives. I also make no assumptions about a firm's risk preferences. The modeled firms do not seek, nor do they try to avoid, risky online trials subject to their current performance. They simply generate and assess new alternatives, independent of which "type" of evaluation (online, offline) is possible.

5 I note that offline evaluations that do not yield a performance improvement are not counted as failures, because they do not require a firm to depart from its status quo. However, incorporating the results of offline evaluations into the failure count does not qualitatively affect the results.

6 I do not discriminate between different degrees of failure, but instead count each period of below-benchmark performance as a failure, independent of whether performance is only slightly or very significantly below the benchmark.

before returning to its previous alternative. But if $PAT = 10$, a firm is much more likely to be exploration-seeking and will tolerate up to ten periods of underperformance.

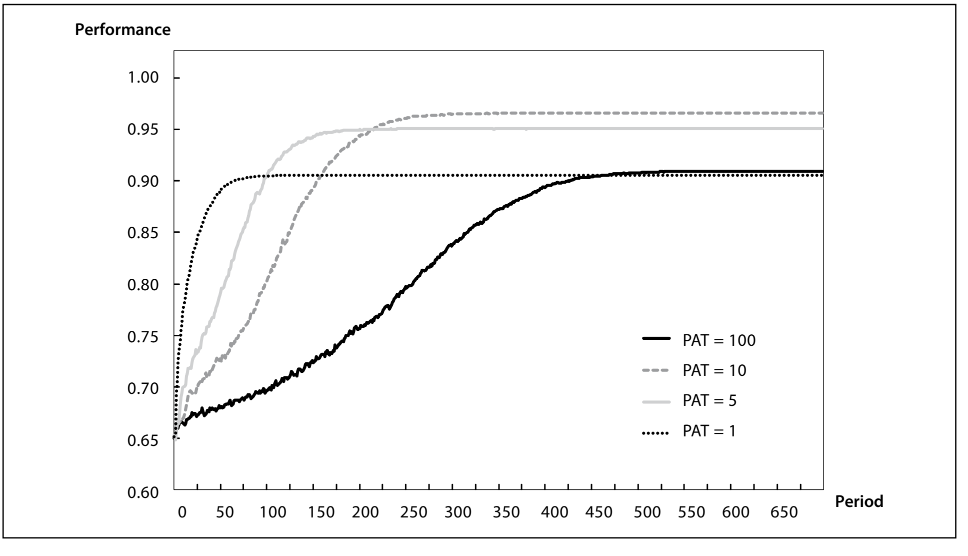
4 Results

To study the effects of patience on the dynamics of search, I place firms that differ in their level of patience (PAT) onto randomly chosen points of stochastically generated performance landscapes. Setting the firm's degree of initial knowledge ($KNOW$) and the size (N) and interdependence (K) of the performance landscapes makes it possible to tune the novelty and complexity of the environment. I then observe the firms' behavior for 1,000 periods, by which time all firms have reached a peak. I measure the performance of each firm relative to the global peak in each landscape. To ensure that performance differences are inherent to the model and do not result from any stochastic effects, I repeat each experiment for 1,000 different landscapes and calculate the average performance for each type of firm across all landscapes. All reported performance differences are significant at the 0.001 level.

4.1 Core Result: The Value of Moderate Patience

The firms that I consider first must explore a completely new $(KNOW = 0)$ and moderately complex $(N = 8,\ K = 4)$ environment, while differing in their patience (PAT) (see *Figure 1*).

Figure 1: Performance implications of different levels of patience

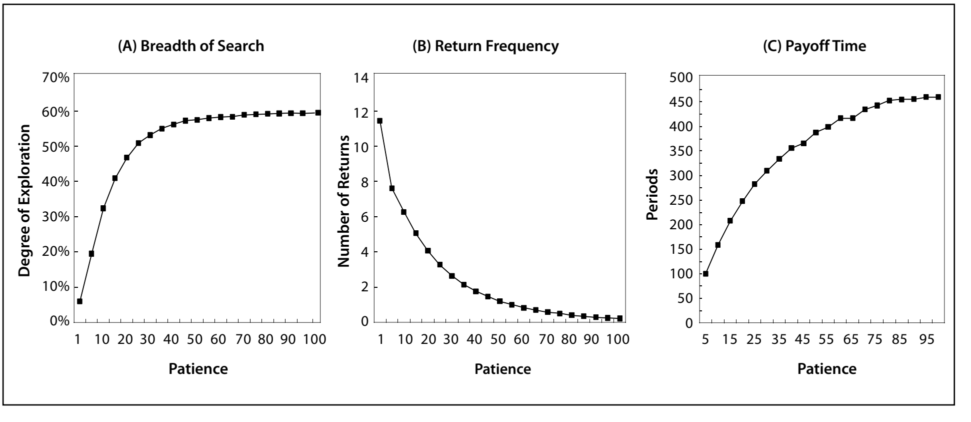


This figure reports the average firm performance over 1,000 landscapes with $N = 8$, $K = 4$. Firms differ in their level of patience *(PAT)*. All firms start their search without any offline knowledge *(KNOW* = 0).

Consider, at first, a firm that has only little patience $(PAT = 1)$. Its performance improves very quickly and then stabilizes. A firm with a medium level of patience $(PAT = 5$ or $PAT = 10)$ requires more time to improve, but eventually reaches a higher performance level. Finally, when the firm's patience is even larger $(PAT = 100)$, performance improves even more slowly, and eventually reaches a level that is even worse than what results from a lower level of patience.

Although these findings support the discussion about low levels of patience summarized in Proposition 2, they are not clear where higher levels of patience are concerned. The results support Proposition 1a for a medium level of patience, but the findings given high patience favor Proposition 1b. To examine the mechanisms that yield these performance implications, I repeat the same experiment for a broad range of the patience parameter. *Figure 2* reports various measures that show how different levels of patience affect the dynamics of search.

Figure 2: Impact of different levels of patience on the dynamics of search



Panel A reports the fraction of all different performance contributions (c_i) that a firm assesses during its search. Panel B reports the number of times that firms give up their search path and "start over" after persistent underperformance. Panel C illustrates the number of periods that firms with a higher level of patience (*PAT*) require to outperform a firm with a low level of patience (*PAT* = 1). All results are averages over 1,000 landscapes with $N = 8$, $K = 4$. Firms search for 1,000 periods. They differ in their level of patience (PAT) and start their search without any offline knowledge (*KNOW* = 0).

A firm with little patience uses online evaluations, but after a single, or even several, trial(s) that prove to be performance-decreasing, it returns to the best alternative that it has thus far encountered. Hence, the firm never dares to go very far from its respective benchmark configuration. Thus, it will explore only a small, local, fraction of the overall performance landscape (*Figure 2*, Panel A) and often return to its respective benchmark (*Figure 2*, Panel B). As the firm quickly creates knowledge about a local part of the landscape, offline evaluation becomes possible and allows the firm to make only performance-improving changes, drawing the firm uphill on a nearby local peak. In consequence, the firm's initial position strongly determines where it will finally end up. Nonetheless, however, the firm can efficiently exploit its local exploration of the landscape and quickly improve its performance.

For levels of moderate patience, the firm is willing to accept longer periods of underperformance; it will automatically move more intensively on the landscape, letting it explore more broadly (*Figure 2*, Panel A). Given the higher degree of exploration, chances increase that the firm identifies superior alternatives. Nevertheless, the firm's limited patience still frequently forces it to return to its respective benchmark configuration after a certain number of periods with below-benchmark performance (*Figure 2*, Panel B). But at the same time, higher degrees of exploration also require more time to improve performance than in the case of very low levels of patience (*Figure 2*, Panel C).

However, when the level of patience is even higher, the results are intriguing. Although high levels of patience yield even higher overall exploration of the landscape (*Figure 2*, Panel A), they also make it very unlikely that the firm will return to a benchmark configuration (*Figure 2*, Panel B). Because high levels of patience make the firm highly exploration-seeking, it drifts around the landscape erratically, thereby exposing itself to a great variety of different alternatives. Thus, instead of focusing its exploration efforts, it chases after every idea that comes its way. When the firm eventually builds up a sufficient amount of local offline knowledge to start hill-climbing, it is at a somewhat average position and consequently will settle on a rather average local peak[7].

Hence, the less patient a firm is, the more quickly it can improve its performance by creating local offline knowledge, but the more patient it is, the more broadly it will explore and the more slowly its performance will increase. However, to also exploit the higher degree of exploration, a moderate value of patience appears to be the most effective strategy. What makes moderate patience valuable is that it helps strike a balance between loosening and confining search efforts. On the one hand, tolerating underperformance for a moderate number of periods may allow a firm to move downhill, entering a valley and reaching the foothills of a better peak, thus escaping from the neighborhood of its current peak. On the other hand, the fact that patience is strictly limited forces the firm to continue to confine its exploration activities and creates a critical amount of local (broadly defined) knowledge that can eventually be exploited, allowing the firm to move uphill. In contrast, very high levels of patience further increase exploration in a time-consuming process, but yield no more gains. Instead, the firm fails to exploit the exploration that higher levels of patience entail and is drawn away from potentially good configurations, only to end up on an average local peak.

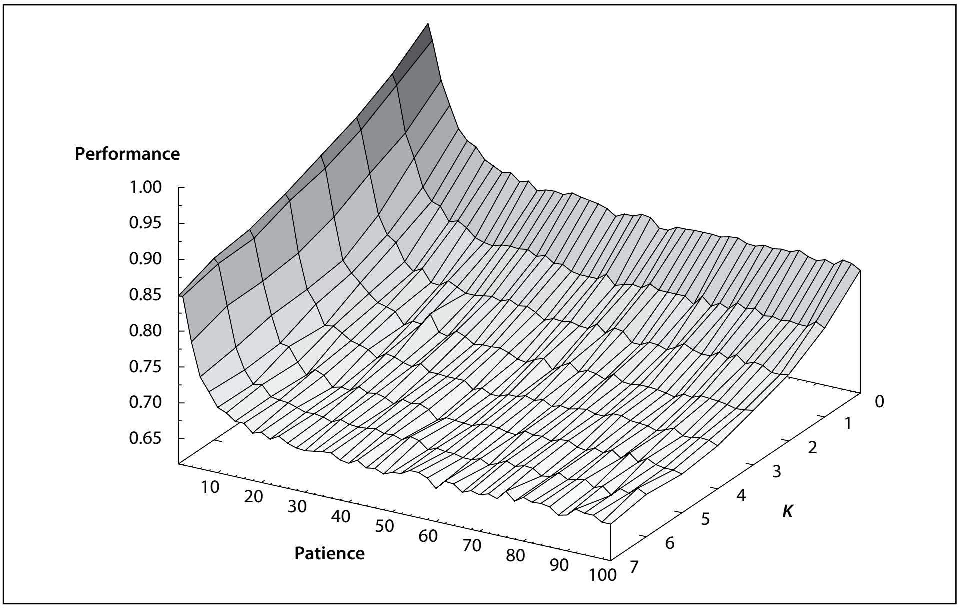
7 In accordance with behavioral accounts of organizational decision making, this behavior reflects the notion that only repeated failure will force a firm to give up its current path and make the major move back to some configuration that is distant in both space and time. However, once a firm can determine by offline evaluation that its current position is at a local peak, the high opportunity costs of giving up a current situation will instead lead to organizational inertia (Greve (2003)).

4.2 The Impact of Complexity on the Appropriate Level of Patience

Propositions 3 and 4, which are based on complex systems theory, state that a higher number of system elements and the interdependencies between them will make a higher level of patience more beneficial.

First, I consider the implications of interdependencies. By varying the degree of interdependence among the elements that the firm needs to explore, *Figure 4* shows partial support for Proposition 3: In the long run, higher degrees of interdependence do make patience more beneficial, but medium, rather than high, levels of patience again yield the highest performance[8]. In the short run (*Figure 3*), low levels of patience always prove beneficial, regardless of the degree of interdependence, thus yielding additional support for Proposition 2[9].

Figure 3: Short-term effects of different levels of interdependence and patience

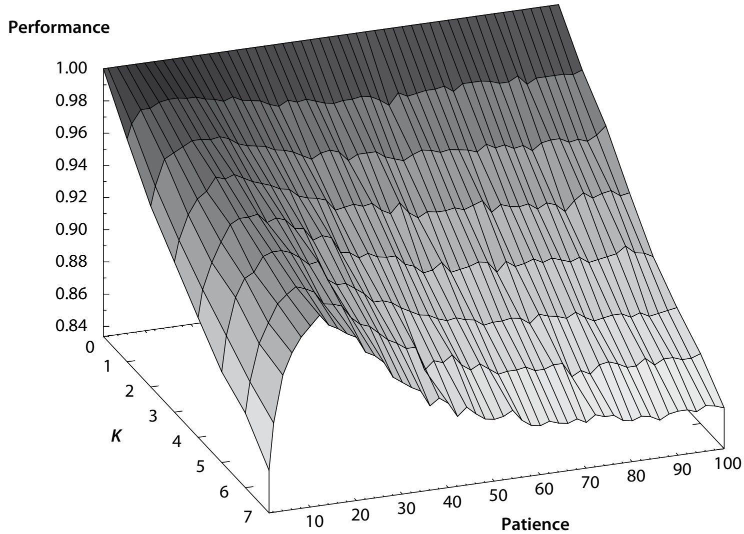


This figure reports the average firm performance in the short run (period 40) over 1,000 landscapes with $N = 8$ and different degrees of complexity ($0 \leq K \leq 7$). Firms differ in their degree of patience (*PAT*) and start their search without any offline knowledge (*KNOW* = 0).

8 The general performance decline for higher levels of interdependence results from the rising number of local peaks that on average tend to trap firms on configurations with lower performance (Kauffman (1995)).

9 In *Figure 3*, I define "short run" as period 40, yet the results are insensitive to this particular choice.

Figure 4: Long-term effects of different levels of interdependence and patience

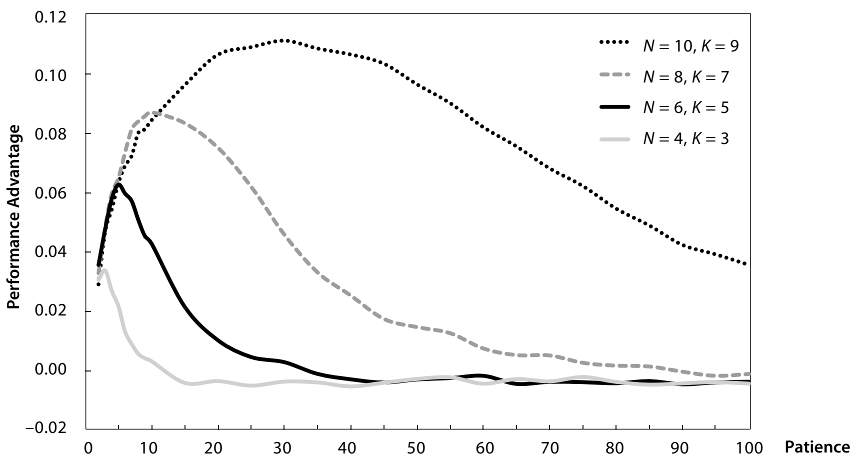


This figure reports the average firm performance in the long run (period 1,000) over 1,000 landscapes with $N = 8$ and different degrees of complexity ($0 \leq K \leq 7$). Firms differ in their degree of patience (*PAT*) and start their search without any offline knowledge (*KNOW* = 0).

If complexity is high and patience is low, a firm will explore only a limited neighborhood around its starting position. Because complex environments contain many local optima (Kauffman (1995)), the firm is likely to search in the neighborhood of an average local peak to which it will eventually be drawn by offline search. Although this search behavior is detrimental in the long run (*Figure 4*), it helps the firm to quickly improve its performance in the short run (*Figure 3*). In contrast, if patience is very high, then the chances are equally high that the firm creates that much offline knowledge in the neighborhood of an average peak that it will get drawn to this peak. Again, a moderate level of patience allows the firm to maximize its overall exploration by giving up less-promising paths before it is drawn to a peak. For lower levels of complexity, the level of patience matters less, since the number of local peaks is lower. The chances increase that a firm can reach an above-average peak by either a restrained neighborhood search or by wide exploration. (However, broad exploration requires more time than having only a low level of patience.) Thus, the more complex the environment, the more the firm should try to find a balance between impatience and patience. Conversely, being impatient (or even overly patient) is less detrimental in a less complex environment.

Considering the impact of problem size, *Figure 5* yields three main findings on the performance advantages of higher levels of patience over the exploitation-focused case of very limited patience ($PAT = 1$). First, the larger a problem gets, the greater the optimal level of patience becomes. Second, as systems get larger, the performance advantage of higher levels of patience grows. Third, medium levels of patience again yield the highest performance, but overly high levels of patience prove detrimental. The first two findings support Proposition 4. However, the third finding does not support Proposition 4, which again reinforces the robustness of my core result.

Figure 5: Effects of the problem size



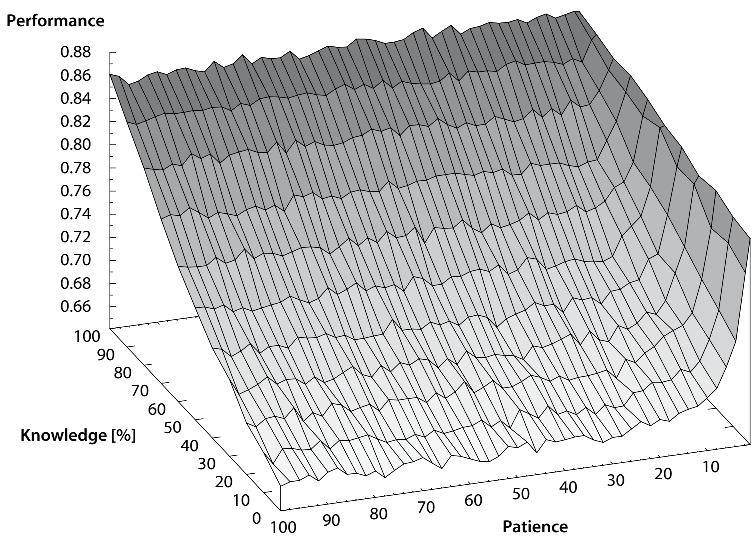
This figure reports the average performance difference between firms with higher levels of patience (*PAT* > 1) and firms with a very low level of patience (*PAT* = 1) over 1,000 landscapes. Landscapes differ in their size (*N*), while the degree of interdependence is set to $K = N - 1$. All firms start their search without any offline knowledge (*KNOW* = 0).

What drives the impact of problem size? Because a greater number of system elements increases the search space that needs to be explored, firms must allow for a higher level of patience to ensure that the exploration process is sustained for a sufficiently long time. Also, being patient proves to be more beneficial, since larger systems contain more local peaks and prolonged exploration (higher patience) increases the chances to move toward one of the better ones. Nonetheless, regardless of the size of the system, the detrimental drift effect of being overly patient eventually sets in. Clearly, larger systems increase the value of being patient as well as the notion of what denotes a moderate level of patience.

4.3 The Impact of Novelty on the Appropriate Level of Patience

In many situations, a firm may have at least some understanding of a problem domain rather than starting its search without any offline knowledge, e.g., when a technological shock alters but does not destroy a firm's existing competencies in a particular domain. In this case, the firm may be able to assess certain alternatives in an offline manner once it has generated the alternatives. To gain further insight into the role of patience under these conditions, *Figures 6* and *7* vary the firms' initial knowledge.

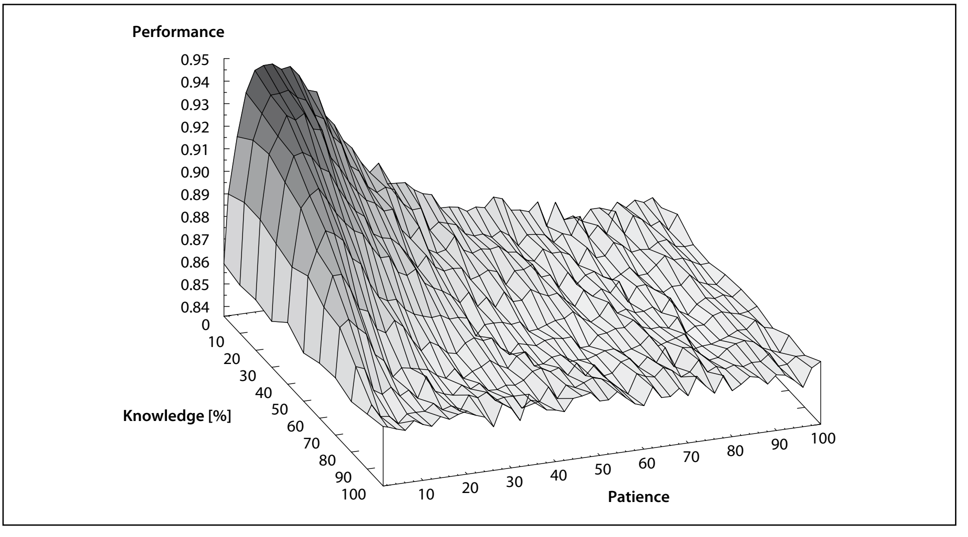
Figure 6: Short-term effects of different levels of initial knowledge and patience



This figure reports the average firm performance in the short run (period 40) over 1,000 landscapes with $N = 8$ and $K = 7$. Firms differ in their level of patience (*PAT*) and their degree of initial knowledge in the problem domain ($0 \leq KNOW \leq 1$).

First, I consider *Figure 6*, which reports the resulting performance values from a short-term planning horizon. It points to the value of (1) having offline knowledge or (2) gaining such knowledge quickly. In the short term, fast exploitation of existing competencies and the identification of adequate solutions are more valuable than a lengthy exploration for superior alternatives. This finding indicates clear support for Proposition 5. A firm that has a high level of offline knowledge can make many offline evaluations and improve its performance directly, and hence quickly. In contrast, a firm with less initial knowledge must search experientially first, and initially will exhibit a lower performance because it will experience some failures. Although the performance discount for lower degrees of initial knowledge is severe, it can be mitigated significantly by very low levels of patience. Again, this finding supports Proposition 2. If a firm with little initial knowledge explores experientially but abandons its current search path after each, or only a few, period(s) of below-benchmark performance, it will quickly generate enough local knowledge to make the same hill-climbing improvements as a firm that started with high degree of domain-specific knowledge. Thus, if the firm chooses the right sampling strategy that supports a generation of offline knowledge that is geared toward the short term, then the level of initial knowledge need not be an obstacle for short-term maximization.

Figure 7: Long-term effects of different levels of initial knowledge and patience



This figure reports the average firm performance in the long run (period 1,000) over 1,000 landscapes with $N = 8$ and $K = 7$. Firms differ in their level of patience (*PAT*) and their degree of initial knowledge in the problem domain ($0 \leq KNOW \leq 1$).

However, if the firm's planning horizon is geared toward the long run, the above wisdom is reversed (*Figure 7*). At this point broad exploration becomes valuable. Yet the higher the initial degree of knowledge, the less broadly a firm will explore, because offline considerations will prevent it from implementing performance-decreasing alternatives[10]. However, as noted above, tolerating failures is necessary if a firm is to leave its local neighborhood and explore more distant, possibly superior, regions. A firm with less offline knowledge will have to make these mistakes and may be able to reap their benefits, but a firm with a higher level of offline knowledge will more often be reluctant, and the chances are greater that it will remain in its initial region of the landscape. The lower a firm's degree

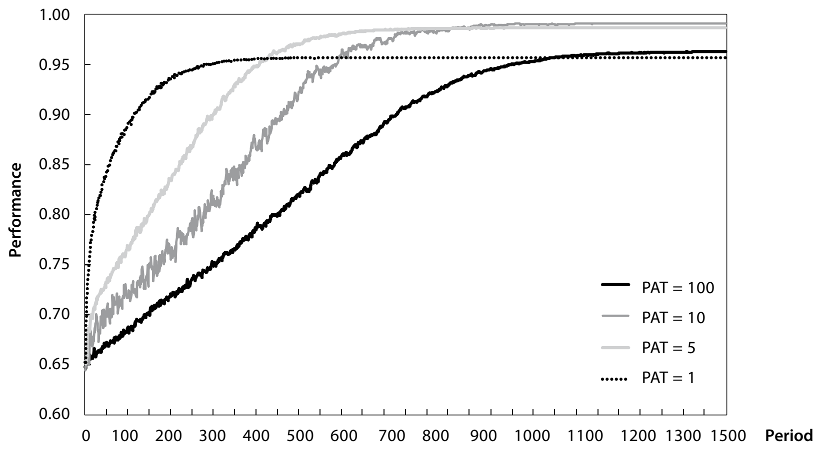
10 I assume that only experimenting with an unknown alternative can result in a performance decline. Firms do not move down-hill on purpose, i.e., they do not implement alternatives which they know would yield a worse performance than their status quo.

of knowledge is, the better it can use it to increase overall exploration, and the more the level of patience matters. This finding partially supports Proposition 6 and yields additional support for my core result.

4.4 Robustness

The core result is highly robust with regard to changes in the parameters problem complexity, such as size (N) and interdependence (K), and the degree of initial knowledge $(KNOW)$. Here, I consider robustness by using a different parameter, a firm's search radius, which indicates how broadly the firm can search for new alternatives. Knowledge that springs from earlier findings suggests that if firms have a larger search radius, i.e., if managers face less severe cognitive bounds, they can come up with more innovative alternatives and will not benefit that much from patience to increase exploration. To test this idea, I consider firms that have a search radius of two (as compared to a search radius of one in *Figure 1*), which enables them to identify new alternatives that differ by up to two decisions from their status quo set of choices.

Figure 8: Performance implications of different levels of patience given a higher search radius



This figure reports the average firm performance over 1,000 landscapes with $N = 8$, $K = 4$. Firms differ in their level of patience (*PAT*). All firms start their search without any offline knowledge (*KNOW* = 0). Firms are less bounded in their rationality and have a search radius of 2, i.e., they can generate alternatives that differ in up to two decisions from their status quo set of choices.

Figure 8 indicates that a higher search radius does decrease the performance differences between firms that have low levels of patience and those with a moderate level of patience. Nonetheless, my core result again proves to be robust[11].

5 Discussion and Avenues for Further Research

The issue of how alternatives are evaluated is a fundamental aspect of problem-solving search. Sometimes, a decision maker may evaluate an idea cognitively and free of risk, but often, he may have to accept that he is "blind", having to implement an alternative in order to learn about its value. Hence, when firms need to solve new, complex problems, for instance when exploring a recently developed technology or a strategy in a new business environment, they must often take the risk of failure and search for a solution through trial-and-error experimentation. In consequence, different areas of study, from engineering history (Vincenti (1990); Petroski (1992; 1994); Flyvbjerg, Bruzelius, and Rothengatter (2003)) to organizational research (Thornhill and Amit (2003); Starbuck and Farjoun (2005)) or psychological accounts of problem solving (Dörner (1997)), yield many cases that document failure that resulted from such online experiments.

As Levinthal (2005) stresses, the dichotomy between offline and online modes of evaluation is not strict. Instead, there is a large gray area between the two poles at which most evaluation processes occur. Online trials do not require completely giving up the current alternative. For instance, individual markets, pilot plants, or subsidiary firms may serve as test areas that provide the experiential basis on which the firm can evaluate a new proposal. For example, in aerospace or automotive design, engineers use wind tunnels to test the characteristics of new design alternatives, substituting for either the risky and costly (online) test of a full-fledged prototype or the fully cognitive route of analytical analysis and computer simulations. As Levinthal further remarks: "In some sense, the issue of on- or off-line search becomes less a categorical distinction than a set of factors that influence the costs, risk, and possible accuracy of the evaluation process. Online search often entails a particular sort of cost, the opportunity cost of not making use of established options. [. . .] the degree to which current operations need [to] be disrupted by the need to evaluate a proposed alternative influences how painful that trade-off is." Hence, albeit it is only a stylized dichotomy, discriminating between cognitive and experiential evaluation remains a helpful way to gain insight into the dynamics of search. Whenever designers or managers need to solve new, complex problems, the value of a particular search strategy depends critically on which form of evaluation mechanism is possible.

Furthermore, failure and patience are closely linked to a fundamental strategic challenge faced by any firm: the trade-off between the short-term and less risky exploitation of old certainties, and the long-term and more risky exploration of new possibilities (Holland (1975); March (1991)). Here, patience is a mechanism that promotes exploration by

11 Also, the other measures introduced in *Figure 2* remain qualitatively similar when the search radius is higher and the degree of patience is varied.

letting firms accept some performance-decreasing (downhill) moves, thus contributing to overcoming the pitfalls of search that would otherwise be overly local. However, this behavior does not guarantee effective search, since high levels of patience lead to excessive search but yield only little gains, as "… adaptive systems that engage in exploration to the exclusion of exploitation are likely to find that they suffer the costs of experimentation without gaining much of its benefit" (March (1991)). However, firms may be able to balance exploration with exploitation by being determined to eventually abandon their current search path and to return to a previous benchmark. Prior research shows how organizational design may help firms to explore widely but also to stabilize around good decisions once they are discovered (Rivkin and Siggelkow (2003)). Here, I suggest that moderate levels of patience may have a similar function. On the one hand, they induce broad search, while on the other hand, they bound the search space such that local problem-specific knowledge can accumulate and eventually be exploited.

However, in many cases, firms will have too little rather than too much patience. Consider the case of the car makers that had to do some basic restructuring if they were going to be able to adapt to a changing business landscape. But in searching for a new strategy that could restore their long-term viability, these firms had to endure some significant short-term pain, requiring a major amount of patience to avoid getting discouraged (Denrell and March (2001)). But because of the immediate performance feedback and public expectations that the car makers show good results quickly, these firms may have had less patience than necessary, a fact that might drive out exploration quickly and prematurely force the firms back into exploitation.

But, as noted above, low levels of patience can also be beneficial. Even if a firm starts with little understanding of what does and does not work, and has only little time available, a low level of patience can help it create local offline knowledge quickly and exploit its current position. For instance, a mechanism of this kind may be underlying concepts such as prototyping in software development (Thomke (1998); Loch, Terwiesch, and Thomke (2001)). Building, and potentially discarding, a lot of prototypes helps to quickly build up knowledge about the value of different alternatives, and thus contributes to rapid exploitation rather than lengthy exploration.

Despite the abstract nature of the findings that I report in this paper, the results still have implications for managers who seek to affect their organizations' level of patience. For examples, measures such as appropriate recruitment policies, the installation of test plants, or funding pet projects might help to increase the level of patience that a firm's decision makers are willing to exhibit, at least in those areas of the organization that are key to innovation. However, embedding constraints into critical search processes, such as milestones and review meetings on new product development projects, may constrain the patience of organizational agents, such as engineers, who might otherwise be tempted to explore too broadly.

While verbal discussions abstract from many real-world intricacies, formal modeling efforts go even further into this direction. This paper is no exception, and various aspects deserve further attention. Here, I point to four potential avenues. One is cognition. Early studies in the tradition of the Carnegie School offer local search by decision makers that possess only bounded rationality as an alternative strategy to the fully rational optimizer of neoclassical theory, but current research is starting to tread a middle ground (Gavetti (2005)). Hence, even when faced with new, complex problems, initially uninformed problem solvers may apply cognitive devices to interpret the knowledge that is generated about the landscape (Farjoun (2008)). Gradually, they might form cognitive maps that provide a big picture of a problem domain (Gavetti and Levinthal (2000)) or help to identify a preferred direction (Winter, Cattani, and Dorsch (2007); Nelson (2008)). With their growing understanding of the performance landscape, firms might then adjust their patience and search behavior accordingly. But as Rosenberg (1995)) remarks, it is a central characteristic of innovation that even pioneers may lack vision. Thus, further investigation of the role of intendedly rational behavior in problem solving appears to be promising.

Another direction for further research concerns the issue of delayed feedback, which has become known as the credit-assignment problem (Holland (1998); Denrell, Fang, and Levinthal (2004)). Often, the performance implications of a particular alternative may not be immediately observable, but seen only after some time has elapsed, during which the firm may have moved on. Performance feedback can also be noisy, raising the issue of how a firm should link current performance feedback to past actions. Also, performance feedback may be ambiguous, requiring several trials to establish a reliable link to performance. Furthermore, new alternatives may have both short- and long-term effects. For instance, in evaluating a new drug, some effects may be assessable instantaneously, but knowledge about other effects can sometimes only be established through long-term studies (Nelson (2008)). Incorporating such considerations into models of search would make them more intricate, but also more realistic.

A third limitation of this study pertains to the fact that it has been somewhat non-organizational. Most processes of problem-solving search and evaluation occur in an organizational context that is characterized by a division of labor, by hierarchical relationships, and by various other formal and informal aspects of organizational reality (March and Simon (1958); Cyert and March (1963)). Despite a few exceptions (Rivkin and Siggelkow (2003); Siggelkow and Rivkin (2005)), models of adaptive search have largely shied away from applying an explicit organizational perspective. However, to bring models closer to how organizations are actually evaluating alternatives, more work along these lines will be necessary (Gavetti, Levinthal, and Ocasio (2007)).

Fourth, my paper has both explicated and clarified why overly high levels of patience, despite inducing a significant amount of search, may have dysfunctional effects. Even under the laboratory conditions of the computational model developed above, i.e., in the absence of selection pressures or resource constraints, overly high levels of patience yield no further gains but instead reduce performance. Clearly, introducing a selection mechanism or equipping firms with limited resources and cost considerations, all of which could dynamically affect the level of patience, might help illuminate further relevant aspects of patience in organizational search, and indicate potential for further work.

6 Conclusion

Despite the limitations noted above, in this paper I introduce an explicit notion of online experimentation into a model of search, shedding light on how patience is linked to innovation. I find that contrary to what conventional wisdom might suggest, high levels of patience are not desirable, despite promoting a high level of exploration. Instead, choosing a level of patience reflects a decision about how firms balance exploration *and* exploitation. If managers want their organizations to innovate, they must embrace the exploration of new possibilities, and they must be willing to tolerate the failures that will inevitably occur along the way. At the same time, they must also limit exploration, since it competes with the exploitation of newly generated opportunities. If a manager seeks to boost innovation, then achieving a good balance between the two becomes necessary. Under a robust set of assumptions, finding this balance can be a matter of moderate patience.

References

Allen, Thomas J. (1977), *Managing the Flow of Technology*, Cambridge, MA: MIT Press.

Baron, Jonathan (1988), *Thinking and Deciding*, Cambridge: Cambridge University Press.

Baumard, Philippe and William H. Starbuck (2005), Learning from failures: Why it may not happen, *Long Range Planning* 38, 281-298.

Biyalogorsky, Eyal, William Boulding, and Richard Staelin (2006), Stuck in the past: Why managers persist with new product failures, *Journal of Marketing* 70, 108-121.

Bourgeois, L. J. and Kathleen M. Eisenhardt (1988), Strategic decision processes in high-velocity environments: Four cases in the microcomputer industry, *Management Science* 34, 816-835.

Cannon, Mark D. and Amy C. Edmondson (2005), Failing to learn and learning to fail (intelligently): How great organizations put failure to work to innovate and improve, *Long Range Planning* 38, 299-319.

Cyert, Richard M. and James G. March (1963), *A Behavioral Theory of the Firm*, Englewood Cliffs, NJ: Prentice Hall.

Davis, Jason P., Kathleen M. Eisenhardt, and Christopher B. Bingham (2007), Developing theory with simulation methods, *Academy of Management Review* 32, 480-499.

Denrell, Jerker and James G. March (2001), Adaptation as information restriction: The hot stove effect, *Organization Science* 12, 523-538.

Denrell, Jerker, Christina Fang, and Daniel A. Levinthal (2004), From T-mazes to labyrinths: Learning from model-based feedback, *Management Science* 50, 1366-1378.

Dörner, Dietrich (1997), *Die Logik des Mißlingens: Strategisches Denken in komplexen Situationen*, Reinbek: Rowohlt.

Eisenhardt, Kathleen M. (1989), Making fast strategic decisions in high-velocity environments, *Academy of Management Journal* 32, 543-576.

Ethiraj, Sendil K. and Daniel A. Levinthal (2004), Modularity and innovation in complex systems, *Management Science* 50, 159-173.

Farjoun, Moshe (2008), Strategy making, novelty, and analogical reasoning – commentary on Gavetti, Levinthal, and Rivkin (2005), *Strategic Management Journal* 29, 1001-1016.

Farson, Richard and Ralph Keyes (2002), *Whoever Makes the Most Mistakes Wins: The Paradox of Innovation*, New York: Free Press.

Fine, Charles H. (1998), *Clockspeed: Winning Industry Control in the Age of Temporary Advantage*, Reading, MA: Perseus Book.

Fleming, Lee (2001), Recombinant uncertainty in technological search, *Management Science* 47, 117-132.

Flyvbjerg, Bent, Nils Bruzelius, and Werner Rothengatter (2003), *Megaprojects and Risk: An Anatomy of Ambition*, Cambridge: Cambridge University Press.

Forbes, Daniel P. (2005), Are some entrepreneurs more overconfident than others?, *Journal of Business Venturing* 20, 623-640.

Freud, Sigmund (1912), Formulierungen über zwei Prinzipien des psychischen Geschehens, in Sigmund Freud (ed.), *Gesammelte Werke*, London: Imago, 910-924.

Garud, Raghu and Andrew H. Van De Ven (1992), An empirical evaluation of the internal corporate venturing process, *Strategic Management Journal* 13, 93-109.

Gavetti, Giovanni and Daniel A. Levinthal (2000), Looking forward and looking backward: Cognitive and experiential search, *Administrative Science Quarterly* 45, 113-137.

Gavetti, Giovanni (2005), Cognition and hierarchy: Rethinking the microfoundations of capabilities' development, *Organization Science* 16, 599-617.

Gavetti, Giovanni, Daniel A. Levinthal, and William Ocasio (2007), Neo-Carnegie: The Carnegie School's past, present, and reconstructing for the future, *Organization Science* 18, 523-536.

Gavetti, Giovanni and Jan W. Rivkin (2007), On the origin of strategy: Action and cognition over time, *Organization Science* 18, 420-439.

Gigerenzer, Gerd, Peter M. Todd, and the ABC Research Group (1999), *Simple Heuristics That Make Us Smart*, New York: Oxford University Press.

Greve, Henrich R. (2003), *Organizational Learning from Performance Feedback: A Behavioral Perspective on Innovation and Change*, Cambridge, MA: Cambridge University Press.

Harrison, J. Richard, Zhiang Lin, Glenn R. Carroll, and Kathleen M. Carley (2007), Simulation modeling in organizational and management research, *Academy of Management Review* 32, 1229-1245.

Hauschildt, Jürgen and Hans-Georg Gemünden (1999), *Promotoren – Champions der Innovation*, Wiesbaden: Gabler.

Holland, John H. (1975), *Adaptation in Natural and Artificial Systems*, Ann Arbor, MI: University of Michigan Press.

Holland, John H. (1998), *Emergence: From Chaos to Order*, Reading, MA: Helix.

Israel, Paul (1998), *Edison: A Life of Invention*, New York: Wiley.

Kahneman, Daniel, Paul Slovic, and Amos Tversky (1982), *Judgment under Uncertainty: Heuristics and Biases*, Cambridge: Cambridge University Press.

Katila, Riita and Gautam Ahuja (2002), Something old, something new: A longitudinal study of search behavior and new product development, *Academy of Management Journal* 45, 1183-1194.

Kauffman, Stuart A. (1993), *Origins of Order: Self-Organization and Selection in Evolution*, New York: Oxford University Press.

Kauffman, Stuart A. (1995), *At Home in the Universe: The Search for the Laws of Self-Organization and Complexity*, New York: Oxford University Press.

Lee, Fiona, Amy C. Edmondson, Stefan H. Thomke, and Monica Worline (2004), The mixed effects of inconsistency on experimentation in organizations, *Organization Science* 15, 310-326.

Lenox, Michael J., Scott F. Rockart, and Arie Y. Lewin (2006), Interdependency, competition, and the distribution of firm and industry profits, *Management Science* 52, 757-772.

Levinthal, Daniel A. and James G. March (1981), A model of adaptive organizational search, *Journal of Economic Behavior and Organization* 2, 307-333.

Levinthal, Daniel A. (1997), Adaptation on rugged landscapes, *Management Science* 43, 934-950.

Levinthal, Daniel A. (2005), Footnotes to the behavioral theory of the firm: Wharton School, University of Pennsylvania.

Levitt, Barbara and James G. March (1988), Organizational learning, *Annual Review of Sociology* 14, 319-340.

Lippman, Stephen A. and John J. McCall (1976), The economics of job search: A survey, *Economic Inquiry* 14, 155-187.

Loch, Christoph H. and Christian Terwiesch (1998), Communication and uncertainty in concurrent engineering, *Management Science* 44, 1032-1048.

Loch, Christoph H., Christian Terwiesch, and Stefan Thomke (2001), Parallel and sequential testing of design alternatives, *Management Science* 47, 663-678.

Lowe, Robert A. and Arvids A. Ziedonis (2006), Overoptimism and the performance of entrepreneurial firms, *Management Science* 52, 173-186.

Mach, Ernst (1905), *Erkenntnis und Irrtum*, Leipzig.

Macy, Michael W. and Robert Willer (2002), From factors to actors: Computational sociology and agent-based modeling, *Annual Review of Sociology* 28, 143-166.

March, James G. and Herbert A. Simon (1958), *Organizations*, New York: Wiley.

March, James G. (1991), Exploration and exploitation in organizational learning, *Organization Science* 2, 71-87.

March, James G. (2006), Rationality, foolishness, and adaptive intelligence, *Strategic Management Journal* 27, 201-214.

Mihm, Jürgen, Christoph H. Loch, and Arnd Huchzermeier (2003), Problem-solving oscillations in complex engineering projects, *Management Science* 49, 733-750.

Milgrom, Paul R. and John Roberts (1990), The economics of modern manufacturing: Technology, strategy, and organization, *American Economic Review* 80, 511-528.

Milgrom, Paul R. and John Roberts (1995), Complementarities and fit: Strategy, structure, and organizational change in manufacturing, *Journal of Accounting and Economics* 19, 179-208.

Nelson, Richard R. and Sidney G. Winter (1982), *An Evolutionary Theory of Economic Change*, Cambridge, MA: Harvard University Press.

Nelson, Richard R. (2008), Bounded rationality, cognitive maps, and trial and error learning, *Journal of Economic Behavior & Organization* 67, 78-89.

Petroski, Henry (1992), *To Engineer is Human: The Role of Failure in Successful Design*, New York: Vintage Books.

Petroski, Henry (1994), *Design Paradigms: Case Histories of Error and Judgment in Engineering*, Cambridge: Cambridge University Press.

Petroski, Henry (2006), *Success Through Failure: The Paradox of Design*, Princeton, NJ: Princeton University Press.

Popper, Karl (1959), *The Logic of Scientific Discovery*, New York: Harper.

Porter, Michael E. (1996), What is strategy?, *Harvard Business Review* 74, 61-78.

Ravasi, Davide and Carlo Turati (2005), Exploring entrepreneurial learning: A comparative study of technology development projects, *Journal of Business Venturing* 20, 137-164.

Rivkin, Jan W. (2000), Imitation of complex strategies, *Management Science* 46, 824-844.

Rivkin, Jan W. and Nicolaj Siggelkow (2003), Balancing search and stability: Interdependencies among elements of organizational design, *Management Science* 49, 290-311.

Rivkin, Jan W. and Nicolaj Siggelkow (2007), Patterned interaction in complex systems: Implications for exploration, *Management Science* 53, 1068-1085.

Rosenberg, Nathan (1995), Innovation's uncertain terrain, *McKinsey Quarterly* 3, 170-185.

Rosenkopf, Lori and Paul Almeida (2003), Overcoming local search through alliances and mobility, *Management Science* 49, 751-766.

Siggelkow, Nicolaj (2002), Evolution toward fit, *Administrative Science Quarterly* 47, 125-159.

Siggelkow, Nicolaj and Jan W. Rivkin (2005), Speed and search: Designing organizations for turbulence and complexity, *Organization Science* 16, 101-122.

Simon, Herbert A. (1955), A behavioral model of rational choice, *Quarterly Journal of Economics* 69, 99-118.

Simon, Herbert A. (1956), Rational choice and the structure of the environment, *Psychological Review* 63, 129-138.

Simon, Herbert A. (1962), The architecture of complexity, *Proceedings of the American Philosophical Society* 106, 467-482.

Simon, Herbert A. (1996), *The Sciences of the Artificial*, Cambridge, MA: MIT Press.

Starbuck, William H. and Moshe Farjoun (eds.) (2005), *Organization at the Limit: Lessons from the Columbia Disaster*, Malden, MA: Blackwell Publishing.

Stuart, Toby E. and Joel M. Podolny (1996), Local search and the evolution of technological capabilities, *Strategic Management Journal* 17, 21-38.

Sutton, Richard and Andrew Barto (1999), *Reinforcement Learning: An Introduction*, Cambridge, MA: MIT Press.

Thomke, Stefan and Takahiro Fujimoto (2000), The effect of 'front-loading' problem-solving on product development performance, *Journal of Product Innovation Management* 17, 128-142.

Thomke, Stefan H. (1998), Managing experimentation in the design of new products, *Management Science* 44, 743-762.

Thomke, Stefan H. (2003), *Experimentation Matters: Unlocking the Potential of New Technologies for Innovation*, Boston: Harvard Business School Press.

Thornhill, Stewart and Raphael Amit (2003), Learning about failure: Bankruptcy, firm age, and the resource-based view, *Organization Science* 14, 497-509.

Tucker, Anita L. and Amy C. Edmondson (2003), Why hospitals don't learn from failures: Organizational and psychological dynamics that inhibit system change, *California Management Review* 45, 55-72.

Välikangas, Liisa (2007), Rigidity, exploratory patience, and the ecological resilience of organizations, *Scandinavian Journal of Management* 23, 206-213.

Vincenti, Walter (1990), *What Engineers Know and How They Know It: Analytical Studies from Aeronautical History*, Baltimore: The Johns Hopkins University Press.

Winter, Sidney G., Gino Cattani, and Alex Dorsch (2007), The value of moderate obsession: Insight from a new model of organizational search, *Organization Science* 18, 403-419.