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REWARDING VALUE-CREATING IDEAS IN ORGANIZATIONS: THE POWER OF LOW-POWERED INCENTIVES

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Ideas from employees are a major source of value creation in firms, yet the merits of rewards for incentivizing the generation of ideas are highly contested. Using a computational model, we show that firms can improve performance by offering low-powered rewards for the selection and implementation of employee ideas. Low-powered incentives provide a sufficient stream of good ideas, but few exceptional ones. Higher-powered incentives, in contrast, do not systematically translate into exceptional ideas either, but generate an excessive number of good ideas. Performance-based rewards thus appear to be a blunt tool to harness the long tail of innovation. We develop propositions to guide empirical research and discuss their implications for strategy and organizational design. Copyright © 2013 John Wiley & Sons, Ltd.

INTRODUCTION

The generation of value-creating ideas is a central concern to managers that want their firms to innovate and adapt (Simon, 1993), but it requires organizations to engage in uncertain and costly search efforts (Cyert and March, 1963; Nelson and Winter, 1982). When it comes to structuring organizational search, the strategy process literature has long stressed the importance of middle managers (Bower, 1970; Burgelman, 1991; Burgelman and Grove, 2007; Wooldridge and Floyd, 1990) and frontline employees (Foss, 2003; Løvås and Ghoshal, 2000; Rotemberg and Saloner, 2000) as a primary source of variation and new strategic initiatives. Consider, for instance, firms such as 3M or Google whose employees can spend a significant part of their working time on their own initiatives. At regular intervals, these initiatives are evaluated by the firms' senior managers that commit substantial resources to turn selected ideas into successful products, and that define the organizational architecture that may promote or stifle organizational search (Løvås and Ghoshal, 2000; Rotemberg and Saloner, 2000). In a similar manner, many firms have established continuous improvement processes, Kaizen policies, or employee suggestion systems. The notion underlying these approaches—that decentralized search efforts by employees denote a valuable source of innovation—is also central to other management concepts such as corporate entrepreneurship or innovation tournaments.

Efforts to tap into the ideas of employees reflect a broader trend of making organizations more adaptive by raising the degree of lower-level autonomy and creating incentives for innovation (Foss, 2003; Makadok and Coff, 2009;

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Zenger, Felin, and Bigelow, 2011). While the beneficial effects of autonomy seem to be widely accepted, however, the question whether managers should also power up the incentives for innovation by rewarding value-creating ideas of their employees is highly contested. Management thinking has traditionally been skeptical about the value of high-powered rewards, i.e., of tying employee compensation closely to the value created (Williamson, 1991), due to their potentially dysfunctional effects on motivation and behavior; instead, it has emphasized different organizational levers to stimulate creativity and search for new ideas (Amabile, 1997; Levinthal and March, 1993; Osterloh and Frey, 2000). Evidence from business practice, in contrast, suggests that many firms do provide rewards for innovation—ranging from modest gratifications to sizeable amounts as in the case of Google (Hamel and Breen, 2007). Likewise, organizational scholars have increasingly argued for decidedly high-powered rewards to incentivize the generation of value-creating ideas by employees (Jones and Butler, 1992; Zenger and Hesterly, 1997). We contribute to this debate by showing that low-powered incentives—the weak coupling of compensation and value created—represent the most effective approach to foster employee innovation, even if we rule out any dysfunctional effects of high-powered incentives that prior work has pointed out (Roberts, 2010).

We emphasize two fundamental features of organizations (as opposed to markets) that have been underappreciated in extant work on incentives and innovation: the fact that employee innovators face a rather low downside risk if they refrain from search or fail to search successfully (Foss, 2003; Williamson, 1991), and the fact that complementary organizational resources are required in order to turn ideas into innovations (Løvås and Ghoshal, 2000; Tat, Nickerson, and Owan, 2007). These two features of organizations, we argue, give rise to a mechanism that links rewards and organizational search (and, ultimately, innovation): While prospects of higher rewards translate into higher search efforts among employees, higher-powered incentives also fuel the rivalry for complementary resources, as more projects compete for selection. More intense competition, in turn, has a dampening effect on search efforts, as it decreases the individual prospects of securing a reward.

Using an agent-based simulation model, we explore the implications of this mechanism. We show that effective reward levels are determined by how rewards moderate the saturation of a firm's stream of strategic initiatives and innovations, relative to the cost of the reward system to establish this stream. Specifically, our findings suggest that low-powered rewards denote a powerful lever to establish a continuous stream of incremental innovations, but only a few radical ones; higher rewards, in contrast, do not systematically foster these outstanding ideas either, but instead lead to a costly oversaturation of the innovation stream with an excessive number of good ideas that lie idle and have a detrimental effect on employee motivation.

PRIOR WORK AND MOTIVATION

Management thinking increasingly recognizes employees as a central source of value-creating ideas in firms. This shift in perspective has raised interest in how firms can manage the organizational search for ideas, and has reinvigorated research into the role of rewards for employee-driven innovation. We review extant research and identify gaps in our current understanding by (1) summarizing the controversial views on the value of rewards for generating value-creating ideas, and (2) discussing work that speaks to how rewards affect the dynamics of organizational search.

The contested value of rewards for ideas

Traditionally, management research has attributed only a limited role to rewards for promoting the search for value-creating ideas. Drawing on psychological work on motivation and creativity, a central argument is that "people will be most creative when they are primarily intrinsically motivated, rather than extrinsically motivated by [...] the promise of rewards" (Amabile, 1997: 39). High-powered rewards are considered to systematically crowd out intrinsic motivation, and thus to be detrimental (Amabile and Pillemer, 2012; Osterloh and Frey, 2000). In consequence, rather than focusing on financial rewards, much emphasis has been put on the design of work environments and its impact on creativity. In a similar manner, the behavioral theory of the firm stresses the provision of slack resources,

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rather than rewards, to promote exploratory search by employees and an organizational tolerance of failure. Levinthal and March (1993: 107), for instance, argue that organizations may be "more effective in removing downside risks than in providing extremely rich rewards for great success" and that they should rather influence the risk perception and risk preferences of their employees.

This skepticism toward high-powered rewards is also reflected in the literature on organizational economics. Here, the argument relates to a fundamental agency problem in organizational search: While the (unobservable) costs of generating and developing value-creating ideas are borne by individual employees, the benefits accrue to the entire organization. Obviously, this setup creates a misalignment of private and organizational interests and implies an underinvestment in innovative search by employees (Aghion and Tirole, 1994; Holmstrom, 1989; Zenger, 1994). Even though a possible solution to this agency problem might be to condition the employees' remuneration to their ideas being adopted and creating value, organizational economics points to some clear limitations: First, team production in organizations tends to obfuscate the link between individual ideas and organizational performance, thus creating assignment problems, as the individual contributions to the success of an innovation are hard to tease out (Nickerson and Zenger, 2004; Williamson, 1991). Second, even if individual contributions are observable, higher rewards for value-creating search may lead to a misallocation of effort away from valuable but hard-to-measure tasks such as engaging in coordination and cooperation with coworkers, or from exploratory tasks to exploitative ones. In other words, the multitasking environment of the workplace may undercut the provision of high-powered incentives (Holmstrom and Milgrom, 1991, 1994).

Current business practice, in contrast, suggests a more nuanced picture. An important (but sometimes overlooked) feature of the often-cited management systems of 3M or Google is the incentive system that often provides financial rewards for value-creating ideas. 3M, for example, offers "rewards that nourish both self-esteem and personal bank accounts" (3M Company, 2002: 32), while Google has "a policy of giving outsized rewards to people who come up with outsized ideas" (Hamel and Breen, 2007: 102). In 2004, Google set up its Founders' Awards program with restricted stock options that were awarded quarterly to those teams that came up with the best ideas to increase profitability.

Likewise, recent psychological research has cast doubt on the hypothesis that extrinsic rewards crowd out intrinsic motivation (e.g., Eisenberger and Aselage, 2009). Instead, evidence increasingly points to a complementary relationship between financial rewards and intrinsic motivation—a result that is mirrored by empirical studies in human resource management that found a positive effect of rewards on employees' innovative behavior (Sauermann and Cohen, 2010) and on intrinsic motivation (Fang and Gerhart, 2012). Similarly, formal models in organizational economics have increasingly looked into how high-powered incentive contracts for innovative behavior can be structured in a multitasking environment (Hellmann and Thiele, 2011; Manso, 2011). Finally, scholars of economic organization have studied how to craft internal hybrid organizations by injecting higher-powered incentives into traditional firms (Foss, 2003; Jones and Butler, 1992; Makadok and Coff, 2009; Zenger and Hesterly, 1997; Zenger and Marshall, 2000). A key idea in this literature is that smaller, autonomous business units face less severe challenges in assigning individual effort to organizational outcomes. Zenger and Hesterly (1997: 213), for instance, suggest explicitly that, under these conditions, higher rewards become beneficial for innovation and performance, since "high-powered incentives [. . .] strongly motivate the development and leveraging of valuable capabilities, routines, and knowledge."

Rewards and the dynamics of organizational search

A central feature of organizations is the presence of an internal selection regime that screens and selects ideas by employees for implementation and resource commitment (Adner and Levinthal, 2004; Foss, 2003; Løvås and Ghoshal, 2000; Tat *et al.*, 2007). It is likewise a crucial fact that firms cannot implement every idea, because their implementation ties up scarce complementary resources (Foss, 2003; Løvås and Ghoshal, 2000; Rotemberg and Saloner, 1994). The resource-based view of strategy, for instance, is centered on the insight that strategic resources cannot be easily replicated or expanded (e.g., Dierickx and Cool,

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1989; Lippman and Rumelt, 2003). Moreover, financial resources are often constrained (Stein, 1997), and managerial attention is limited (Ocasio, 1997). As a consequence of these organizational resource constraints, employees do not search in isolation for value-creating ideas, but compete for the selection of their ideas and for the rewards that are tied to their implementation (Foss, 2003). In such a competitive setting, the relative value of an idea becomes crucial for selection, and the likelihood of implementation depends on the entire pool of ideas that senior management selects from. If an organization faces a dearth of good ideas, even an average idea might be selected and rewarded, while good ideas may be passed over if many excellent ones are available for implementation.

Competition for prizes within organizations denotes the central topic of tournament theory that studies how rewards such as financial bonuses or promotions can be structured to induce optimal effort among employees (Lazear and Rosen, 1981; Prendergast, 1999). The central finding of this literature is that an employee's optimal effort level is strictly increasing with the value of the prize and strictly decreasing with the number of contestants (Hellmann and Thiele, 2011). The downside of high prizes in tournament settings, however, is that they may also motivate excessive risk taking (Hvide, 2002) or sabotage (Chen, 2003).[1]

The extent to which insight from tournament theory can be applied to search within organizations, however, appears to be limited. First, tournaments are typically conceived of as competitive processes with a predetermined 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 (incremental and radical) innovations 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, March, and Olsen, 1972; Foss, 2003; Løvås and Ghoshal, 2000), especially if employees continue to improve them. Second, tournament theory also assumes that the principal designing the tournament has perfect information about the potential for value creation, thus allowing 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. Hence, because the costs and benefits of search are often unpredictable (Fleming, 2001), optimal responses to the provision of incentives are likely extreme cases—a notion that is supported by experimental research that documents how, even in simple tournament settings, decision making proceeds in a fairly heuristic manner (Orrison, Schotter, and Weigelt, 2004; Vandegrift, Yavas, and Brown, 2007).

MODEL

To study how rewards affect the dynamics of search for value-creating ideas among employees, we use an agent-based simulation model. Computational models have become popular among scholars of organizational search for a number of reasons (Harrison *et al.*, 2007). For instance, although they cannot yield "exact" solutions as algebraic modeling might, they allow for incorporation of 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 that search adaptively, as they know neither the expected outcomes of search nor their own marginal productivity. 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. For example, our model allows us to study an arbitrarily large number of employees, and thus to represent different firm sizes, which would be harder to accomplish with a closed-form approach. Finally, our model represents a "virtual laboratory" to systematically experiment with the most salient aspects of organizational search in response to rewards, while

[1] 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 Ulrich, 2009; Terwiesch and Xu, 2008). The analysis of incentives in innovation tournaments rests largely on models developed in contest theory (Morgan and Wang, 2010). An important early contribution is Taylor (1995) who showed that restricting access to innovation tournaments and softening competition among participants may improve performance (cf. Boudreau, Lacetera, and Lakhani, 2011). Terwiesch and Xu (2008) offered a detailed analysis of incentive design in external innovation tournaments and demonstrate that seekers may compensate the detrimental effect of strong competition by offering performance-contingent awards.

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excluding any undesired effects of incentives that extant work has pointed out (i.e., assignment problems, multitasking, cooperation and coordination issues, decisions between exploration and exploitation, (excessive) risk taking, sabotage, or other detrimental employee actions). And even though a simulation-based approach grants higher degrees of freedom, our model does not attempt to represent any specific real-world context. Instead, it contains stylized elements to shed light on the abstract problem under investigation, thus following a time-honored tradition in management research to develop parsimonious yet insightful models (Harrison *et al.*, 2007). In the following, we describe the structure of these elements and their implementation.

Structure of the model

Our model consists of two organizational levels: (1) the level of the employees (or agents) that search for value-creating ideas (projects), and (2) the level of a firm's senior management that screens and selects projects for implementation. We assume that the agents' search effort is unobservable by the senior management, whereas the value of projects is fully observable. Importantly, we assume that projects are specific to the firm and require access to complementary organizational resources in order to be implemented. In a stylized manner, this assumption reflects how existing organizational resources channel creativity and provide cues in the search space (Cyert and March, 1963; Stuart and Podolny, 1996).[2]

Due to scare organizational resources, only a limited number of projects may be implemented in each period. Rotemberg and Saloner (1994, 2000) argued that the limited ability of firms to implement value-creating ideas may be a primary motive to craft strategy on core competencies of the firm. The resource-based view of the firm has identified various factors that prevent the replication and expansion of scarce organizational resources and capabilities (Dierickx and Cool, 1989). Likewise, the behavioral theory of the firm highlights the limits to managerial attention, which is required for turning a business idea into reality (Cyert and March, 1963; Lippman and Rumelt, 2003; Ocasio, 1997). Furthermore, and in contrast to the market competition faced by entrepreneurs, the employees in our model do not face a downside risk 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 spillovers among employees.

The model highlights two effects that appear to be of major relevance when rewarding search in organizations. First, higher-powered rewards motivate each employee to exert higher effort in her search activities. As search effort is correlated with the potential value of a project, higher effort improves the likelihood of project selection and remuneration. This effect of expected rewards on effort is a central tenet in organizational economics. Second, the likelihood of securing a reward also depends on the search efforts of other employees in the organization. Because scarce complementary resources constrain the number of ideas that may be implemented, the relative value of projects will decide about selection and implementation. Strong competition among projects, in turn, reduces search efforts among employees, as it decreases the likelihood that their projects will be selected and remunerated (Rotemberg and Saloner, 1994, 2000). In sum, stronger incentive intensity has two opposing effects on the proclivity of employees to engage in search for value-creating ideas: Higher rewards increase the potential gains from search activities, but also amplify competition among employees, thus decreasing the individual likelihood of succeeding.

Implementation

Determining the search effort

Our modeled organization consists of N agents that compete with each other for the selection and implementation of their projects by the senior management. In each period t, the agents decide about their effort level $e_t \in [0;1]$ with which they search for value-creating projects. The effort level

[2] Hellmann and Thiele (2011) provide an analysis of how the degree of an idea's firm specificity impacts incentives. If innovative ideas are not specific to the firm, employees have an outside option to pursue the innovation on their own, e.g., through a start-up or in a different firm (cf. Stieglitz and Heine, 2007). This increases the private gains from search and may lead to an overinvestment by employees into idea generation. In this context, we also do not consider problems of ex post bargaining between the firm and an agent (that suggests a firm-specific project), because prior work showed that credible commitment to a reward system is a necessary condition to motivate effort (Foss, 2003; Hart, 1995).

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determines the probability of finding a project idea or refining an existing one.[3]

Building on the conceptual discussion above, the agents consider three factors when determining their search effort (see Equation 1): the reward level β, the current level of competition among projects $\frac{R}{X_{t-1}}$, and the agents' private costs of exerting search effort ω:

$$e_t = \left(\frac{R}{X_{t-1}} \times \beta\right)^{\omega} \tag{1}$$

First, the reward level $\beta \in [0;1]$ reflects the extent of value-sharing between the firm and its employees. If $\beta = 0$, incentives are ultimately 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 percent of the value that is created by an implemented project will accrue to the employee who propagated the idea. In sum, higher incentive levels β translate into higher search efforts. (In the robustness section, we also consider the case that the agents' search effort is partially independent of potential rewards.)

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. Hence, the higher the R, the less scarce are the complementary resources that are required to implement projects. We further assume that 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 all agents can observe this number), then competitive considerations are expressed by the ratio $\frac{R}{X_{t-1}}$. Put simply, the more projects that compete for selection, and the more severe the resource constraint (the lower R), the more pronounced the perceived competition and, hence, the lower the agents' search effort will be.[4]

Third, the parameter ω captures the agents' private search costs, governing how changes in the incentive intensity and the level of competition map onto search effort. When $\omega = 1$, private costs increase linearly, while $\omega = 0.5$ corresponds to a quadratic cost function. If ω is very low, the private search costs become negligible, and a small rise of the incentive level (or, conversely, a small reduction of the level of competition) invokes a disproportionate increase of the search effort.

Creating and refining projects

In our model, search effort e_t determines the agents' probability of finding or refining a project idea in period t. For example, if $e_t = 0.3$, each agent's search effort in period t will be successful with a probability of 30 percent. We assume that each of the N agents can work on at most one project. For each agent i, we distinguish the following three cases in each period t of the simulation:

(1) If search is unsuccessful (i.e., with probability $1\text{-}e_t$), the agent either remains without a project or keeps her existing project (whose value remains unchanged compared to the previous period).
(2) If search is successful, and the agent does not own a project yet, he will create a new project idea of initial value $y_{i,1}$, with $y_{i,1} \sim N[\mu_i, \sigma^2]$. The parameter μ_i with $\mu_i \sim N[\mu;\sigma^2]$ represents the agent's individual ability, which 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 abilities.[5] Note that this setup allows for negative draws to capture the risks inherent in the search process. An agent can come up with an idea that is worthless. In this case, the project idea is discarded right away.
(3) If search is successful, and the agent already owns a project, her search effort evokes a further change $y_{i,x}$ in the value of the project, with $y_{i,x} \sim N[\mu_i, \sigma^2]$. This procedure reflects that, in many contexts, projects need to be refined before they can be evaluated for implementation, i.e., their value is a

[3] 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 ability 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. All results are available from the authors.

[4] If the number of current projects, X_{t-1}, equals *0* (as, for example, in the first period), $\frac{R}{X_{t-1}}$ is set to 1, and search effort is solely determined by the reward level.

[5] We use $\mu = 1$ and $\sigma^2 = 10$ throughout all experiments. As we report in the robustness section, our results are qualitatively insensitive to the choice of these parameters.

function of both "inspiration" (the initial idea) and "transpiration" (the subsequent refinement work). It also implies that, over time, projects may increase in value, but can likewise suffer from value erosion. Similar to the case of project inception, if the value of a project becomes negative, the project is discarded.

As summarized in Equation 2, if agent i holds a project in period t, the value q of the project depends on the number of periods t_i in which the agent could successfully refine the project:

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

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 might represent a product development context, where ideas need to be considerably developed once they are conceived; a low level of α, in contrast, might reflect the incremental process improvements in the context of an employee suggestion system.

Selecting and implementing projects

At any point in time, the organization may thus consist of up to N active projects that differ in their value (and their state of refinement), and that compete for selection. In each period t, after the agents have engaged in search, senior management ranks all active projects according to their value and selects the R best project(s) that the resource constraint R allows them to implement. Each of the selected projects is implemented and removed from the project pipeline. The agent i that developed a selected project is awarded a reward of $\beta \times q_{i,t}$, while the organization appropriates the remaining share of the created value, $(1-\beta) \times q_{i,t}$.

RESULTS

Below, we first report the basic effects of rewards on organizational search, assuming a medium-sized firm ($N = 100$) with very scarce organizational resources ($R = 1$), quadratic search costs ($\omega = 0.5$), and a low refinement potential of project ideas ($\alpha = 0.1$). Subsequently, we characterize the innovation streams that result from offering rewards and probe the role of the scarcity of complementary resources. We then demonstrate how our results are affected if we vary key parameters and assumptions of the model, before discussing limitations and possible extensions. 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.

Effects of rewards on organizational search

To disentangle the effects of the reward level on organizational search, Figure 1 reports the resulting (1) search effort, (2) number of projects in the organization, (3) quality of the selected projects, and (4) accumulated value (specifically, the value that is created in total, as well as the part of the value that the firm can appropriate).

Dynamics without competition

To establish a baseline, consider first the case of "no competition" for project selection. Here, we assume that the employees, when setting their search effort, disregard competitive intensity, i.e., they respond solely to the reward level β.[6] Little surprisingly, the search effort increases in the reward level Figure 1A, with the concave shape being determined by the quadratic private search costs ($\omega = 0.5$). More interestingly, the reward level has only an insignificant effect on the number of active projects in the organization (Figure 1B). For a reward level $\beta > 0$, the organization has on average 80 projects to choose from. Intriguingly, however, the reward level leads to significant differences in terms of the quality of the selected projects (Figure 1C). Hence, 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

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

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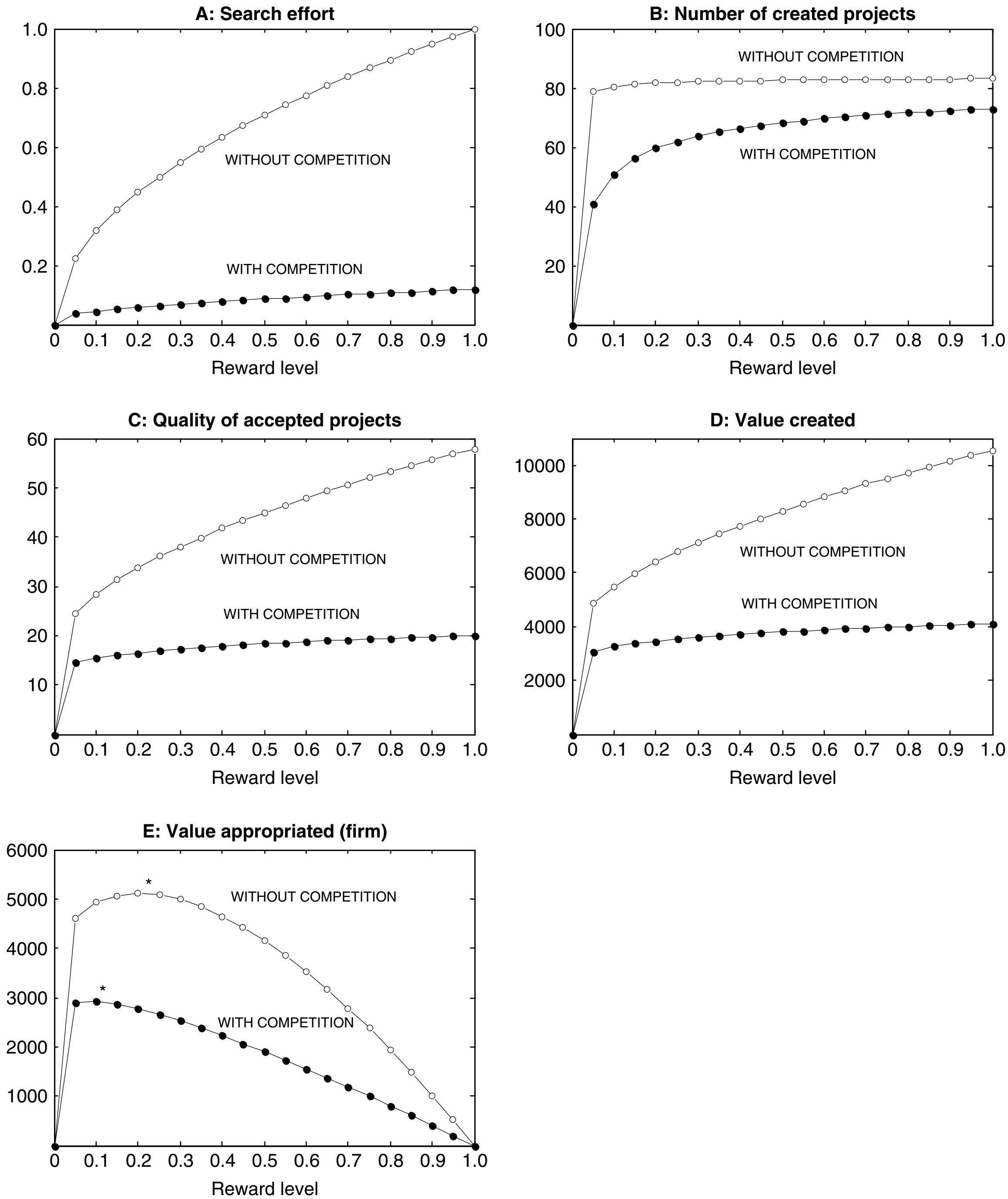

Figure 1. (A–E) Effects of rewarding value-creating ideas. The five panels measure the dynamics of the model in response to the reward level (β), both without competition (the agents disregard their competitive interaction) and with competition (the agents do consider the level of competition). All results are based on a setup 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 (E), the asterisk indicates the reward level that results in the highest firm performance

to a higher overall (accumulated) performance over time (Figure 1D). However, taking the costs of the incentive system into account, the highest organizational performance is obtained for a reward level of 0.2, i.e., if the firm shares 20 percent of the added value of implemented project proposals with the employees who proposed the projects.

Dynamics with competition

The above analysis misrepresents the impact of rewards on organizational search. By ignoring the influence of competition on the likelihood of project selection, the agents were overly optimistic about securing a reward and systematically overestimated the expected value of their search efforts. Consider now the case "with competition," where the agents' search effort is determined by the incentive level *and* the perceived level of project competition (Figure 1). Again, search effort rises in response to higher incentives (A), yet the scale is much lower, and the increases are much more gradual. (To induce a doubling of search effort, for instance, the reward level must rise from $\beta = 0.05$ to 0.25; in the absence of competitive considerations, 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 (B). In contrast to the baseline case, the reward level now has a significant impact on the size of the project pipeline, i.e., the number of projects in the organization. Importantly, the differences in adopted project quality become much less pronounced (C). Without competitive considerations, increasing the reward level from $\beta = 0.05$ to 1 more than doubled project quality. In the present setup, the gains in terms of project quality are much smaller. In sum, the benefits of higher rewards now mainly accrue in the number of projects, but less in project quality, which has important ramifications for the most effective incentive intensity (D): The incentive level that results in the highest organizational performance drops to a low value of 0.1.

Underlying mechanism

Why is the most effective reward level rather low, even though higher rewards lead to higher search efforts and projects of higher value? This finding is driven by the endogenous effects of incentives on the organizational search process and its creation of value (Figure 2).

First, consider Figure 2A, which reports the "sampling efficiency," defined as the ratio of the value of the best project and the number of successful search attempts (sample size). Higher-powered incentives induce higher search efforts and entail a larger sample size (a higher number of successful search attempts to create and refine project ideas). But as Figure 2A indicates, the increases of the sample size decrease in the reward level (as shown by the distance between the markers becoming smaller.) For example, in the case without competition, increasing the reward level from $\beta = 0.05$ to 0.1 raises the average sample size from 22.3 to 31.5, whereas going from $\beta = 0.45$ to 0.5 only increases it by an additional 3.6 samples. Furthermore, the sampling efficiency decreases because the expected maximum project value increases in the sample size (Dahan and Mendelson, 2001), but with a decreasing rate (as indicated by Figure 1C). Hence, trying to reap particularly valuable projects requires disproportionately higher sample sizes, which call for disproportionately higher incentives, but those still result only in small quality improvements. As an additional indicator, note that the sampling efficiency of the second best project converges with that of the best project, indicating that the difference between the selected projects and those that remain in the pipeline decreases as the sample size expands.

"With competition," i.e., when the employees consider the degree of competition, the nature of the sampling process changes. As Figure 1A indicates, more realistic estimates of the likelihood of project selection result in notably lower sample sizes. Furthermore, the sampling efficiency deteriorates very rapidly in the lower region of the sampling curve. At the same time, inducing even these slight increases in sample size requires considerably higher rewards to overcome the demotivating effects of stronger competition. For instance, while a very low reward 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 ($\beta = 1$). Without competition, the corresponding sample sizes were 22.2 and 99.5, respectively.

While disproportionately higher rewards to induce larger sample sizes are not harmful per se, they become relevant once value creation and

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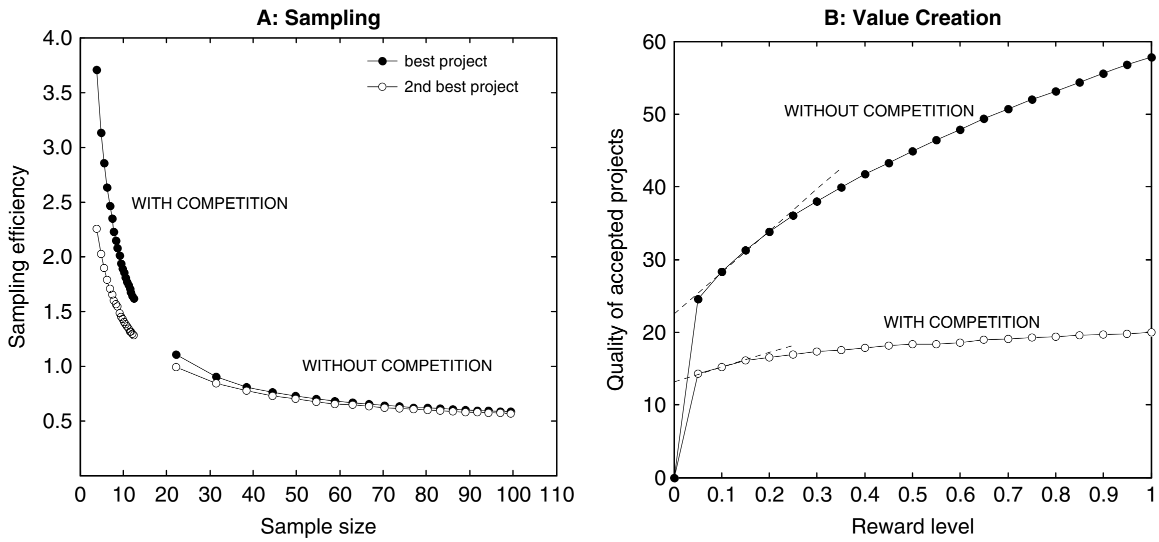

Figure 2. Sampling dynamics and value creation. (A) Compares the sample size—the number of successful search attempts that are induced by different reward levels (β)—with the sampling efficiency—the ratio of the average quality of the best (second best) project and the underlying sample size. (B) Compares the costs of the reward system (which increase linearly) and the quality of the accepted project (which exhibits diminishing marginal benefits) in response to the reward level (β). All results are based on a setup 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

incentive costs are compared. Figure 1B reports the average quality of the accepted project, indicating the decreasing marginal gains in response to higher rewards. The dotted straight line indicates the linear increase in incentive costs. For example, raising the reward level from $\beta = 0.2$ to 0.4 implies that twice as much of the created value will be shared with the employee. It therefore becomes progressively more expensive for the firm to raise the expected quality of the best project. The tangent in Figure 1B characterizes the state in which the marginal gains of higher incentives equal the marginal costs of value sharing, which in the case "without competition" is reached for a reward of $\beta = 0.2$. Because the increases in marginal gains are less steep in the case "with competition," the most effective reward level is lower, and higher rewards do not result in a higher firm performance.

In sum, our results indicate that organizations are better off stimulating organizational search by offering rather low-powered rewards for value-creating ideas. 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. To motivate additional search effort, the firm faces increasing incentive costs, whereas the marginal gains from search decrease rapidly.

Innovation streams resulting from rewards for search

An important test for overall validity is whether a simulation model reproduces empirically observed patterns. A basic fact in the context of this study is that the distribution of innovations is highly skewed and corresponds to a log-normal or Pareto distribution (e.g., Scherer and Harhoff, 2000; Silverberg and Verspagen, 2007). Figure 3 reports how the quality of the accepted projects in our model is distributed. It reveals a distribution that is clearly skewed to the right, with many mediocre projects and very few extremely valuable innovations, thus corresponding to empirical accounts of the quality of innovations.

Moreover, the findings show that high-powered rewards, in contrast to low-powered ones, do not shape the innovation stream in fundamentally different ways, but only shift the mean slightly to the right. In other words, while rewards are an effective means to generate numerous good ideas,

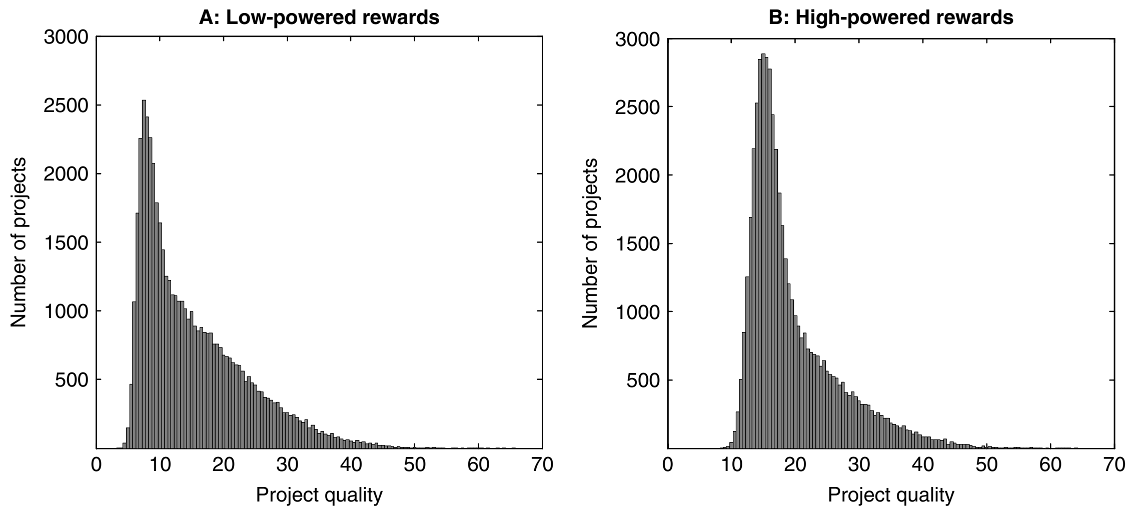

Figure 3. Innovation streams resulting from high-powered and low-powered rewards. This figure reports the frequency distributions of the accepted projects in period 200 over 10,000 replications, given (A) low-powered rewards ($\beta = 0.1$) and (B) high-powered rewards ($\beta = 0.9$). The results are based on a setup 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 ($\alpha = 0.1$), and quadratic private costs ($\omega = 0.5$)

they appear to be rather ineffective for reaping the long tail of the innovation distribution.

The moderating role of the resource scarcity

While the experiments above assumed complementary organizational resources to be very limited, the results of relaxing this assumption are intriguing (Figure 4).

We find a nonlinear relationship between resource scarcity and the effective reward level. Reducing the resource scarcity first lowers and, as resources become more abundant, then increases the most effective reward level. Being able to adopt a higher number of projects in each period has two distinct effects: First, lower resource scarcity lessens project competition and motivates the agents to exert higher search efforts, 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 de-motivating effect of a large project pipeline is less pronounced. The former effect dominates for scarce organizational resources up to $R = 14$, while the latter is stronger if resources are even more abundant. Overall, these results also demonstrate the robustness of our main finding, given that low reward levels prove most effective under a broad range of conditions.

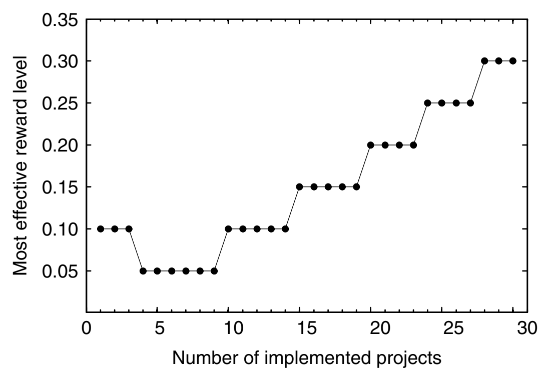

Figure 4. Role of the scarcity of complementary organizational resources. This figure reports the most effective reward level (β^*), subject to how constrained the complementary organizational resources are (the number of projects, R, that can be accepted in every period). The results are based on a setup with $N = 100$ agents that consider their competitive interaction, 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

Implications of key organizational factors

To gain further insight into the design of reward systems for value-creating ideas, and to establish the boundary conditions of our main results, we explored four key assumptions and parameters of our model that represent important contextual factors for organizations: (1) the size of the

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organization as captured by the number of agents (N), (2) the refinement potential of the projects (α), (3) an active selection policy by the senior management, and (4) environmental turbulence, i.e., the stability of the project pipeline. In Figure 5, we report the effects of varying each parameter individually.

First, we find that the most effective reward level decreases in the number of agents, or, reversely, that smaller organizations tend to have higher rewards than larger firms (Figure 5A). 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 more active searchers in the organization. In this situation, higher rewards only have a negligible effect on search effort (due to 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, a smaller organization also has a smaller project pipeline, and higher rewards are effective in motivating additional individual effort that is not annihilated by the rising level of competition.

Second, 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 becomes (Figure 5B). If refinement is of little importance, it is mainly the initial idea for a project that matters. In consequence, lower reward levels, which are effective in filling up the project pipeline, are sufficient to simply generate 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 de-motivating effect of a large project pipeline.

Third, in order to soften project competition, organizations might implement an 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 a certain fraction of the last accepted project. Applying this policy and increasing the threshold level that must be met first leads to a drop in the most effective reward level and, subsequently, to a rise again (Figure 5C). (It also changes the quality distribution of the adopted projects, as the mean increases, while the variance decreases, and the long tail becomes shorter.) In other words, an active selection policy fosters lower incentives and favors mean-enhancing exploitation activities over variance-enhancing exploration. Even 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 consider the stability of the project pipeline (Figure 5D). Turbulence in the task environment of the organization could render more project ideas obsolete. To study environmental turbulence, we introduced a parameter, τ, which represents the (constant) probability in each period that each unselected project becomes obsolete and is abandoned. Despite being a stylized representation, this approach captures three aspects of environmental turbulence: First, it 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. Our results indicate that turbulence does not have a strong impact on the effective reward level. As project obsolescence reduces the number of competing projects, it softens competition (making higher rewards more valuable). This reduction in competition, in turn, increases the agents' search effort and translates into a higher project quality among surviving projects (making higher rewards less valuable). Indeed, the latter effect tends to dominate for intermediate levels of turbulence, leading to an inverted U-shaped relationship between turbulence and effective reward levels.

Validity and robustness

To further probe the robustness of our results, we also considered (1) different assumptions about private search costs (ω), (2) restricting the access to the competition for selection, and (3) varying the

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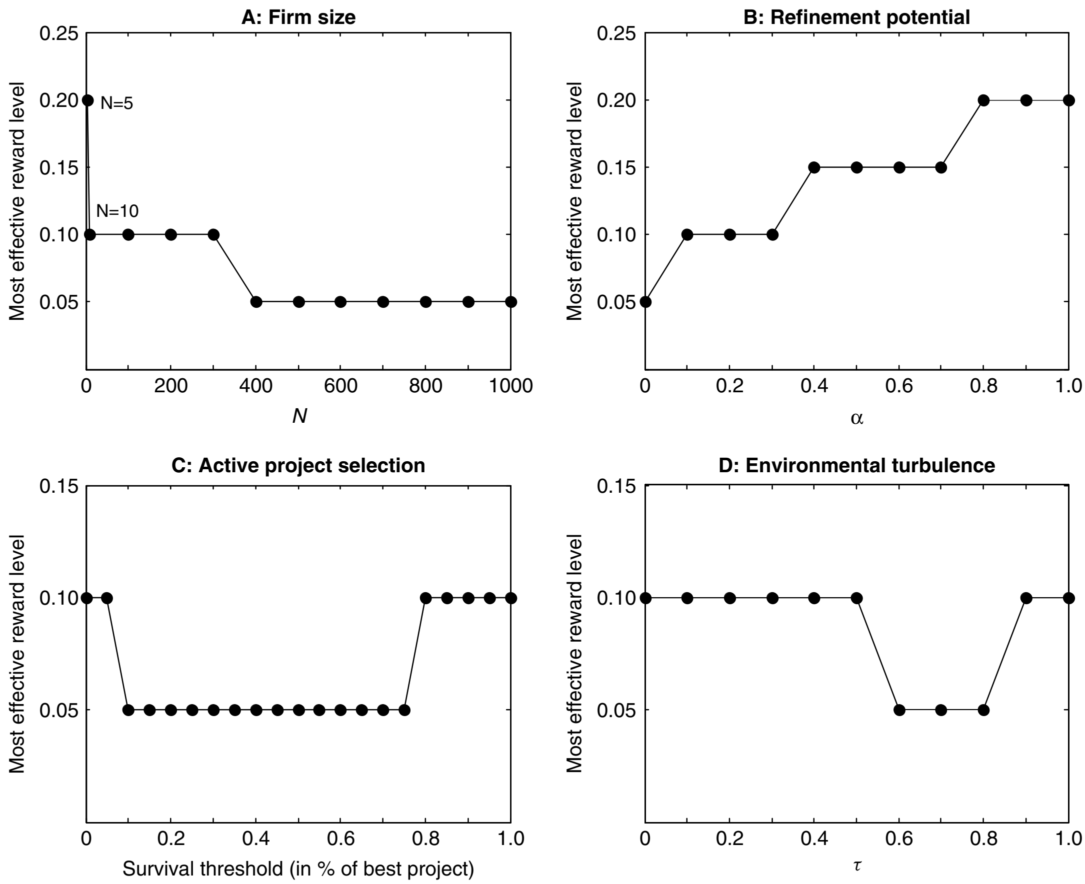

Figure 5. Implications of key organizational factors. All panels measure how the most effective incentive level (β^*) is affected when key assumptions and main elements of the model are relaxed. All measures are averages in period 200 over 10,000 replications. In (C) and (D), the very left node represents the baseline model under the conditions of Figure 1, i.e., $N = 100$ agents, which consider 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 ($\omega = 0.5$). (In (A) and (B), the main model is represented by the third and second node, respectively.) In (A) the firm size (N) is varied; (B) varies the refinement potential (α) of the projects; in (C) all projects with a value below a threshold (in % relative to the performance of the currently accepted project) are discontinued in each period; and (D) represents environmental turbulence, assuming that, in each period, each project is rendered obsolete with probability τ

mean and variance of the distribution from which the projects' qualities are drawn.[7]

First, private search costs have a nonlinear effect on the appropriate incentive level. If costs are very low ($\omega = 0.1$), a very weak reward level is sufficient to stimulate search ($\beta = 0.05$ instead of $\beta = 0.1$ as in 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 private search costs increase linearly ($\omega = 1$), in contrast, modest increases in search effort are quite costly to the employee. Stronger incentives then become ineffective, because the modest increase in additional search effort and the related benefits in terms of project quality are offset by the substantial incentive costs. Again, we find very low-powered rewards ($\beta = 0.05$) to be most effective in this case. We observe the same effects when agents have a baseline search effort that is independent of the incentive level.

Second, we also tested whether restricting access to the competition (Rotemberg and Saloner, 1994) would soften the de-motivating effect of project competition. We randomly selected ten

[7] Detailed results for all cases are available from the authors.

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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.[8]

Finally, we systematically varied the mean and the variance of the normal 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.

Limitations and extensions

Our model structure admits a number of limitations that point to potential for future research. One is that senior management's selection of projects is assumed to be perfect. A noisy selection environment would likely aggravate the problems created by high-powered rewards, as screening a larger project pipeline became more difficult. Moreover, the model focuses on competitive interactions among employees. Cooperative interactions such as knowledge sharing, in contrast, are clearly important as well, and a central result in the tournament literature is that competitive incentives reduce cooperation and knowledge sharing (Prendergast, 1999). Our model supports this argument by pointing out that high rewards have detrimental effects even when we abstract from cooperation. Another simplification is that the model is eclectic as to whether agents represent individual employees or teams, and thus disregards team formation processes that play a crucial role in value creation within firms (Foss, 2003). Hence, the model does not contribute to the important question whether incentives should be personalized or team based. The model also 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 higher search efforts (Aghion *et al.*, 2005). In the context of innovation within organizations, however, these situations seem to be quite rare. Finally, the model does not address problems of designing innovation contests, in which competitors search for solutions to a well-defined problem (Boudreau *et al.*, 2011; Terwiesch and Xu, 2008)—a setup that contrasts with the search for value creation as an organizational process that is ongoing and less well defined.

DISCUSSION AND CONCLUSION

Our results suggest that low-powered incentives are the most effective approach to induce organizational search under a broad range of conditions. Higher-powered rewards, in contrast, come at a hefty price for the organization, even though they have beneficial effects in terms of value creation. While higher rewards increase the number of project proposals substantially, the best proposals improve only disproportionately. At the same time, the rising number of proposals is a mixed blessing that entails two 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, but if complementary resources are scarce, the organization cannot take advantage of them. Higher-powered incentives are thus 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. Lower-powered incentives, in contrast, 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. Rewards thus appear to be a rather blunt tool to harness the long tail of innovation.

The mechanism we describe appears to have face validity. Returning to the case of Google, anecdotal evidence suggests that the firm recently experienced problems with its innovation and incentives systems (*The New York Times*, 2010). In fact, as Google continued to grow significantly throughout the past years, it appears

[8] 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 setup, since management would have to learn how to screen the quality of employees. We leave that issue for further research.

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that implementing new products, rather than devising them, has become the critical bottleneck for the firm—a challenge that former CEO Eric Schmidt described: "I think it's absolutely harder to get things out the door. That's probably our biggest strategic issue" (*The New York Times*, 2010). In consequence, Google employees are reported to have worked on countless projects, many of which ended up to be minor enhancements only. Moreover, the outsized Founders' Awards appear to have backfired in the sense that their negative effects on those employees who did not get them by far outweighed their positive ones. For these reasons, "Google rarely gives Founders' Awards now, preferring to dole out smaller executive awards" (*Forbes*, 2007). In sum, thus, we suggest:

Proposition 1: Firms use low rewards to motivate the decentralized search for value-creating ideas by employees.

We are not aware of any large-scale empirical work that specifically addresses the use and effectiveness of rewards to promote decentralized innovation by employees. Consistent with the predictions of our model, Honig-Haftel and Martin (1993) found evidence for the effectiveness of low-powered bonus plans, but did not find any positive impact of higher-powered reward mechanisms such as equity stakes, royalty payments, or the sharing of venture returns with the participating employees. Lerner and Wulf (2007), in 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 competition for application slots among employees will likely be limited. Based on our model, we would also 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. Further business practice also appears to be in line with our first proposition. In their discussion of innovation tournaments, Terwiesch and Ulrich (2009) report numerous related examples. Dow Chemical, for example, reports an average return of 204 percent from implemented process innovations that were suggested by employees—a clear indication of the value of low-powered incentives in organizational search.

Our results also show that the appropriate incentive intensity depends on organizational and environmental factors. For instance, the results point to a clear negative relationship between firm size and reward levels. In small firms, the search effort of each individual employee is comparatively more important for firm performance than in larger organizations. At the same time, 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: Small firms employ higher rewards to motivate the decentralized search for value-creating ideas by employees.

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 is echoed by similar studies (Beugelsdijk, 2008; Honig-Haftel and Martin, 1993; Leiblein and Madsen, 2009; Zenger and Marshall, 2000). Extant research has explained these differences with the argument that assignment problems are less severe in smaller firms. Our paper adds to this line of work by suggesting that the dynamics of search can be sufficient to make higher rewards advisable for smaller firms.

A further 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 idea—and the reward level. Higher-powered rewards are important to promote the sustained refinement of nascent ideas and to overcome the de-motivating effect of many competing projects, which suggests:

Proposition 3: The longer the development time for innovation projects, the higher the reward level.

Lastly, our findings also suggest that low-powered rewards systematically foster incremental innovations in organizations, and that high rewards do not lead to a proliferation of high-value, radical innovations either. 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

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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, by addressing the effects of rewards in stimulating organizational search, the paper contributes to work that has sought to (re)integrate organizational economics and organization theory (Kaplan and Henderson, 2005). While interactions between reward systems and organizational search have 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 the dynamics of search 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.

Second, research in organizational psychology has pointed to the role of intrinsic motivation for explaining individual creativity and innovation. In this context, the argument features prominently 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, organizations that provide high extrinsic incentives may face undesired side effects. At the same time, however, empirical evidence suggests that intrinsic incentives often coexist with extrinsic rewards, even in the context of innovation where intrinsic motivation is considered to be particularly crucial (Sauermann and Cohen, 2010; Terwiesch and Ulrich, 2009). Adding to this discussion, our findings suggest that the conflict between extrinsic and intrinsic motivation and, thus, the risk of crowding out effects, may not be that pronounced, given that the most effective reward levels are rather low under most circumstances, in particular, as our model likely 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 do face a shortage of exceptional ideas, but higher-powered incentives do not seem to be an effective tool for searching this long tail of innovation. The crucial bottleneck, on the other hand, is the scarce complementary resources that prevent organizations from pursuing a larger number of valuable business proposals (Lippman and Rumelt, 2003; Rotemberg and Saloner, 1994). More generally, a stylized empirical fact is the relative stability of many business organizations, which strategy research (Lippman and Rumelt, 2003; Teece, 1986) and work on the theory of the firm (Hart, 1995; Williamson, 1991) have explained by pointing to the role of sticky tangible and intangible resources. If large organizations really faced a persistent shortage of good ideas to make use of corporate resources, we would expect much larger fluctuations in the population of firms. Most business firms, however, do not seem to be that brittle.

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