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

Motivating Organizational Search

Oliver Baumann

Marketing & Management
oliv@sam.sdu.dk

Nils Stieglitz

nst@sam.sdu.dk

Abstract

This paper investigates the value of high-powered incentives for motivating search for novelty in business organizations. While organizational search critically depends on the individual efforts of employees, motivating search effort is challenged by problems of unobservable behavior and the misalignment of individual and organizational interests. Prior work on organizational design thus suggests that stronger incentives can overcome these problems and make organizations more innovative. To address this conjecture, we develop a computational model of organizational search that rests on two opposing effects of high-powered incentives: On the one hand, they promote higher effort by increasing the potential rewards from search; on the other hand, they increase the competition among ideas, as the ability of an organization to implement and remunerate good ideas is limited by its resource base. Our results indicate that low-powered incentives are effective in generating a sufficient stream of incremental innovations, but that they also result in a shortage of more radical innovations. Stronger incentives, in contrast, do not systematically foster radical innovations either, but instead create a costly oversupply of good ideas. Nonetheless, higher-powered incentives can still be effective in small firms and if strong persistence is required to develop a new idea.

Jelcodes:M00,O31

Motivating Organizational Search

Abstract: This paper investigates the value of high-powered incentives for motivating search for novelty in business organizations. While organizational search critically depends on the individual efforts of employees, motivating search effort is challenged by problems of unobservable behavior and the misalignment of individual and organizational interests. Prior work on organizational design thus suggests that stronger incentives can overcome these problems and make organizations more innovative. To address this conjecture, we develop a computational model of organizational search that rests on two opposing effects of high-powered incentives: On the one hand, they promote higher effort by increasing the potential rewards from search; on the other hand, they increase the competition among ideas, as the ability of an organization to implement and remunerate good ideas is limited by its resource base. Our results indicate that low-powered incentives are effective in generating a sufficient stream of incremental innovations, but that they also result in a shortage of more radical innovations. Stronger incentives, in contrast, do not systematically foster radical innovations either, but instead create a costly oversupply of good ideas. Nonetheless, higher-powered incentives can still be effective in small firms and if strong persistence is required to develop a new idea. Based on the analysis of our model, we develop a set of propositions that appear to be consistent with extant evidence and point to new avenues for empirical research.

Keywords: Organizational search, incentives, innovation, agent-based simulation

1 Introduction

The generation of value-creating ideas is at the heart of innovation but likewise denotes a major challenge, as it requires organizations to engage in costly and uncertain search activities (March and Simon 1958; Cyert and March 1963; Nelson and Winter 1982). As extant research has established, appropriate organizational designs can help managers shape the effectiveness of their firms' search activities (Rivkin and Siggelkow 2003; Nickerson and Zenger 2004; Knudsen and Levinthal 2007). This paper studies the role of one basic design element – a firm's incentive system. How incentives can be leveraged to motivate organizational search is an underexplored question despite the fact that innovation often critically depends on the creativity and efforts of an organization's employees.

Consider, for instance, firms such as 3M or Google, whose employees can spend a significant part of their working time on their own product ideas. At regular intervals, these ideas are screened by the firms' senior managers that select projects and commit substantial resources to turn them into successful products. Likewise, many firms have established continuous improvement processes, Kaizen policies (Adler et al. 1999), or employee suggestion systems (Giummo 2010) to solicit, implement, and reward good ideas by employees. In a similar manner, other management concepts such as corporate entrepreneurship (Burgelman 1983), strategic initiatives (Burgelman 1991), or innovation tournaments (Terwiesch and Ulrich 2009) also consider the decentralized search efforts of employees as a central source of strategic, organizational, and product innovation (Rotemberg and Saloner 1994; Foss 2003).

How should firms remunerate such decentralized search activities? Even though managers may hope that their employees are intrinsically motivated (Osterloh and Frey 2000), empirical evidence suggests that the prospects of monetary gains do play an important motivational role, even in the context of innovation (Sauermann and Cohen 2010). Yet rewarding the search efforts of employees appears to be challenged by the familiar agency problems of unobservable behavior (Levinthal 1988) and the misalignment of private and organizational interests (Zenger 1994). Prior studies thus suggest that "firms should pay large monetary premiums" (Jones and Butler 1992: 744) to motivate organizational search and reward the ideas of employees (cf. Holmstrom 1989; Zenger and Lazzarini 2004; Ruckes and Rønde 2010). Some scholars in the tradition of the behavioral theory of the firm, in contrast, remain more skeptical about the value of strong incentives, arguing that organizations may be "more effective in removing downside risks than in providing extremely rich rewards for great success" (Levinthal and March 1993: 107). Whether high levels of incentive intensity do really prove most effective in motivating organizational search thus appears to be an open question.

To address this question, we develop an agent-based simulation model that combines insights from research on adaptive organizational search and organizational economics. The structure of our model reflects important aspects that make search "organizational:" First, there is a hierarchy, as senior management selects and implements projects that employees propose. Second, and in contrast to market competition, employees do not face a downside risk or other negative consequences if they fail to innovate (Levinthal and March 1993). Third, the employees' projects are highly specific to the scare organizational resources and capabilities of the organization (Rotemberg and Saloner 1994; Rajan and Zingales 2001; Foss 2003). These stylized facts about business organizations (Demsetz 1991) create an important trade-off that managers face when designing reward systems for search activities: On the one hand, greater incentive intensity motivates employees to exert higher search efforts, since the prospective gains from project selection are higher; on the other hand, stronger incentives fuel the rivalry for scarce organizational resources, as more projects will compete for selection, which decreases the individual likelihood of securing a reward and thus dampens the motivation for search.

Our results make a case for weak incentive intensity in organizations – a finding that arises even though our model excludes all mechanisms that extant research suggests may undo the effects of high-powered rewards. We show that strong incentive intensity results in a higher search effort and, thus, the generation of a higher number of ideas. The gains in terms of higher project quality that are induced by increasing the incentive intensity, however, are outweighed by the additional costs that the organization incurs when doing so. In addition to the incentive costs, high-powered rewards create an excessive pipeline of good projects that lie idle and have a detrimental effect on the employees' motivation for further search effort. Our findings suggest that organizations with strong incentive intensity generate an abundant supply of good ideas – but a systematic shortage of outstanding ideas. Lower levels of incentive intensity, in contrast, do not provide these outstanding ideas either, but serve to generate a sufficient stream of good ideas at much lower costs. However, our findings further suggest that smaller firms can employ stronger incentive intensity, and that organizations benefit from offering higher rewards when ideas need long gestation. Based on these findings, we develop a set of empirical propositions and discuss the broader implications of our results for innovation management and organizational design.

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

2 Prior research

Organizational search – creating new alternatives about "how to approach old problems in novel ways or [how] to tackle relatively new challenges" (Zollo and Winter 2002: 343) – is an important driver of innovation and competitive advantage (Teece 2007). Our understanding of search has been greatly improved by behavioral accounts of organizational learning and adaptation (e.g., Levinthal and March 1981; March 1991), with recent work addressing how search activities are shaped by organizational design elements such as the structure of decision-making processes (Rivkin and Siggelkow 2003; Knudsen and Levinthal 2007). With regard to the effects of incentives on organizational search, prior work in the behavioral tradition has mainly emphasized their role in coordinating decentralized search activities, affecting, e.g., how managers evaluate new alternatives (Rivkin and Siggelkow 2003), share knowledge (Nickerson and Zenger 2004), balance specialization and coordination (Kretschmer and Puranam 2008), or allocate attention to the pursuit of multiple performance goals (Ethiraj and Levinthal 2009). The motivational effects of reward systems on organizational search, in contrast, are considerably less explored, despite the fact that foundational work on the behavioral theory of the firm already points to the influence of incentive schemes on the creation of new alternatives (March and Simon 1958). Instead, extant research offers conflicting advice: While, for instance, Zollo and Winter (2002) claim that organizations need to provide sufficiently powerful incentives for the initiation of search activities, Levinthal and March (1993) express skepticism about the value of strong incentives, arguing instead that organizations should rather influence the risk perception and risk preference of their employees (cf. March 1988).

Organizational economics provides a useful lens for studying the motivational effects of incentives on organizational search, given that empirical work points to extrinsic motivation as a driver of search activities (Sauermann and Cohen 2010).[1] In organizations, salaried employees bear the costs and risks of engaging in uncertain and unpredictable search activities, while the benefits accrue to the organization. What is more, search activities are notoriously hard to observe and monitor (Holmstrom 1989; Aghion and Tirole 1994), which prevents a comprehensive contracting and gives rise to a misalignment of interests (Zenger 1994). The misalignment of interests, in turn, denotes a central issue in both transaction cost economics and agency models (Levinthal 1988; Gibbons 1998; Kaplan and Henderson 2005).

According to transaction costs economics (TCE), organizations are characterized by low-powered incentives, i.e., by a prevalence of fixed salaries that are complemented by administrative controls (Nickerson and Zenger 2004). The reason for why organizations are not amenable to strong incentive intensity is that team production and bilateral dependencies create assignment problems that obfuscate the link between individual efforts and organizational outcomes, making individual contributions hard to observe and challenging adaptation (Williamson 1985). Recent work on the intersection of TCE and organization design has built on this notion and argued that smaller firms and autonomous business units face less severe challenges in linking individual effort to outcomes (Zenger and Hesterly 1997; Zenger and Marshall 2000; Makadok and Coff 2009). Zenger and Hesterly (1997: 213), for instance, suggest that under these conditions, higher rewards may become beneficial for innovation and performance, since

[1] Similarly, March and Simon (1958: 61) claim that "a model of man that does not give a prominent place to economic incentives is, for most humans, a poor model" and argue that search within organizations is challenged by the potential misalignment of individual and organizational interests.

"high-powered incentives […] strongly motivate the development and leveraging of valuable capabilities, routines, and knowledge."

More fundamentally, this call for higher rewards rests upon insights from work on principal-agent problems. Because an agent's search effort cannot be directly observed by the principal, performance-based rewards must be conditioned on a signal that correlates with the agent's effort level (Holmstrom and Tirole 1991; Prendergast 1999). For instance, as search effort is often correlated with the quality of the idea that an employee proposes, the principal could remunerate the agent based on the value that the idea creates for the organization (Holmstrom and Milgrom 1994). In sum, given that confounding factors such as multitasking (Holmstrom and Milgrom 1994) are negligible, principal-agent theory suggests that stronger incentive intensity will be an effective instrument for stimulating search and innovation in organizations (Holmstrom 1989; Holmstrom and Milgrom 1994; Ruckes and Rønde 2010).[2]

Standard models of principal-agent relationships, however, abstract from an important facet of organizational search – the presence of an internal selection regime that screens and selects ideas for implementation and resource commitment (Lovas and Ghoshal 2000; Adner and Levinthal 2004; Knudsen and Levinthal 2007). Firms typically cannot implement every proposal that is potentially valuable (Rotemberg and Saloner 1994; Lovas and Ghoshal 2000; Foss 2003), as strategic resources cannot be easily replicated and expanded (Dierickx and Cool 1989; Rajan and Zingales 2001; Lippman and Rumelt 2003), because managerial attention is limited (Ocasio 1997), and since financial resources are often constrained (Stein 1997). As a consequence of scarce organizational resources, employees do not search in isolation, but compete for the selection of their proposals and for the rewards that are tied to their implementation. In addition, it is often the relative value of proposals, rather than their absolute

[2] Stronger incentive intensity misallocates effort in multi-tasking environments (Holmstrom and Milgrom 1991; 1994) that are characterized by a mixture of hard-to-measure tasks (low correlation between effort and signal) such as engaging in cooperation and coordination, and easy-to-measure tasks. According to Holmstrom and Milgrom (1994: 989), "the use of low-powered incentives within the firm, although sometimes lamented as one of the major disadvantages of internal organization, is also an important vehicle for inspiring cooperation and coordination." Furthermore, Manso (forthcoming) and Ederer and Manso (2010) add a further qualification to pay-for performance schemes for search tasks: When agents allocate search effort between explorative and exploitative search activities, high-powered incentives for long-term performance lead to superior performance compared to fixed-wage and standard pay-for-performance contracts.

quality, that is of higher relevance in organizations, as the differential value of a proposal depends on the current pool of ideas that senior management may tap into. Hence, if an organization faces a dearth of good proposals, even an average idea might be selected and rewarded, whereas even excellent ideas could be passed over if the organization has many outstanding ideas to choose from.

The competition among projects affects the agents' motivation for search. In general, the study of competition within organizations as well as relative performance measurement denote the central themes of tournament theory that studies how prizes such as bonuses or promotions can be structured to induce effort among employees (Lazear and Rosen 1981; Lambert et al. 1993; Prendergast 1999). Among other findings, this literature has established that effort levels tend to increase with the value of the prize (as the potential gains from winning the tournament increase), and that the larger the number of participants, the higher the prize needs to be in order to induce optimal effort (to overcome the higher levels of competition that result from a larger group of participants). Yet high prizes in tournaments may also invoke excessive risk taking (Hvide 2002), sabotage (Chen 2003), and a reduced willingness to cooperate (Lazear 1989). These issues notwithstanding, however, tournament theory suggests that higher rewards translate into more intense search activities.[3]

The extent to which insights from tournament theory can be applied to problems of motivating organizational search, however, is limited. First, tournaments are typically conceived of as competitive processes with a pre-determined ending, after which winners and losers are clearly delineated. Organizational search, in contrast, is an open-ended process, and the survival of an organization often depends on a constant stream of proposals rather than a single idea. Moreover, proposals that were initially unsuccessful in securing implementation often survive within the organization and may be selected at a later point (Cohen et al. 1972; Lovas and Ghoshal 2000; Foss 2003), especially if employees

[3] Recently, scholars of technology management have also shown an increasing interest in internal and external innovation tournaments to harness the benefits of a large population of searchers (Terwiesch and Xu 2008; Terwiesch and Ulrich 2009). The analysis of incentives in innovation tournaments largely rests on models developed in agency theory (Morgan and Wang 2010). An important early contribution is Taylor (1995) who shows that restricting access to innovation tournaments and lowering competition may improve performance. Terwiesch and Xu (2008) offer a detailed analysis of incentive design in external innovation tournaments and show that seekers may compensate the detrimental effect of strong competition by offering performance-contingent awards.

continue to improve them. Second, tournament theory also assumes that the principal designing the tournament possesses superior processing capabilities as well as knowledge about the potential for value creation, which allows him to determine a prize that induces optimal efforts. The literature on organizational search, in contrast, builds upon the central premise that decision makers are largely ignorant about the search spaces they are facing (Rivkin 2000). Third, as the search for novelty is motivated by the possible gains from search (Lippman and Rumelt 2003), value creation and value distribution become closely intertwined in the sense that all value that can be distributed between the firm and the employees first needs to be generated through search; search activities, in turn, are triggered by the share that the employees can appropriate from the created value, which again affects the costs that will incur to the organization (Williamson 1991). Fourth, because the costs and benefits of search are often unpredictable, optimal behavioral responses to the provision of incentives are likely extreme cases – a notion that is supported by experimental research documenting that even in simple tournament settings, decision making proceeds in a fairly heuristic manner (Orrison et al. 2004; Vandegrift et al. 2007).

3 Model

To study how incentives induce search among employees, we use an agent-based simulation model (Axelrod 1997). For a number of reasons, computational models have gained broad popularity among scholars of organizational search (cf. Davis et al. 2007; Harrison et al. 2007). For instance, although they cannot yield "exact solutions" in contrast to algebraic modeling, they allow incorporating a richer set of features into the analysis. In particular, our paper is concerned with the question of how incentives affect a population of interacting agents that are boundedly rational and search adaptively, as they do not know the potential outcomes of search, nor their own marginal productivity (cf. Jovanovic 1979). While exploring the emerging dynamics is possible with a computational approach, an algebraic model would require much more restrictive assumptions in order to remain analytically tractable. In addition, our model allows us to study an arbitrarily large number of employees, thus representing different firm sizes, which would be impossible with a closed-form approach. Finally, our model represents a "virtual laboratory" that allows us to systematically experiment with the most salient aspects of organizational search in response to incentives, while excluding all factors that extant work has shown to disrupt the direct effects of incentives.[4] And although a simulation-based approach thus grants high degrees of freedom to the modeler, our model does not attempt to represent any specific real-world context. Instead, it contains stylized elements that are essential to shed light on the abstract problem under investigation, thus following a time-honored tradition in computational research to develop parsimonious yet insightful models (Cohen et al. 1972; Nelson and Winter 1982; Burton and Obel 1995).

3.1 Structure

Similar to a principal-agent set-up, our model consists of two main groups of actors: 1) employees (the agents) that search for value-creating proposals, which we call projects, and 2) a firm's senior management (the principal) that screens and selects projects for implementation. We assume that the agents' search effort is unobservable by senior management, but that the quality of project proposals, in contrast, is fully observable. We thus abstract from problems of alternative evaluation, which have been studied elsewhere (Knudsen and Levinthal 2007; Christensen and Knudsen 2010). Importantly, we further assume that all projects are specific to the firm and require access to other organizational resources, if they are to be implemented. In a stylized manner, this reflects how the existing organizational resources channel creativity and provide cues in the search space of business opportunities (Cyert and March 1963; Stuart and Podolny 1996). Given that employees depend on access to organizational resources to unlock the value of a project, we thereby also abstract from problems of renegotiation and ex-post bargaining (Rajan and Zingales 2001; MacDonald and Ryall 2004). Because complementary organizational resources are scarce, only a limited number of projects may be implemented in each period. The resource-based view of the firm has identified many factors that prevent the expansion of scarce organizational resources and capabilities (Dierickx and Cool 1989; Barney 1991). Likewise, the behavioral theory of the firm

[4] In particular, the model excludes all confounding factors that were discussed in the previous section, i.e., assignment problems, multitasking, cooperation and coordination issues, decisions between exploration and exploitation, (excessive) risk taking, sabotage, or other detrimental employee actions.

highlights the limits to managerial attention, which is required for turning a business idea into reality (Cyert and March 1963; Ocasio 1997; Lippman and Rumelt 2003). Furthermore, and in contrast to competition in markets, the employees in our model do not face a downside risk or other negative consequences if they fail to secure project selection. Rather, their projects survive in the organization and may be selected at a later point, or not at all. Lastly, we do not consider cooperation and knowledge-sharing among employees. (In sections 4.3 and 4.4, we discuss extensions in which we relax several of these assumptions.)

Our model structure highlights two mechanisms that appear to be of central relevance in motivating organizational search. First, stronger incentive intensity motivates each employee to exert higher effort in his search activities. Given that search effort is correlated with the quality of a proposal, higher effort improves the likelihood of proposal selection and remuneration. This well-known effect of expected monetary gains on motivation is a central tenet in the organizational economics literature. Second, the likelihood of securing a reward also depends on the search efforts of the other employees in the organization. Because scarce organizational resources (Teece 1986; Ocasio 1997; Lippman and Rumelt 2003) typically preclude that all value-creating proposals can be implemented, the relative quality of proposals determines which one will eventually be selected. Strong competition among proposals, however, reduces the employees' search efforts, as it reduces their likelihood of proposal selection and remuneration (Rotemberg and Saloner 1994; 2000). These facets of organizational search are, among others, highlighted by Foss (2003) in his empirical analysis of new organizational forms; similarly, Monsen et al. (2009) find evidence that they are important drivers of employees' decisions to participate in corporate ventures. In sum, stronger incentive intensity has two opposing effects on the motivation of employees to engage in organizational search: On the one hand, higher rewards increase the potential gains from search activities, while on the other they amplify competition among employees and decrease the individual likelihood of proposal selection.

3.2 Implementation

3.2.1 Determination of the search effort

Our modeled organization consists of N agents. In each period t, the agents choose an effort level $e_t \in [0;1]$ with which they search for value-creating projects. The effort level, in turn, determines the probability of finding or refining a project idea (as described in section 3.2.2). When choosing their search effort, we assume the agents to consider three factors (see equation 1): the incentive intensity β, the current level of competition among projects $\frac{R}{X_{t-1}}$, and the agents' private costs of exerting search effort ω:[5]

$$e_t = (\frac{R}{X_{t-1}} \cdot \beta)^{\omega} \qquad (1)$$

First, the incentive intensity $\beta \in [0;1]$ reflects the extent of value-sharing between the organization and its employees. If $\beta = 0$, incentives are extremely low-powered in the sense that an employee whose project is implemented will not be compensated at all. In consequence, search effort will be zero. In contrast, if $\beta = 1$, incentives are very high-powered, because 100% of the value that is created by an implemented project will accrue to the employee who propagated the idea. In sum, thus, higher incentive levels β translate into a higher search effort.

Second, we assume that the organization faces a (fixed) resource constraint R, which reflects the number of value-creating projects that can be implemented in each period. Put differently, the higher R, the less scarce are the organizational resources that are required for project implementation. We further assume that the agents form adaptive expectations about the level of competition. Let X_{t-1} denote the number of active projects in the previous period (assuming that this number can be observed by all agents), then competitive considerations are expressed by the ratio $\frac{R}{X_{t-1}}$. Put simply, the more projects

[5] The effort level is the same for all agents. Prior versions of the model included more elaborate decision rules, in which the agents also considered their individual capabilities and competitive positions, resulting in agent-specific effort levels. These versions yielded results that were qualitatively similar to those generated by the current, more parsimonious model. (Additional effects that could be observed were, for example, the self-selection of more capable agents.) All results are available from the authors.

compete for selection, and the more severe the resource constraint is (the lower R), the more pronounced the perceived competition and, in turn, the lower the agents' search effort will be.[6]

Third, the parameter ω captures the agents' private costs of search, reflecting how changes to the incentive intensity and the level of competition map onto the agents' search effort. When $\omega = 1$, private costs increase linearly, while $\omega = 0.5$ corresponds to a quadratic cost function. If ω is very low, in contrast, the private costs of search become negligible, and a small rise of the incentive level (or, conversely, a small reduction of the level of competition), would invoke a disproportionate increase of the search effort. The latter case might, for instance, reflect agents with a high level of intrinsic motivation, as even very weak incentive intensity induces a high search effort, whereas further increases of the incentive level would only have a small additional impact on search effort.

3.2.2 Project creation and refinement

In our model, search effort e_t is correlated with search performance in the sense that it determines the agents' probability of finding or refining a project idea in period t. For example, if $e_t = 0.3$, the probability is 30% that each agent's search effort in period t will be successful. Furthermore, we assume that each of the n agents can work on (at most) one project, or have no project at all. Depending on these conditions, we distinguish the following three cases for each agent i in each period t:

1) If search is not successful (i.e., with a likelihood of $1 - e_t$), the agent either remains without a project (if she was searching for a project idea in the current period) or keeps her existing project (which remains unchanged compared to the previous period).
2) If search is successful and the agent does not own a project yet, the agent will create a new project idea of initial quality $y_{i,1}$, with $y_{i,1} \sim N[\mu_i, \sigma^2]$. (The parameter μ_i with $\mu_i \sim N[\mu;\sigma^2]$ represents the individual capability level of agent i that is randomly determined at the outset for the population of n agents, with μ and σ^2 being the mean and variance of the population-level distribution of capabilities.) Note that this set-up allows for negative draws in order to reflect the

[6] If the number of current projects, X_{t-1}, equals 0 (as, for example, in the first period), then $\frac{R}{X_{t-1}}$ is set to 1.

uncertainties and risks inherent in the search process. Put differently, an agent can come up with a project idea that seems worthless. In this case, the project idea is discarded right away.

3) If search is successful and the agent already owns a project, the agent's search effort will evoke a further quality change $y_{i,x}$ of the project, with $y_{i,x} \sim N[\mu_i, \sigma^2]$. This procedure reflects the fact that in many business and innovation contexts, projects need to be refined before they can be implemented. Put differently, the quality of a project often tends to be a function of "inspiration" (the quality of the initial idea) and "transpiration" (the subsequent refinement work). It also implies that, over time, projects may increase in quality, but can likewise suffer from quality degradation. Similar to the case of project inception, if the quality of a project becomes negative, the project will be discarded.

As summarized in equation 2, if agent i owns a project in period t, the quality q of the project then depends on the number of periods t_i that the agent has successfully exerted search effort on the project:

$$q_{i,t} = \begin{cases} (1-\alpha)y_{i,1} & \text{, if } t_i = 1 \\ (1-\alpha)y_{i,1} + \alpha \sum_{x=2}^{t_i} y_{i,x} & \text{, if } t_i > 1 \end{cases} \qquad (2)$$

In equation 2, the parameter $\alpha \in [0;1]$ reflects the importance of project refinement. A high level of α implies a high refinement potential, and vice versa. For example, a high level of α could represent the considerable development potential of a new product idea, while a low level of α might correspond to incremental process improvements in the context of an employee suggestion system.

3.2.3 Project selection and implementation

In each period t, after the agents have (or have not) engaged in search, senior management ranks all current projects according to their quality and selects the R best project(s) that the resource constraint R allows implementing. Subsequently, each of the selected projects is implemented and removed from the project pipeline. The agent i that has developed a selected project is awarded a reward of $\beta \cdot q_{i,t}$, while the organization appropriates the remaining share of the created value, $(1-\beta) \cdot q_{i,t}$.

4 Results

To ensure that any differences result from our model rather than from stochastic interference, we report averages over 10,000 individual simulation runs. Each run lasted for 200 time steps to allow sufficient time for the dynamics of search and selection to reach a steady state. Below, we first report the results of a baseline experiment, in which the agents, when setting their search effort, disregard the fact that they compete for selection with other projects. Instead, they only base their search effort on the incentive intensity β and do not factor in the probability of successful project selection and remuneration.[7] We then extend this analysis by introducing competitive considerations. This procedure allows us to a) establish a benchmark for the incentive intensity and b) to clearly disentangle the effects of incentives on organizational search and performance. In both sets of experiments, we report results for a medium-sized firm ($N = 100$) with very scarce organizational resources ($R = 1$), quadratic search costs ($\omega = 0.5$), and very low refinement potential ($\alpha = 0.1$). Subsequently, we show how our results are affected if we vary the key parameters of our model. Lastly, we analyze their robustness to further variations and discuss the limitations and possible extensions of the model.

4.1 Effects of incentive intensity in the absence of project competition

4.1.1 Key dynamics

Figure 1 reports how a) the search effort, b) the number of projects in the organization, c) the quality of the selected projects, and d) the accumulated total and firm performance (i.e., the accumulated value that is created or appropriated by the firm, respectively) vary with the incentive intensity.

< Insert Figure 1 about here >

Unsurprisingly, the search effort increases in the incentive intensity (panel A), with the concave shape determined by the assumption about quadratic private search costs ($\omega = 0.5$). More interestingly, the incentive intensity only has an insignificant effect on the number of active projects in the organization

[7] "Turning off" the agents' competitive considerations is achieved by setting $\frac{R}{X_{t-1}} = 1$ in equation (1).

(Panel B). For an incentive intensity $\beta > 0$, the organization has, on average, a pipeline of 80 projects to choose from. The reason for why the number of projects is not even higher (given that we model $N = 100$ agents and only one project that is selected in each period) is that search effort does not always translate into a project with a positive quality. Due to the heterogeneity of the agents and the stochastic nature of search, search effort also turns up projects with a negative quality, which are abandoned right after project inception (if the initial signal is negative) or during subsequent project refinement (as further signals reveal that a project, which seemed positive at the outset, has in fact no value). Intriguingly, while incentive intensity does not have a differential effect on the number of projects, it leads to significant differences in terms of the quality of the selected projects (Panel C). In sum, the advantages of stronger incentive intensity and higher search effort accrue in terms of much better project quality, whereas they have a negligible effect on the size of the project pipeline. Finally, higher rewards clearly lead to a higher overall (accumulated) performance over time (Panel D). However, the organization likewise needs to consider the costs of the incentive system – the extent to which the created value is shared with the employee inventors. For the organization, the highest accumulated performance is obtained for an incentive intensity of 0.2, i.e., if the firm shares 20% of the added value of selected project proposals with the employees who proposed the projects. This finding raises the question of why the most effective incentive level is rather low, even though stronger incentive intensity leads to higher search effort and projects of higher quality.

4.1.2 Underlying mechanism

The fairly weak incentive intensity of $\beta = 0.2$ can be explained by the endogenous effect of incentives on the organizational sampling process.[8] To probe into this mechanism, it is useful to distinguish between its statistical and economic implications (Figure 2).

< Insert Figure 2 about here >

[8] Essentially, the marginal gains in terms of quality improvement decrease with an increasing rate in the incentive level (that determines the sample size), while the incentive costs increase linearly.

First, consider Panel A that reports the "sampling efficiency," which we define as the ratio between the quality of the best project and the number of successful search attempts (sample size). Stronger incentive intensity motivates higher search efforts and leads to a higher number of successful search attempts to create and refine project ideas, i.e., to a higher sample size. Yet as Panel A indicates, the increases of the sample size decrease in the incentive intensity (as shown by the distance between the markers becoming smaller.) For example, increasing incentive intensity from $\beta = 0.05$ to $\beta = 0.1$ raises the average sample size from 22.25 to 31.47, whereas going from $\beta = 0.45$ to $\beta = 0.5$ only increases the sample size by an additional 3.61. Furthermore, the sampling efficiency decreases because following from extreme value theory (Dahan and Mendelson 2001), the expected maximum project value increases in the sample size, but with a decreasing rate (as indicated also by Panel C in Figure 1). Put differently, in order to reap particularly valuable projects, disproportionately higher sample sizes are required, which require disproportionately higher incentives, but still result only in small quality improvements. As an additional indicator, consider also the sampling efficiency of the second best project, which converges with that of the best project, indicating that the quality difference between the selected projects and those that remain in the pipeline decreases as the sample size expands.

While this statistical property of the underlying mechanism – disproportionally higher incentives and sample sizes that become necessary to achieve further quality improvements – is not harmful per se, it becomes relevant once incentive costs are considered. Panel B again reports the average quality of the accepted project, indicating the decreasing marginal gains in response to higher incentives. In addition, the dotted straight line represents the fact that the costs of the incentive system increase linearly. For example, raising the incentive level from $\beta = 0.2$ to $\beta = 0.4$ denotes a doubling of the proportion of the created value that is shared with the employee. In other words, it becomes progressively more expensive for the organization to raise the expected quality of the best project. Thus, the tangent in Panel B characterizes the state in which the (marginal) gains of higher incentives equal the (marginal) costs of the incentive system. For the current parameter set-up of scarce organizational resources and no competitive interaction, this balance is reached for an incentive level of $\beta = 0.2$.

4.2 Effects of incentive intensity in the presence of project competition

The baseline case presented above misrepresents the impact of incentives on organizational search, since it deliberately ignored the influence of competition on the motivation of the agents. Put differently, the agents have been overly optimistic about securing a reward for their search efforts, as they did not consider the likelihood of project selection. In the following, we consider how our results are affected if the agents' search effort is also determined by the perceived level of project competition rather than by the incentive level alone. Figure 3 shows the resulting dynamics of the model.

< Insert Figure 3 about here >

Again, the search effort rises in response to stronger incentives (Panel A), yet the absolute scale is much lower. This difference is to be expected, since the agents systematically overestimated the expected value of their search effort in the baseline case. The increase in search effort is also much more gradual. For example, incentive intensity must rise from $\beta = 0.05$ to $\beta = 0.25$ to induce a doubling of the search effort. In the baseline case, in contrast, an increase to $\beta = 0.2$ had more than doubled it. As a result of the agents' lower search effort, the project pipeline also fills up less noticeably (Panel B). In contrast to the baseline case, incentive intensity now has a significant impact on the number of projects in the organization, as the size of the project pipeline increases in the incentive level. Importantly, the differences in adopted project quality become much less pronounced (Panel C). In the baseline case, increasing incentive intensity from $\beta = 0.05$ to $\beta = 1$ (the maximum level) had more than doubled project quality. In the present set-up, in contrast, the gains in terms of project quality are much smaller, rising only from 14 to 20. In sum, the advantages of higher rewards mainly accrue in the number of projects, but less in project quality, which has important ramifications for the most effective incentive intensity (Panel D): The incentive level that results in the highest organizational performance drops to 0.1, from 0.2 in the baseline case.

< Insert Figure 4 about here >

This result is driven by the way in which project competition changes the organizational sampling process. As Panel A of Figure 4 indicates, more realistic estimates of the likelihood of project selection result in a notably lower sample size. Furthermore, the sampling efficiency deteriorates very rapidly in the lower region of the sampling curve. At the same time, motivating even these slight increases in sample size require considerably higher rewards to overcome the demotivating effects of stronger competition. For instance, while a very low incentive level ($\beta = 0.05$) results in an average of 3.8 samples per period, it only increases to 12.3 samples when the incentive intensity is raised to its maximum ($\beta = 1$). In the baseline case, the respective sample sizes were 22.2 and 99.5. The sample size, in turn, has an impact on the marginal gains of search (Panel B). As the increases in marginal gains are less steep compared to the baseline case, the most effective incentive intensity is lower, and higher rewards do not result in a higher firm performance.

In sum, our results indicate that organizations are better off by motivating organizational search with a low incentive intensity. If organizational resources are scarce, higher-powered incentives result in a larger project pipeline, but not in a significant increase in the average quality of the accepted projects. The larger project pipeline, however, boosts competition among employees and leads to a reduction in search effort. At the same time, the firm will incur increasing incentive costs to motivate additional search effort, while the marginal gains of search decrease rapidly.

4.3 Effects of organizational factors on the incentive intensity

To gain further insight into the design of incentive systems and to establish the boundary conditions of our main results, we explored four key parameters of our model that represent important contextual factors for organizations: 1) the size of the organization as captured by the number of agents (N), 2) the scarcity of organizational resources (R), 3) the refinement potential of the projects (α), and 4) environmental turbulence, i.e., the stability of the project pipeline. In Figure 5, we report how the most effective incentive level is affected when we vary each parameter individually.

< Insert Figure 5 about here >

First, we find that the most effective incentive level decreases in the number of agents (Panel A). Put differently, smaller organizations can support stronger incentive intensity than larger firms. The reason for this difference is that even in the presence of very low individual effort, larger organizations still generate a sufficiently high sample size and, thus, project pipeline, because there are simply more active searchers in the organization. In this situation, higher rewards only have a negligible effect on search effort (because of strong project competition), while creating substantial incentive costs in terms of value sharing. Smaller organizations, in contrast, consist of fewer individual searchers, thus making individual effort relatively more important for firm performance. At the same time, the organization also has a smaller project pipeline, and higher rewards are effective in motivating additional individual effort that is not undone by the rising levels of competition. (Note, however, that incentive intensity remains well below the baseline level, even for very small firms.)

Second, we find a nonlinear relationship between resource scarcity and incentive intensity (Panel B), as reducing the scarcity of resources first lowers and, as organizational resources become abundant, increases the effective incentive level. Being able to adopt a higher number of projects in each period has two distinct effects: First, a reduction of resource scarcity lessens project competition and motivates the agents to exert higher search effort, as remuneration becomes more likely. This in turn lowers the most effective incentive level. At the same time, lower levels of project competition increase the value of offering higher rewards, since the demotivating effect of a large project pipeline is less pronounced. The former effect dominates for scarce organizational resources up to $R = 14$ (for $N = 100$), while the latter is stronger if resources are even more abundant. Overall, these results also demonstrate the robustness of our main finding, since weak incentive intensity appears to be most effective under a broad range of conditions.

Third, varying the refinement potential (α) of the projects reveals that higher levels of α (a high refinement potential) make stronger incentives more valuable, whereas the lower the refinement potential (the lower α), the lower the most effective incentive level gets (Panel C). If refinement is of little importance, it is mainly the initial idea for a project that matters. In consequence, lower incentive levels, which are effective in filling up the project pipeline, are sufficient to achieve the objective of simply generating ideas. If, in contrast, the refinement potential is very large, then projects must be developed through ongoing work. In this situation, somewhat higher-powered incentives become valuable, as they not only create a sufficiently large number of projects, but also motivate the ongoing effort to refine the existing projects in the face of strong competition by other employees. Thus, given a large refinement potential, relatively stronger incentive intensity is needed to countervail the demotivating effect of a large project pipeline.

Lastly, we consider the stability of the project pipeline (Panel D). While in all experiments reported above, project ideas may already deteriorate over time, turbulence in the task environment of the organization could be a powerful source of external selection. That is, what once was a valuable project idea could become obsolete due to external changes. By abstracting from turbulence in the task environment, our main model might overestimate the project pipeline and thus underestimate the value of stronger incentives. To study the role of environmental turbulence, we introduced a new a parameter, τ, into the model, which represents the (constant) probability that in each period, each unselected project becomes obsolete and is abandoned. While admittedly a stylized representation of environmental turbulence, this approach captures three essential properties: First, environmental turbulence adds an external selection mechanism to complement internal selection; second, the organization does not derive value from an obsolete idea, and third, the cumulative probability of obsolescence increases, the longer a project lingers in the pipeline. Intriguingly, our results suggest that environmental turbulence does not have a significant impact on the appropriate incentive level. The reason is that project obsolescence reduces the set of competing projects and thereby lessens project competition (making higher incentives more valuable). This reduction, in turn, increases the agents' search effort, which translates into a higher project quality among surviving projects (making higher incentives less necessary).

4.4 Validity and robustness

An important test for overall model validity (Burton and Obel 1995) is whether a simulation model reproduces empirical patterns. A basic empirical fact in the context of our study is that the distribution of innovations is highly skewed and corresponds to a lognormal or Pareto distribution (e.g., Scherer and Harhoff 2000; Silverberg and Verspagen 2007). Figure 6 reports how the quality of the accepted projects in our model is distributed, revealing a distribution that is clearly skewed to the right, with many mediocre projects and a handful of extremely valuable innovations. In other words, the distribution corresponds to a lognormal distribution and thus reproduces empirically observed innovation patterns.[9]

< Insert Figure 6 about here >

To further probe the robustness of our results, we also considered a) different assumptions about private search costs (ω), b) restricting the access to the competition for selection, c) a more active selection policy, and d) the mean and variance of the distribution from which the projects' qualities are drawn. Our results are qualitatively robust to changes in these parameters.[10]

First, search costs have a non-linear effect on the appropriate incentive level. If search costs are very low ($\omega = 0.1$) – for example, due to the intrinsic motivation of employees – an even weaker incentive intensity than before is sufficient to stimulate sufficient search effort ($\beta = 0.05$ instead of $\beta = 0.1$ as reported in section 4.2 for the case of $\omega = 0.5$). Under these conditions, increasing the incentive level has only a minor effect on the agents' search effort (which is already high), while substantially increasing the incentive costs. If, in contrast, search costs increase linearly ($\omega = 1$), modest increases in search effort are quite costly to the employee. Stronger incentives then become a blunt tool, since the modest increase in additional search effort and the ensuing benefits for the organization in terms of adopted project quality are offset by the substantial incentive costs. Again, we find very weak incentive intensity ($\beta = 0.05$) to be

[9] The model generates a lognormal distribution by the translation of normally distributed traits (skills and success rates of search effort) via a multiplicative process (multistage random trials) in refining a project.
[10] Detailed results for all cases are available from the authors.

most effective in this case. Also, we find much the same effects when we assume that agents have a baseline preference for search that is independent of the incentive level.

Second, we also tested whether restricting the access to the competition could improve firm performance. Organizations might soften the demotivating effect of project competition by preventing some agents from participating. We randomly selected ten agents in each run and prevented them from searching. We then compared firm performance at the end of the simulation run. The organization with unrestricted access consistently and significantly outperformed the one with restricted access.[11]

In order to soften project competition, organizations might also implement a more active selection policy by forcing employees with low-quality projects to abandon their projects without remuneration. Specifically, we considered a policy that selects out projects if their quality falls below the average quality of all projects in the pipeline. The application of this policy led to a drop in the most effective incentive level. Furthermore, it also changed the quality distribution of the adopted projects, as the mean increased, while the variance decreased, and the long tail became shorter. In other words, an active selection policy fosters lower incentives and favors mean-enhancing exploitation activities over variance-enhancing exploration (Taylor and Greve 2006). More importantly, an active selection policy likely also has further effects on the motivation of the employees (e.g., Foss 2003), which go beyond our model.

Lastly, we systematically varied the mean and the variance of the normal probability distribution that is underlying our model, which yielded qualitatively similar results to the ones we reported. We did not experiment with alternative probability distributions, since the model reproduces empirical innovation patterns such as a "long tail of innovation" (Fleming and Sorenson 2004).

4.5 Limitations and extensions

Our model structure admits a number of limitations. First, senior management's selection of projects that are proposed by employees is assumed to be perfect. A noisy selection environment, in

[11] We consider this result a robustness check. An organization that could differentiate high- and low-quality searchers might benefit from restricting access by discriminating against low-quality searchers. However, pursuing this line of thought would require a very different model set-up, since management would have to learn how to screen the quality of employees. We leave that for further research.

contrast, would likely aggravate the problems created by stronger incentive intensity, since it would become more costly to screen the project pipeline. Second, the model only focuses on competitive interactions among employees, whereas cooperative interactions such as knowledge sharing are clearly also important for decentralized innovation within firms. In this context, an important result from the tournament literature is that higher incentives reduce the agent's willingness to cooperate. Our model supports this argument by pointing out that high rewards have detrimental effects even when we abstract from cooperation. Lastly, our model assumes that organizations do not punish employees that fail to develop a proposal or win in the project selection stage. This assumption contrasts with situations like patent races among firms, or with product market competition, where higher levels of rivalry may induce a higher search effort among firms (Aghion et al. 2005). Within the context of innovation in organizations, however, these situations seem to be quite rare.

5 Discussion and conclusion

It is a central tenet in the literature on organizational evolution and change that firms need to search for new value-creating products or services in order to innovate and survive (Cyert and March 1963; Nelson and Winter 1982). How incentive systems can be leveraged to motivate a firm's employees to engage in search activities, however, is a less explored question. While a considerable literature has pointed to the beneficial effects of strong incentive intensity (Holmstrom 1989; Jones and Butler 1992; Zenger and Hesterly 1997), some scholars have remained skeptical about the value of high-powered reward systems in organizations and about their importance relative to other functions of organizing collective human action (Levinthal and March 1993). Yet the question of how to reward decentralized search efforts denotes a managerial challenge in various contexts. For instance, should firms such as 3M or Google offer high rewards to their employees that work on their own product ideas? Is strong incentive intensity beneficial in rewarding employee participation in continuous improvement processes? And should managers establish high-powered reward systems to motivate their employees to participate in corporate entrepreneurship activities, strategic initiatives, or innovation tournaments?

We developed an agent-based simulation model to address these questions. Our model captures three fundamental aspects of decentralized search within firms: that senior management selects project proposals for implementation; that employees do not face a downward risk or negative consequences if they fail to innovate; and that projects are specific to the scare resources of the organization. The model addresses a basic trade-off in organizational search that designers of organizational reward systems face: One the one hand, stronger incentive intensity raises the potential gains of the agents and, hence, their motivation to exert search effort; on the other hand, however, stronger incentives also fuel competition for scarce organizational resources, decreasing the individual likelihood of succeeding and, thus, the motivation for search.

Our results suggest that weak incentive intensity provides the most effective stimulus to motivate organizational search under a broad range of conditions. While higher-powered incentives have beneficial effects in terms of value creation, they come at a hefty price for the organization. Higher incentives increase the number of project proposals substantially, but the best proposals improve only disproportionately. At the same time, the rising number of proposals is a mixed blessing, as it has a number of distinct negative effects. First, the higher number of projects translates into much stronger competition, which has a detrimental effect on the agents' motivation. Second, many more good proposals are generated than in the case of weaker incentive intensity, yet the organization may not take advantage of them due to scarce organizational resources. Higher-powered incentives are therefore wasteful: The higher costs of incentivizing the employees only have an insignificant impact on the quality of the best proposal(s), while generating many good projects that are not implemented. Put differently, organizations that establish higher-powered incentives will generate an abundant supply of good ideas – but a systematic shortage of outstanding ideas. In contrast, lower-powered incentives serve to generate, at a much smaller cost, a sufficient number of good ideas, while the best ideas are nearly as good as under strong incentive intensity. More broadly, when seen from this perspective, incentives appear to be a rather blunt tool to harness the "long tail of innovation" (Fleming and Sorenson 2004). These findings suggest:

Proposition 1: Firms use weak incentive intensity to motivate the decentralized search for new alternatives by employees.

We are not aware of any large-scale empirical work that specifically addresses the use and effectiveness of incentives to promote decentralized innovation by employees. In their study of the effectiveness of employee reward systems on innovative output, for instance, Honig-Haftel and Martin (1993: 267) found that "informal award programs will have the most consistent impact on patent output." Consistent with the predictions of our model, they report evidence for the effectiveness of low-powered bonus plans, but did not find any positive impact of higher-powered reward systems like equity stakes, royalty payments, or sharing venture returns with the participating employees. Lerner and Wulf (2007), contrast, report a higher reliance on high-powered, long-term incentives for managers of centralized R&D departments. Both studies, however, use patent applications as the dependent variable, which is not a very resource-consuming process, so that the competition among employees for application slots will likely be limited. Based on our model, we would likewise expect higher-powered incentives under these conditions. What is more, patents just represent the tip of the iceberg of product and process innovation in business firms. Other empirical observations also appear to be in line with our first proposition. In their detailed discussion of innovation tournaments, Terwiesch and Ulrich (2009) report numerous instances of firms using low-powered monetary rewards to incentivize search. For example, Dow Chemical reports an average return of 204 percent from implemented process innovations that were suggested by employees – a clear indication of the value of weak incentive intensity in organizational search.

Our results also show that the appropriate incentive intensity depends upon organizational and environmental contingency factors. For instance, our model uncovered a very clear negative relationship between firm size and the most effective incentive intensity. In small firms, the search effort of each individual employee is comparatively more important for firm performance than in larger organizations. Furthermore, small firms can also provide higher-powered incentives, since the detrimental effect of competition will be less pronounced. Put differently, to guarantee a stable supply of good ideas, small firms need to share a larger part of the value that is created by an innovation, suggesting:

> *Proposition 2: Smaller firms employ relatively higher-powered incentives to motivate the decentralized search for new alternatives by employees.*

Concerning some initial empirical corroboration of this proposition, Zenger and Lazzarini (2004) report size-related differences in the incentive intensity of rewards, with smaller firms using higher-powered reward systems – a finding that finds support in similar studies by Honig-Haftel and Martin (1993), Zenger and Marshall (2000), and Beugelsdijk (2008).

Another important contingency factor is the nature of the innovation process. Our results point to a positive relationship between the refinement potential – how persistently employees have to develop a new alternative – and incentive intensity. Higher-powered incentives are important to promote the sustained refinement of nascent ideas and to overcome the demotivating effect of many competing projects, which suggests:

> *Proposition 3: The longer the development time for innovation projects, the higher the incentive intensity.*

Lastly, and more speculatively, our findings also suggest that weak incentive intensity systematically fosters incremental innovations in organizations, and that high rewards do not lead to a proliferation of high-value, radical innovations. This result appears to imply that performance-based reward systems cannot contribute in a significant manner to the creation of radical innovations in organizations – a conjecture for which some support has been provided recently (Beugelsdijk 2008; Cabrales et al. 2008) and that merits further investigation:

> *Proposition 4: The primary beneficial effect of low-powered incentives in organizations pertains to the generation of incremental innovations.*

Besides offering a set of testable propositions, our paper makes a number of further contributions. First, in addressing the effects of incentives in motivating organizational search, our paper contributes to work that has sought to (re-)integrate organizational economics and organization theory (Kaplan and Henderson 2005). Despite the fact that the interdependence of incentive systems and organizational search has already been noted in the initial accounts of the behavioral theory of the firm, subsequent work has developed the two concepts largely independently. While our paper does not speak to the psychological effects of incentives, it probes into the dynamics of search that results in response to the provision of rewards. In addition, we model a search process that is truly organizational, in contrast to much extant research that has represented organizations as individual decision makers (cf. Gavetti et al. 2007).

Second, research in organizational psychology has pointed to the role of intrinsic motivation for explaining individual creativity and innovation. In this context, some scholars have argued that intrinsic and extrinsic forms of motivation are substitutes, and that extrinsic motivation can have a "corruption effect" and crowd out intrinsic motivation (Osterloh and Frey 2000). Hence, organizational designs that provide high extrinsic incentives may have undesired side effects. At the same time, though, empirical evidence suggests that intrinsic incentives often co-exist with extrinsic rewards, even in the context of innovation where intrinsic motivation is considered to be particularly crucial (Terwiesch and Ulrich 2009; Sauermann and Cohen 2010). Adding to this discussion, our findings suggest that the conflict between extrinsic and intrinsic motivation and, thus, the risk of crowding-out effects, may in fact not be that pronounced, given that the most effective incentive intensity is rather low under most circumstances, in particular as our model likely even overstates rather than understates the value of extrinsic incentives.

More broadly, an important implication of our analysis is that good ideas are often not the bottleneck in large business organizations. Firms face a shortage of exceptional ideas – and higher-powered incentives do not seem to be an effective tool for searching this "long tail of innovation" (Fleming and Sorenson 2004). The crucial bottlenecks are the scarce strategic, managerial, or financial resources that prevent the organizations from pursuing a larger number of valuable business proposals (Rotemberg and Saloner 1994; Lippman and Rumelt 2003). More generally, a stylized fact is the relative stability of many business organizations (Demsetz 1991), which strategy research (Teece 1986; Lippman and Rumelt 2003) and work on the theory of firm (Williamson 1985; Hart 1995; Grant 1996) has explained by pointing to the role of tangible and intangible resources. If large organizations really faced a persistent shortage of good ideas to make use of their resources, we would expect larger fluctuations in the population of firms. Most business firms, however, do not seem to be that brittle (Hannan 2005).

To conclude, the past decades have seen a wave of scholarship addressing questions of how to design efficient incentive structures that can solve the organizational "motivation problem." And even though incentive thinking has subsequently permeated large parts of modern business firms, the domain of innovation seems to have resisted a (complete) takeover by incentive-based thinking. Based on the analysis of our model, we have pointed to a – we believe – novel mechanism for why this might be the case: the endogenous negative effects of high-powered rewards on the dynamics of decentralized search. As there is little reason to believe that our stylized model has provided an exhaustive set of answers, worthy opportunities exist for future research on the interaction of incentives, motivation, and organizational search.

References

Adler, P. S., B. Goldoftas, D. I. Levine. 1999. Flexibility versus efficiency? A case study of model changeovers in the Toyota production system. *Organization Science* 10(1) 43-68.

Adner, R., D. A. Levinthal. 2004. What is not a real option: Identifying boundaries for the application of real options to business strategy. *Academy of Management Review* 29(1) 74-85.

Aghion, P., J. Tirole. 1994. The management of innovation. *The Quarterly Journal of Economics* 109(4) 1185-1209.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, P. Howitt. 2005. Competition and innovation: An inverted-U relationship. *Quarterly Journal of Economics* 120(2) 701-728.

Axelrod, R. 1997. *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration*, Princeton University Press, Princeton.

Barney, J. B. 1991. Firm resources and sustained competitive advantage. *Journal of Management* 17(1) 99-120.

Beugelsdijk, S. 2008. Strategic human resource practices and product innovation. *Organization Studies* 29(6) 821-847

Burgelman, R. A. 1983. A process model of internal corporate venturing in the diversified major firm. *Administrative Science Quarterly* 28(2) 223-244.

Burgelman, R. A. 1991. Intraorganizational ecology of strategy making and organizational adaptation: Theory and field research. *Organization Science* 2(3) 239-262.

Burton, R., B. Obel. 1995. The validity of computational models in organization science: From model realism to purpose of the model. *Computational and Mathematical Organization Theory* 1(1) 57-72.

Cabrales, Á. L., C. C. Medina, A. C. Lavado, R. V. Cabrera. 2008. Managing functional diversity, risk taking and incentives for teams to achieve radical innovations. *R&D Management* 38(1) 35-50.

Chen, K.-P. 2003. Sabotage in promotion tournaments. *Journal of Law, Econonmics, and Organization* 19(1) 119-140.

Christensen, M., T. Knudsen. 2010. Design of decision-making organizations. *Management Science* 56(1) 71-89.

Cohen, M. D., J. G. March, J. P. Olsen. 1972. A garbage can model of organizational choice. *Administrative Science Quarterly* 17(1) 1-25.

Cyert, R. M., J. G. March. 1963. *A Behavioral Theory of the Firm*, Prentice Hall, Englewood Cliffs, NJ.

Dahan, E., H. Mendelson. 2001. An extreme-value model of concept testing. *Management Science* 47(1) 102-116.

Davis, J. P., K. M. Eisenhardt, C. B. Bingham. 2007. Developing theory with simulation methods. *Academy of Management Review* 32(2) 480-499.

Demsetz, H. 1991. The theory of the firm revisited. O. E. Williamson, S. G. Winter, eds., *The Nature of the Firm*. Blackwell, Oxford, 159-178.

Dierickx, I., K. Cool. 1989. Asset stock accumulation and sustainability of competitive advantage. *Management Science* 35(12) 1504-1511.

Ederer, F., G. Manso. 2010. Is pay-for-performance detrimental to innovation? Working paper, University of California.

Ethiraj, S. K., D. Levinthal. 2009. Hoping for A to Z while rewarding only A: Complex organizations and multiple goals. *Organization Science* 20(1) 4-21.

Fleming, L., O. Sorenson. 2004. Science as a map in technological search. *Strategic Management Journal* 25(8/9) 909-928.

Foss, N. J. 2003. Selective intervention and internal hybrids: Interpreting and learning from the rise and decline of the Oticon spaghetti organization. *Organization Science* 14(3) 331-349.

Gavetti, G., D. Levinthal, W. Ocasio. 2007. Neo-Carnegie: The Carnegie School's past, present, and reconstructing for the future. *Organization Science* 18(3) 523-536.

Gibbons, R. 1998. Incentives in organizations. *The Journal of Economic Perspectives* 12(4) 115-132.

Giummo, J. 2010. German employee inventors' compensation records: A window into the returns to patented inventions. *Research Policy* 39(3) 969-984.

Grant, R. M. 1996. Toward a knowledge-based theory of the firm. *Strategic Management Journal* 7(winter special issue) 109-122.

Hannan, M. T. 2005. Ecologies of organizations: Diversity and identity. *The Journal of Economic Perspectives* 19(1) 51-70.

Harrison, J. R., Z. Lin, G. R. Carroll, K. M. Carley. 2007. Simulation modeling in organizational and management research. *Academy of Management Review* 32(4) 1229-1245.

Hart, O. 1995. *Firms, contracts, and financial structure*, Oxford University Press, Oxford.

Holmstrom, B. 1989. Agency costs and innovation. *Journal of Economic Behavior & Organization* 12(3) 305-327.

Holmstrom, B., P. Milgrom. 1991. Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics, & Organization* 7 24-52.

Holmstrom, B., J. Tirole. 1991. Transfer pricing and organizational form. *Journal of Law, Economics, & Organization* 7(2) 201-228.

Holmstrom, B., P. Milgrom. 1994. The firm as an incentive system. *The American Economic Review* 84(4) 972-991.

Honig-Haftel, S., L. R. Martin. 1993. The effectiveness of reward systems on innovative output: An empirical analysis. *Small Business Economics* 5(4) 261-269.

Hvide, H. K. 2002. Tournament rewards and risk taking. *Journal of Labor Economics* 20(4) 877-898.

Jones, G. A., J. E. Butler. 1992. Managing internal corporate entrepreneurship: An agency theory perspective. *Journal of Management* 18(4) 733-749.

Jovanovic, B. 1979. Job matching and the theory of turnover. *The Journal of Political Economy* 87(5) 972-990.

Kaplan, S., R. Henderson. 2005. Inertia and incentives: Bridging organizational economics and organizational theory. *Organization Science* 16(5) 509-521.

Knudsen, T., D. A. Levinthal. 2007. Two faces of search: Alternative generation and alternative evaluation. *Organization Science* 18(1) 39-54.

Kretschmer, T., P. Puranam. 2008. Integration through incentives within differentiated organizations. *Organization Science* 19(6) 860-875.

Lambert, R. A., D. F. Larcker, K. Weigelt. 1993. The structure of organizational incentives. *Administrative Science Quarterly* 38(3) 438-461.

Lazear, E. P., S. Rosen. 1981. Rank-order tournaments as optimum labor contracts. *The Journal of Political Economy* 89(5) 841-864.

Lazear, E. P. 1989. Pay equality and industrial politics. *The Journal of Political Economy* 97(3) 561-580.

Lerner, J., J. Wulf. 2007. Innovation and incentives: Evidence from corporate R&D. *The Review of Economics and Statistics* 89(4) 634–644.

Levinthal, D., J. G. March. 1981. A model of adaptive organizational search. *Journal of Economic Behavior & Organization* 2(4) 307-333.

Levinthal, D. 1988. A survey of agency models of organizations. *Journal of Economic Behavior & Organization* 9(2) 153-185.

Levinthal, D. A., J. G. March. 1993. The myopia of learning. *Strategic Management Journal* 14(special issue) 95-112.

Lippman, S. A., R. P. Rumelt. 2003. A bargaining perspective on resource advantage. *Strategic Management Journal* 11(11) 1069-1086.

Lovas, B., S. Ghoshal. 2000. Strategy as guided evolution. *Strategic Management Journal* 21(9) 875-896.

MacDonald, G., M. D. Ryall. 2004. How do value creation and competition determine whether a firm appropriates value? *Management Science* 50(10) 1319-1333.

Makadok, R., R. Coff. 2009. Both market and hierarchy: An incentive-system theory of hybrid governance forms. *Academy of Management Review* 34(2) 297-319.

Manso, G. forthcoming. Motivating innovation. *Journal of Finance*.

March, J. G., H. A. Simon. 1958. *Organizations*, Wiley, New York.

March, J. G. 1988. Variable risk preferences and adaptive aspirations. *Journal of Economic Behavior & Organization* 9(1) 5-24.

March, J. G. 1991. Exploration and exploitation in organizational learning. *Organization Science* 2(1) 71-87.

Monsen, E., H. Patzelt, T. Saxton. 2009. Beyond simple utility: Incentive design and trade-offs for corporate employee-entrepreneurs. *Entrepreneurship Theory and Practice* 34(1) 105-130.

Morgan, J., R. Wang. 2010. Tournaments for ideas. *California Management Review* 52(2) 77-97.

Nelson, R. R., S. G. Winter. 1982. *An Evolutionary Theory of Economic Change*, Harvard University Press.

Nickerson, J. A., T. R. Zenger. 2004. A knowledge-based theory of the firm: The problem-solving perspective. *Organization Science* 15(6) 617-632.

Ocasio, W. 1997. Towards an attention-based view of the firm. *Strategic Management Journal* 18(summer special issue) 187-206.

Orrison, A., A. Schotter, K. Weigelt. 2004. Multiperson tournaments: An experimental examination. *Management Science* 50(2) 268-279.

Osterloh, M., B. S. Frey. 2000. Motivation, knowledge transfer, and organizational forms. *Organization Science* 11(5) 538-550.

Prendergast, C. 1999. The provision of incentives in firms. *Journal of Economic Literature* 37(1) 7-63.

Rajan, R. G., L. Zingales. 2001. The firm as a dedicated hierarchy: A theory of the origins and growth of firms. *The Quarterly Journal of Economics* 116(3) 805-851.

Rivkin, J. W. 2000. Imitation of complex strategies. *Management Science* 46(6) 824-844.

Rivkin, J. W., N. Siggelkow. 2003. Balancing search and stability: Interdependencies among elements of organizational design. *Management Science* 49(3) 290-311.

Rotemberg, J. J., G. Saloner. 1994. Benefits of narrow business strategies. *The American Economic Review* 84(5) 1330-1349.

Rotemberg, J. J., G. Saloner. 2000. Visionaries, managers, and strategic direction. *The RAND Journal of Economics* 31(4) 693-716.

Ruckes, M., T. Rønde. 2010. Dynamic incentives in organizations: Success and inertia. Working paper, Karlsruhe Institute of Technology.

Sauermann, H., W. M. Cohen. 2010. What makes them tick? Employee motives and firm innovation. *Management Science* 56(12) 2134–2153.

Scherer, F. M., D. Harhoff. 2000. Technology policy for a world of skew-distributed outcomes. *Research Policy* 29(4-5) 559-566.

Silverberg, G., B. Verspagen. 2007. The size distribution of innovations revisited: An application of extreme value statistics to citation and value measures of patent significance. *Journal of Econometrics* 139(2) 318-339.

Stein, J. C. 1997. Internal capital markets and the competition for corporate resources. *The Journal of Finance* 52(1) 111-133.

Stuart, T. E., J. M. Podolny. 1996. Local search and the evolution of technological capabilities. *Strategic Management Journal* 17(7) 21-38.

Taylor, A., H. R. Greve. 2006. Superman or the fantastic four? Knowledge combination and experience in innovative teams. *Academy of Management Journal* 49(4) 723-740.

Taylor, C. R. 1995. Digging for golden carrots: An analysis of research tournaments. *The American Economic Review* 85(4) 872-890.

Teece, D. J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy* 15(6) 285-305.

Teece, D. J. 2007. Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal* 28(13) 1319-1350.

Terwiesch, C., Y. Xu. 2008. Innovation contests, open innovation, and multiagent problem solving. *Management Science* 54(9) 1529-1543.

Terwiesch, C., K. T. Ulrich. 2009. *Innovation Tournaments: Creating and Selecting Exceptional Opportunities*, Harvard Business School Press, Boston.

Vandegrift, D., A. Yavas, P. Brown. 2007. Incentive effects and overcrowding in tournaments: An experimental analysis. *Experimental Economics* 10(4) 345-368.

Williamson, O. E. 1985. *The Economic Institutions of Capitalism*, Free Press, New York.

Williamson, O. E. 1991. Comparative economic organization: The analysis of discrete structural alternatives. *Administrative Science Quarterly* 36(2) 269-296.

Zenger, T. R. 1994. Explaining organizational diseconomies of scale in R&D: Agency problems and the allocation of engineering talent, ideas, and effort by firm size. *Management Science* 40(6) 708-729.

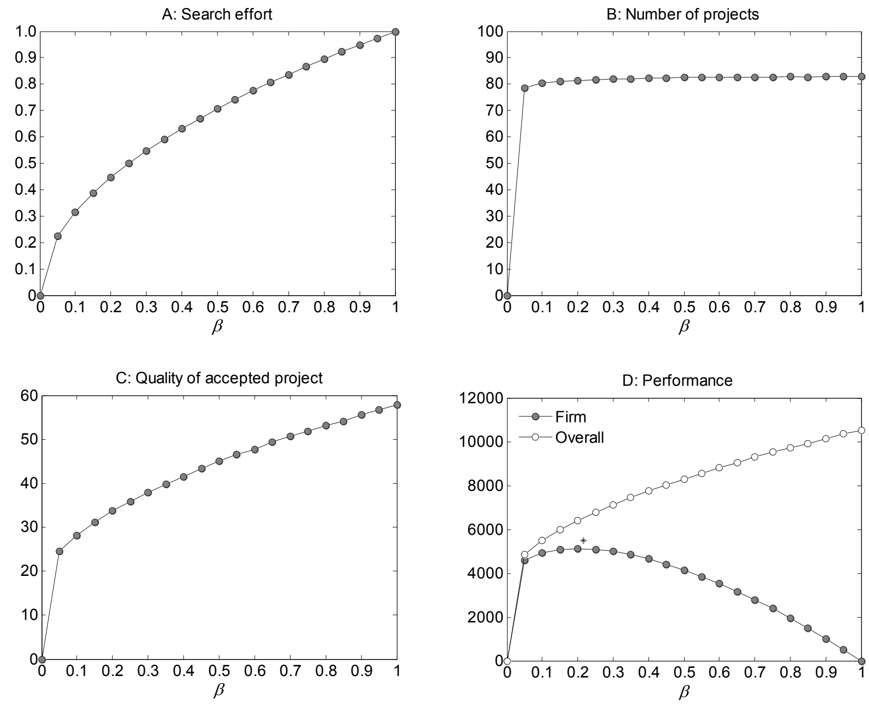
Zenger, T. R., W. S. Hesterly. 1997. The disaggregation of corporations: Selective intervention, high-powered incentives, and molecular units. *Organization Science* 8(3) 209-222.

Zenger, T. R., C. R. Marshall. 2000. Determinants of incentive intensity in group-based rewards. *The Academy of Management Journal* 43(2) 149-163.

Zenger, T. R., S. G. Lazzarini. 2004. Compensating for innovation: Do small firms offer high-powered incentives that lure talent and motivate effort? *Managerial and Decision Economics* 25(6-7) 329-345.

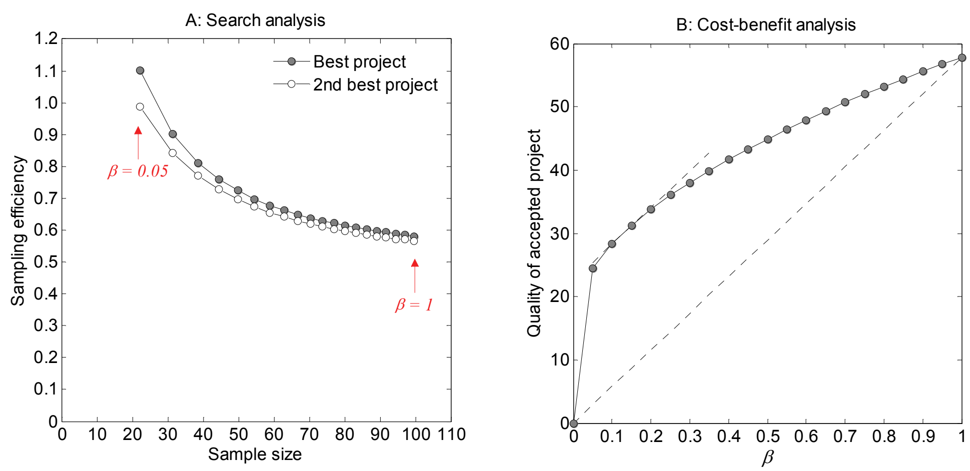
Zollo, M., S. G. Winter. 2002. Deliberate learning and the evolution of dynamic capabilities. *Organization Science* 13(3) 339-351.

Figure 1: Effects of the incentive level in the absence of competition among agents



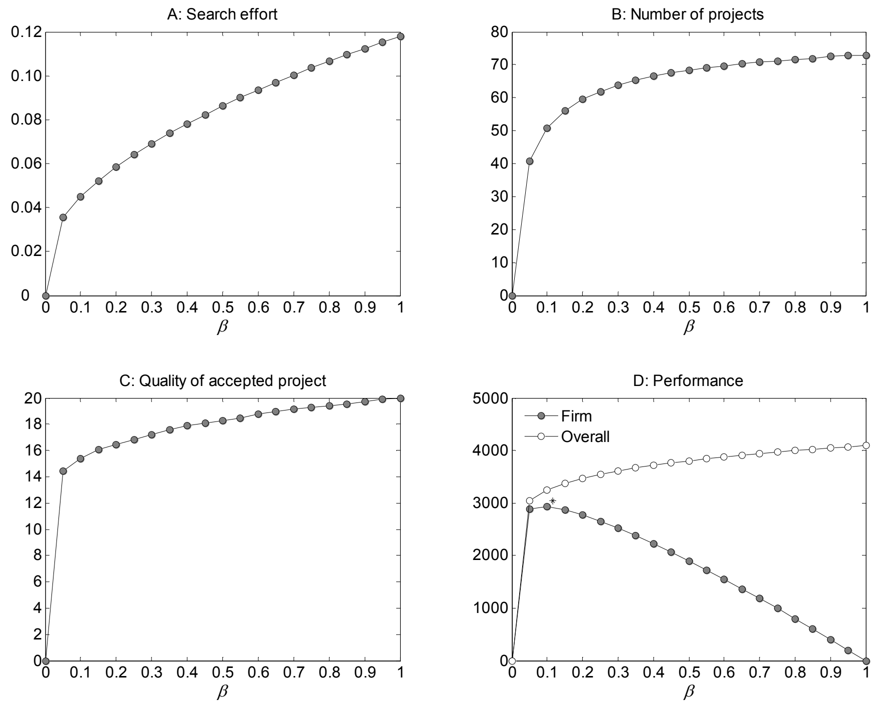
The four panels measure the dynamics of the model in response to the incentive level (β), given that the agents disregard their competitive interaction. All results are based on a set-up with $N = 100$ agents, a resource constraint of one accepted project in each period ($R = 1$), a low refinement potential of the projects ($\alpha = 0.1$), and quadratic private costs ($\omega = 0.5$). All measures are averages in period 200 over 10,000 replications. In panel D, the asterisk indicates the incentive level that results in the highest firm performance.

Figure 2: Economics of search in the absence of competition among agents



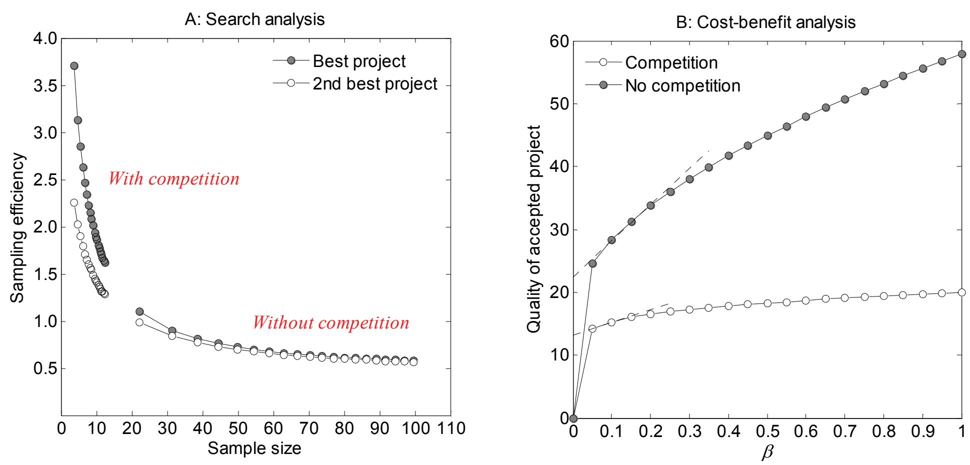
Panel A reports the number of successful search attempts ("sample size") that are induced by the incentive level (β), as well as the ratio of the average quality of the best (second best) project and the underlying sample size ("sampling efficiency"). Panel B compares the incentive costs (that increase linearly) and the quality of the accepted project (that exhibit diminishing marginal benefits) in response to the incentive level (β). All results are based on a set-up with $N = 100$ agents that disregard their competitive interaction, a resource constraint of one accepted project in each period ($R = 1$), a low refinement potential of the projects ($\alpha = 0.1$), and quadratic private costs ($\omega = 0.5$). All measures are averages in period 200 over 10,000 replications.

Figure 3: Effects of the incentive level in the presence of competition among agents



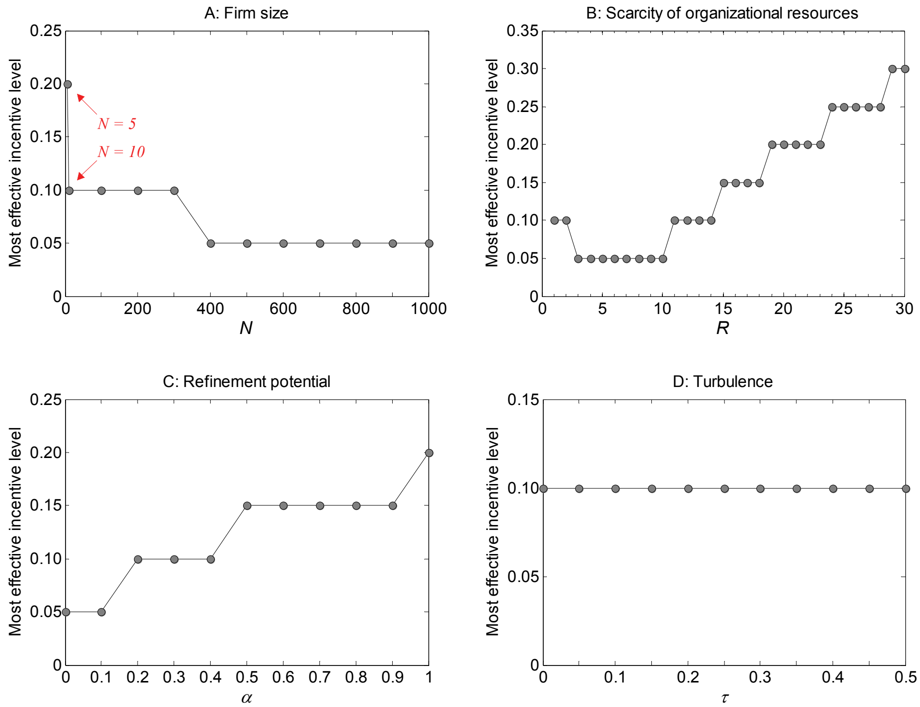
The four panels measure the dynamics of the model in response to the incentive level (β), given that the agents take their competitive interaction into account. All results are based on a set-up with N = 100 agents, a resource constraint of one accepted project in each period (R = 1), a low refinement potential of the projects (α = 0.1), and quadratic private costs (ω = 0.5). All measures are averages in period 200 over 10,000 replications. In panel D, the asterisk indicates the incentive level that results in the highest firm performance.

Figure 4: Economics of search with and without competition among agents



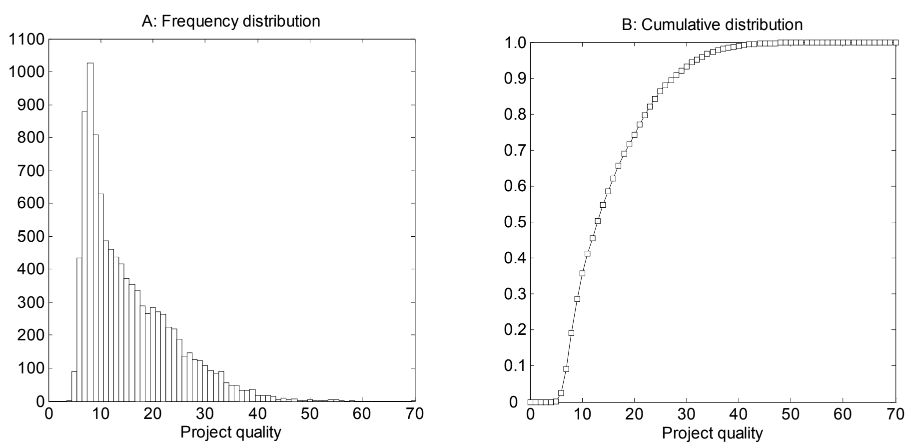
Panel A reports the number of successful search attempts ("sample size") that are induced by the incentive level (β), as well as the ratio of the average quality of the best (second best) project and the underlying sample size ("sampling efficiency"). Panel B compares the incentive costs (that increase linearly) and the quality of the accepted project (that exhibit diminishing marginal benefits) in response to the incentive level (β). All results are based on a set-up with two sets of N = 100 agents that take into account (disregard) their competitive interaction, a resource constraint of one accepted project in each period (R = 1), a low refinement potential of the projects (α = 0.1), and quadratic private costs (ω = 0.5). All measures are averages in period 200 over 10,000 replications.

Figure 5: Effects of organizational factors on the most effective incentive level



All panels measure how the most effective incentive level (β^*) is affected when the main elements of the model are relaxed individually. All measures are averages in period 200 over 10,000 replications. In each panel (except A and C), the very left node represents the baseline model under the conditions of Figure 3, i.e., N = 100 agents that consider their competitive interaction, a resource constraint of one accepted project in each period (R = 1), a low refinement potential of the projects (α = 0.1), and quadratic private costs (ω = 0.5). (In panel A and panel C, the main model is represented by the third and second node, respectively.) In panel A, the firm size (N) is varied. In panel B, the resource constraint (R) is relaxed. Panel C varies the refinement potential (α) of the projects. Panel D introduces turbulence, assuming that in each period, each project is rendered obsolete with probability τ.

Figure 6: Distribution of the quality of the accepted projects



This figure reports the frequency (panel A) and cumulative (panel B) distributions of the accepted projects in period 200 over 10,000 replications, given the most effective incentive level (β = 0.1). The results are based on a set-up with N = 100 agents that consider their competitive interaction, a resource constraint of one accepted project in each period (R = 1), a low refinement potential of the projects (α = 0.1), and quadratic private costs (ω = 0.5).