MANAGEMENT SCIENCE
Vol. 57, No. 6, June 2011, pp. 1042–1054
ISSN 0025-1909 | EISSN 1526-5501 | 11 | 5706 | 1042

DOI 10.1287/mnsc.1110.1331

Why Genius Leads to Adversity: Experimental Evidence on the Reputational Effects of Task Difficulty Choices

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We use a behavioral laboratory experiment to study how agents with reputation concerns select the difficulty of their tasks. Drawing upon existing theory, we subjected participants in our study to a context in which they had to convince a principal of their capability to reap financial benefits. Our results show that participants tended to increase the difficulty of their task to enhance their reputation. In addition, we provide evidence that performance rewards reduce a less capable agent's tendency to choose a more difficult task, whereas a highly capable agent's pattern of choices is unaffected by performance rewards. Although the productivity of agents in our experiment therefore decreased if they had to convince a principal of their capability, we show that these detrimental performance implications can to some degree be overcome for less capable agents through performance rewards or by ensuring that the principal can interpret the agent's choice.

Key words: incentives in R&D; behavioral operations; career concerns; decentralization
History: Received June 20, 2008; accepted January 17, 2011, by Christoph Loch, R&D and product development. Published online in *Articles in Advance* April 11, 2011.

1. Introduction

The nature of work has dramatically changed in recent decades. Increasingly, routine tasks are being replaced by nonroutine cognitive and interactive tasks (Autor et al. 2003), and more work is therefore becoming white collar (Hopp et al. 2009). A mounting challenge to the management of processes is the need to understand the behavior of employees engaged in nonroutine tasks. Thus, understanding employee behavior is crucial to a better understanding of modern work (Bendoly et al. 2006).

Two critical behavioral elements of nonroutine tasks, especially in new product development, are operational autonomy and decentralized decision making (Loch and Terwiesch 2007). Employees responsible for nonroutine tasks have some freedom in the way they approach these tasks. Research and development (R&D) professionals, for example, can choose from a range of technological solutions for their design tasks, which can include cutting-edge technology, a greater number of features, greater (or lesser) modularity, and/or higher performance levels. They may also select solutions that are simply more elegant, aesthetically pleasing, and sophisticated. A major challenge in the management of new product development is to align these design choices with customer needs and marketability (Rust et al. 2006). As the technology investment analyst Coburn (2006, p. 1) noted, such decisions are often not made with the interests of the final consumer in mind, but rather are "all about the smart technologists, and the 'magic' that the smart technologists had created." It is therefore crucial to develop a better understanding of the way that R&D professionals select designs and ideas to implement.

The theoretical perspective we put forward in this paper is that the need of R&D professionals to prove their talent within their organization (or their broader community) drives them to implement design solutions that are unnecessarily difficult, resulting in a higher likelihood of project or task failure. The difficulty of a task influences the information content of the outcome as a signal of capability; therefore, R&D professionals have an incentive to choose solutions that are not necessarily the most likely to succeed and that are by no means automatically aligned with the requirements of existing or novel markets. The underlying theory behind this perspective has been developed by Siemsen (2008). The current research tests these ideas in a behavioral laboratory experiment.

In the next section, we describe the model of our experimental setting and the hypotheses derived from this model. In §3, we review relevant experimental literature in economics. In §4, we describe our laboratory setting, the experimental design, and the protocol. In §5, we discuss the analysis of our data and the results of our hypotheses tests. We summarize the experiment and results in §6, where we also discuss the managerial implications of our work and directions for future research.

2. Model and Hypotheses

The model described by Siemsen (2008) was used to analyze a decision context in which an agent with operational autonomy (henceforth referred to as "he") chooses how to approach his organizational task. A simple solution to his task has a higher likelihood of success than a more difficult solution. A principal (henceforth referred to as "she"), who unlike the agent himself is uncertain about the agent's true capability, observes the difficulty of the task and the task outcome (which is a limited performance signal) and updates her belief about the agent's capability. The agent's incentives are such that he maximizes his reputation (i.e., his assessment of the principal's expected value of his capability).

The success probability of an agent with capability $c \in \{h, l\}$ (where h stands for a highly capable agent and l stands for a less capable agent) who chooses the solution $s \in \{d, e\}$ (where d denotes a difficult solution and e an easy solution) is given by p_s^c. Let ψ^c be a measure of productivity that differentiates highly capable from less capable agents, such that $\psi^h > \psi^l$. Let φ^s be a similar measure of task difficulty that differentiates difficult from easy solutions, such that $\varphi^e < \varphi^d$. We use a latent variable model to define the underlying tendency of the agent to succeed as $o = \psi^c - \varphi^s + \varepsilon$, where ε is a random noise component with a mean centered, unimodal, and symmetric distribution with cumulative density function $F(x)$. Following common conventions in probit/logit modeling, success is observed if $o > 0$. The model therefore defines the likelihood of the agent's success as $p_s^c = P[\psi^c + \varepsilon > \varphi^s] = 1 - F[\varphi^s - \psi^c]$. Assuming for simplicity that the prior probability of the agent being highly capable is $\rho = 1/2$, and assuming that the principal updates information in a way that is consistent with the Bayes theorem, the agent's expected reputation from choosing solution s can be expressed as follows:

$$E[R]_s^c = \psi^h\left(p_s^c \frac{p_s^h}{p_s^h + p_s^l} + (1-p_s^c)\frac{(1-p_s^h)}{(1-p_s^h)+(1-p_s^l)}\right) + \psi^l\left(p_s^c \frac{p_s^l}{p_s^h + p_s^l} + (1-p_s^c)\frac{(1-p_s^l)}{(1-p_s^h)+(1-p_s^l)}\right). \tag{1}$$

Analyzing this objective function reveals that its mode is given by $\hat{\varphi}^s = (\psi^h + \psi^l)/2$, with this mode being a maximum for $c = h$ and a minimum for $c = l$. Furthermore, $E[R]_s^c$ is symmetric around this mode. Assuming $\varphi^e \le (\psi^h + \psi^l)/2$, we can say that $E[R]_d^h \ge E[R]_e^h$ if $\varphi^d \le \psi^h + \psi^l - \varphi^e$ (and vice versa). Because we can also say that $E[R]_s^h = \psi^h - E[R]_s^l$, it follows that $E[R]_d^l \ge E[R]_e^l$ if $\varphi^d \ge \psi^h + \psi^l - \varphi^e$ (and vice versa). Formal proofs of these relationships can be found in Siemsen (2008). It follows that highly capable agents prefer a solution that is as close to $\hat{\varphi}^s$ as possible, that is, a solution that has a probability of success that is as close as possible to

$$p_{\hat{s}}^h = 1 - F\left[\frac{\psi^l - \psi^h}{2}\right] > 50\%. \tag{2}$$

Less capable agents prefer a solution that is as far away from $\hat{\varphi}^s$ as possible, that is, as far away as possible from

$$p_{\hat{s}}^l = 1 - F\left[\frac{\psi^h - \psi^l}{2}\right] < 50\%. \tag{3}$$

This analysis leads us to the following hypotheses:

Hypothesis 1. (a) *The highly capable agent's tendency to choose a difficult option is different from the less capable agent's tendency to choose a difficult option.*

(b) *The greater the agent's expected gain in reputation* ($E[R]_s^c$) *from choosing a difficult option, the greater the likelihood that he will choose that option.*

A central insight from this model is that the agent's expected reputation changes with the difficulty level of the chosen solution. Highly capable agents can gain expected reputation by choosing a moderately more difficult solution, because succeeding with such a solution increases the information of the outcome signal while not considerably lowering the overall likelihood of success. Less capable agents can avoid losing reputation by choosing a highly difficult solution, because they have less hope of success to begin with, and such highly difficult solutions mask their lack of capability in case of failure. Thus, the motivations of the agents are inherently different in this decision problem. Whereas the highly capable agent wants to convince the principal of his capability, the less capable agent tries to avoid losing the reputation he currently enjoys. Reputation concerns, therefore, push agents to pursue more difficult options than would have been chosen without concerns for their reputation.

Hypothesis 2. *Both the highly capable and the less capable agent have a lesser tendency to choose the more difficult option if they have no reputation concerns.*

It is important to emphasize that the above analysis contains an inherent signaling model. In addition to using the difficulty of his solution to influence the information content of the outcome, the agent could choose a solution to signal his true type to the principal. Such a signal can only be effective, however, if the principal can somehow interpret the choice, that is, either observe the set of solutions available to the agent or have some knowledge about the distribution from which these solutions are drawn. To see why the principal cannot interpret choice without such knowledge, consider the following argument. Assume that the principal's prior distribution for draws of solution difficulty φ^s is uninformative, or diffuse.[1] The principal knows only that the agent has two solutions from which to choose. For the sake of argument, assume temporarily that the support for φ^s is finite, such that the principal's prior belief is uniform over $[-b, b]$. Because the principal observes (or can infer) the actual difficulty φ^s of the chosen solution, she could attempt to use that choice to update her prior belief ρ about the agent being highly capable. Suppose that the principal believes in a separating equilibrium, such that the highly capable agent always chooses the difficult solution d, and the less capable agent always chooses the easy solution e. This would lead the principal to update her prior beliefs about ρ, such that we can express her posterior estimate of ρ as

$$\tilde{\rho} = \frac{p((\varphi^s + b)/(2b))}{p((\varphi^s + b)/(2b)) + (1-p)((b-\varphi^s)/(2b))}. \quad (4)$$

It is then easy to see that $\lim_{b\to\infty} \tilde{\rho} = \rho$. A similar argument holds if the principal believes that the separating equilibrium is such that the highly capable agent always chooses the easy solution and the less capable agent always chooses the difficult solution. In other words, with an uninformative prior belief, choice becomes uninformative, and we can abstract from the inherent signaling game. The inherent signaling game only comes into play if the principal is not completely ignorant of the distribution from which solutions are drawn.

Now assume the opposite of complete ignorance, that is, that the principal can fully observe the agent's choice set. Under this condition, she knows which option the agent has chosen. Choice itself could therefore become an informative signal. In a nutshell, this forces less capable agents to pool on the strategy of highly capable agents, because any separating equilibrium (without mixed strategies by highly capable agents) would result in the principal perfectly identifying less capable agents and less capable agents receiving the lowest possible payoff. The highly capable agent's strategy would remain unchanged. He could not alter his strategy to force the less capable agent not to pool, because any deviation from his strategy would not be costly but only beneficial to the less capable agent.

More formally, we allow highly capable agents in this scenario to choose the difficult option with likelihood θ_H and less capable agents to do so with likelihood θ_L. We further made the simplifying assumptions of $\psi_L = 0$ and ε being distributed with a logistic distribution with mean 0 (see Siemsen 2008). After observing the agent's choices (but before observing the outcome of the task), the principal's belief about the agent's capability therefore becomes

$$\tilde{\rho}_{s=d} = \frac{\theta_H}{\theta_H + \theta_L}; \qquad \tilde{\rho}_{s=e} = \frac{(1-\theta_H)}{(1-\theta_H) + (1-\theta_L)}. \quad (5)$$

This changed belief then has implications for the agent's expected reputation. We can therefore rewrite Equation (1) as follows:

$$\begin{aligned} E[R]_s^c = {}& \psi^h\bigg[p_s^c \frac{\tilde{\rho}_s p_s^h}{\tilde{\rho}_s p_s^h + (1-\tilde{\rho}_s)p_s^l} \\ &\qquad + (1-p_s^c)\frac{\tilde{\rho}_s(1-p_s^h)}{\tilde{\rho}_s(1-p_s^h) + (1-\tilde{\rho}_s)(1-p_s^l)}\bigg] \\ &+ \psi^l\bigg[p_s^c \frac{(1-\tilde{\rho}_s)p_s^l}{\tilde{\rho}_s p_s^h + (1-\tilde{\rho}_s)p_s^l} \\ &\qquad + (1-p_s^c)\frac{(1-\tilde{\rho}_s)(1-p_s^l)}{\tilde{\rho}_s(1-p_s^h) + (1-\tilde{\rho}_s)(1-p_s^l)}\bigg]. \quad (6) \end{aligned}$$

We then specify the objective function for highly capable agents as $\Pi_H = \theta_H E[R]_d^h + (1-\theta_H)E[R]_e^h$. Some analysis shows that $\theta_H E[R]_d^h$ is convex increasing in θ_H, and $(1-\theta_H)E[R]_e^h$ is convex decreasing in θ_H. Therefore, Π_H, is convex in θ_H, and the reputation maximizing likelihood $\hat{\theta}_H$ is a corner solution, that is, $\hat{\theta}_H \in \{0, 1\}$. In other words, the highly capable agent does not pursue a mixed strategy.

The objective function for the less capable agent is $\Pi_L = \theta_L E[R]_d^l + (1-\theta_L)E[R]_e^l$. Analysis of this function reveals that if $\hat{\theta}_H = 1$, then $\partial_{\theta_L}\Pi_L \geq 0$, and therefore $\hat{\theta}_L = 1$. Similarly, if $\hat{\theta}_H = 0$, then $\partial_{\theta_L}\Pi_L \leq 0$, and therefore $\hat{\theta}_L = 0$. In other words, a less capable agent will pool on the strategy of the highly capable agent. It follows that choice itself will contain no information on agent type. Highly capable agents will choose the solution that maximizes their expected reputation according to Equation (1), and less capable agents are forced to pool on that strategy. Therefore, we propose Hypothesis 3.

[1] A diffuse prior belief, which is often used to model complete ignorance, assigns equal weight to all states over the whole support; thus, in our context this implies a uniform distribution over $[-\infty, \infty]$.

Hypothesis 3. *If the principal can observe the agent's choice set,*

(a) *the highly capable agent's tendency to choose the more difficult option remains unchanged compared to a situation in which the principal cannot observe this choice set;*

(b) *the less capable agent's tendency to choose the more difficult option becomes similar to that of the highly capable agent's.*

Hypothesis 3 suggests an important managerial intervention. If performance evaluations are made by technocrats who have adequate knowledge of the agent's technical domain, and who can therefore interpret the agents' choice, less capable agents are forced to act like highly capable agents. This can have positive or negative implications for their productivity. In contexts where without observability of choice they would have preferred highly complex solutions, they will prefer simple solutions under observability. However, in contexts where without observability of choice they would have preferred simple solutions, they will prefer moderately more difficult solutions under observability. In any case, however, this behavior should improve the principal's ability to differentiate highly capable from less capable agents in the long run, because both highly and less capable agents now select solutions that in expectation reveal the most about their type.

Hypothesis 3 lends itself to characterizing different managerial challenges in radical versus incremental development projects. The information asymmetry between principals and agents about the underlying choice set is attenuated in radical projects, because those projects rely less on the execution of preexisting solutions, but rather involve the decentralized search for solutions in a complex space. The challenge in those projects, therefore, becomes one of managing the potential bias toward unnecessary task difficulty. In incremental projects, the information asymmetry between principal and agent in this regard is much lower, leading to highly capable and less capable agents making similar task difficulty decisions. The challenge in such projects is less related to reducing information asymmetry or interpreting decisions, but rather related to obtaining clearer signals about the degree to which task outcomes are the consequence of agent capability.

Another important managerial remedy to counter an agent's tendency to select more difficult solutions is to provide him with performance-based incentives. Without such incentives, an agent cares about achieving a successful task outcome only to the degree that such success increases his reputation. Consider, therefore, that the agent cares about success in addition to and independent of the effect that success has on reputation with a factor α, so that we can say

$$E[\Pi]_s^c = E[R]_s^c + \alpha p_s^c. \quad (7)$$

Clearly, then, $\partial_s E[\Pi]_s^c < \partial_s E[R]_s^c$ with $\alpha > 0$, because increasing the solution difficulty lowers the likelihood of achieving success. With performance-based incentives, the agent cares about success independent of the effect of success on reputation. This, ceteris paribus, lowers his tendency to choose more difficult solutions to further his reputation, because such solutions have a lower likelihood of leading to performance-based rewards. We therefore propose the following hypothesis:

Hypothesis 4. *If the agent is rewarded for successful task outcomes, then the tendency of both types of agents to choose a more difficult option is lower compared to situations without such performance-based incentives.*

3. Related Literature

The reputational concerns we study have been analyzed in the economics literature under the label of career concerns. The idea that such career concerns are important incentive devices dates back to Holmström (1999) and Fama (1980). Holmström's (1999) approach was based on the notion that the agent's performance depends on his ability and effort. When a principal wishes to reward an agent for his ability, but she can only observe performance (which is a function of both ability and effort), agents can have an incentive to exert greater levels of costly effort to increase the principal's beliefs in their ability. Although in a rational expectations equilibrium this information distortion can be offset by the principal, the agent still needs to exert this extra effort because it is expected by the principal. This attempt to distort the signal value of performance is sometimes called *signal jamming*.

The model underlying our research was distinct along several dimensions from this classic career concerns model. Specifically, whereas the classic career concerns model assumes that information is symmetric between the principal and the agent, our model explicitly recognizes informational asymmetry between the two players by assuming that the agent has more knowledge about his true type than does the principal. Furthermore, the classic career concerns model assumes a continuous performance signal, whereas we assume a limited (dichotomous) performance signal. With a continuous performance signal, a principal can essentially filter out her rational expectations of the agents' action from the observed performance. Calculating such a revised performance signal is impossible in our context, which provides the agent the effective potential to manipulate the information content of his performance signal (Siemsen 2008). In other words, signal jamming, in our model, is not an ultimately futile endeavor.

Table 1 Summary of the Four Experimental Conditions

	Principal observes				
Condition	Probabilities	Task outcome	Promotion represents	Employee reward	No. of participants
Unobservable (baseline)	p_s^h, p_s^l	Yes	$P(h \mid \textit{task outcome})$	*Promotion*	64
Observable	$p_d^h, p_d^l, p_e^h, p_e^l$	Yes	$P(h \mid \textit{task outcome})$	*Promotion*	64
Performance reward	p_s^h, p_s^l	Yes	$P(h \mid \textit{task outcome})$	*Promotion + bonus*	32
No reputation concerns	p_s^h, p_s^l	No	$P(\textit{success})$	*Promotion*	32

Notes. We abbreviate $p_s^h = P(\textit{success} \mid h, s)$. It also follows that $P(\textit{success}) = p_s^h \rho + p_s^l (1-\rho)$. The *promotion* is a payment from the principal to the agent that is based on the agent's reputation, i.e., the principal's estimate of the likelihood of him being highly capable.

Testing the classic career concerns model, Koch et al. (2009) reported on a laboratory experiment that compared a setting in which the principal observes the sum of the effort and ability to a setting in which the principal observes the two variables separately. In both settings, the principal's earnings were based on the agent's ability and not on his performance. Koch et al. (2009) reported that, consistent with the theoretical prediction, an agent's effort is greater when his abilities are hidden. Moreover, and also consistent with theoretical predictions, the wages that the agent receives from the principal are correlated with the effort level when the ability is unknown, but not when the ability is known. Irlenbusch and Sliwka (2006) considered a setting in which the principal's earnings were based on the agent's performance rather than on his ability alone. In this setting, exerting costly effort early on serves as a way to signal one's willingness to exert it in the future, and this reciprocity motive actually causes agents to exert greater effort in the experimental condition in which the ability is known compared to the condition in which it is unknown.

4. Experimental Design and Protocol

Our experiment was based on a repeated single-period game played between a human principal and a human agent. There was no real task involved in this game. All interactions between principals and agents were made through networked computers using the z-Tree software (Fischbacher 2007). Participating principals made promotion decisions, and participating agents made task difficulty selection decisions. Participants did not know with whom they were paired, and they were randomly assigned to a new partner after each of the multiple rounds of the game. Participants knew that there were equal numbers of highly capable and less capable agents in the population of our experiment, that is, $\rho = 1/2$. Participants kept the same role (principal or agent) and agents kept the same type (highly capable or less capable) for the duration of their session.[2] We subjected each agent to 12 different probability profiles, varying the expected reputational gain of choosing the difficult option as well as other probability-related measures.

We conducted a partial factorial experiment, varying three factors: whether agents have reputation concerns, whether their choice set is observable, and whether they receive performance rewards. This design resulted in four conditions, summarized in Table 1. A compendium of the instructions provided to participants for all conditions in our study is available in the online appendix (provided in the e-companion).[3]

As the first step in the game, agents chose between the easy and the difficult solution (neutrally labeled as option A and option B). In addition to knowing their type, agents also knew their probability of success as well as the probability of success that an agent of the other type would have with each of these solutions. After the agents made their decisions, principals observed information about these decisions (i.e., only the likelihood of both types of agents' success, given the choice, or the choice itself as well as all relevant likelihoods in the observable condition) and the task outcome, depending on the condition. Based on this information, the principals formed their opinion of the agent being highly capable and then selected the amount of the promotion P that agents would earn accordingly. In the performance rewards condition, agents also earned a bonus for succeeding in the task. In all conditions except the no-reputation-concerns condition, principals earned $(P - 1/2P^2)$ if the agent turned out to have high capability and $(-1/2P^2)$ if the agent turned out to be less capable. In the no-reputation-concerns condition, principals earned $(P - 1/2P^2)$ if the agent succeeded in the task and $(-1/2P^2)$ if he did not. Structuring the principal's incentives in this way ensured (in theory) that in all conditions with reputation concerns, she

[2] Note that agent types were not labeled neutrally for subjects, but contain some value judgment. This may have created the risk of subjects reacting particularly to that frame. However, because the same frames were used in all different conditions and profiles, this frame should not affect intercondition and interprofile comparisons.

[3] An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

Table 2 Probability Profiles Used in the Experiment

Profile	φ^d	φ^e	p_d^h	p_e^h	p_d^l	p_e^l	$\Delta E[R]^h$	$\Delta E[R]^l$	Δp^h	Δp^l	$\Delta V[o]^h$	$\Delta V[o]^l$
1	−3.98	−8.60	0.92	0.97	0.65	0.81	0.0213	−0.0213	0.05	0.16	0.04	0.07
2	1.08	−7.20	0.81	0.96	0.46	0.76	0.0245	−0.0245	0.15	0.30	0.12	0.07
3	5.17	−5.80	0.69	0.94	0.30	0.72	0.0331	−0.0331	0.25	0.42	0.16	0.01
4	8.27	−4.40	0.57	0.93	0.20	0.67	0.0194	−0.0194	0.36	0.47	0.18	−0.06
5	10.37	−3.00	0.49	0.90	0.15	0.62	0.0126	−0.0126	0.41	0.47	0.16	−0.11
6	11.47	−1.60	0.44	0.88	0.13	0.56	−0.0045	0.0045	0.44	0.43	0.14	−0.13
7	11.55	−0.20	0.44	0.85	0.12	0.51	−0.0029	0.0029	0.41	0.39	0.12	−0.14
8	10.60	1.20	0.48	0.81	0.14	0.45	−0.0019	0.0019	0.33	0.31	0.10	−0.13
9	8.64	2.60	0.55	0.77	0.19	0.40	−0.0009	0.0009	0.22	0.21	0.07	−0.09
10	5.62	4.00	0.67	0.73	0.29	0.34	−0.0041	0.0041	0.06	0.05	0.02	−0.02
11	—	—	0.80	1.00	0.00	0.50	0.1667	−0.1667	0.20	0.50	0.16	−0.25
12	—	—	0.90	1.00	0.05	0.50	0.1955	−0.1955	0.10	0.45	0.09	−0.20

Notes. The probability of an agent with capability c ($c = h$ means highly capable, $c = l$ means less capable) succeeding with solution s ($s = d$ means difficult solution, $s = e$ means easy solution) is given by p_s^c. See the main body of the text for the derivation of other values shown in this table.

reported her probability assessments of the agent's capability truthfully. It also ensured that the agent gained an incentive to maximize his expected reputation (i.e., the principal's estimate of his being highly capable), which was a central assumption of Siemsen (2008). Both agents and principals were informed that the optimal decision for the principal was to set P exactly equal to her probability assessment of the agent being highly capable. We emphasize that this information should not influence how principals form their beliefs. This information should only reinforce their reporting of beliefs as their promotion decisions.

We systematically varied p_e^c and p_d^c in each condition. To that purpose we generated 12 different probability profiles. A common assumption underlying profiles 1–10 was that $\psi^h = 10$ and $\psi^l = 0$, and $\varepsilon \sim \mathrm{N}(0, 10)$. Profiles 11 and 12 were designed to be extreme. A summary of these profiles is provided in Table 2. They vary the expected gains in reputation from choosing the difficult option ($\Delta E[R]^c = E[R]_d^c - E[R]_e^c$) as well as the success probabilities of the highly capable and the less capable agents' choosing the difficult or easy solution ($\Delta p^c = p_e^c - p_d^c$). The profiles also vary in the difference in the variance of the outcome between the two options ($\Delta V[o]^c = p_d^c(1 - p_d^c) - p_e^c(1 - p_e^c)$). Varying these three measures allowed us to, at least to some degree, separate the effects of these three measures on behavior. The implications of paying a bonus, as in our performance rewards condition, on the expected benefit of the difficult option are summarized in Table A.1 in the appendix.

We conducted each experimental condition in (multiple) cohorts of eight participants. Each cohort included four principals, two highly capable agents, and two less capable agents. The unobservable and observable conditions included eight cohorts each, and the performance rewards and no-reputation-concerns conditions included four cohorts each, for a total of 192 participants. Each person participated only once in the experiment. The sessions each included 48 rounds: participants played four rounds with each of the 12 probability profiles. Our analysis is therefore based on 4,608 task difficulty decisions made by agents and an equal number of promotion decisions made by principals. We randomized the order of the profiles and the matching and then used the same order and matching for each cohort in each condition. Participants interacted only with participants in their own cohort. We conducted all sessions at the University of Cologne experimental economics laboratory (Kölner Laboratorium für Wirtschaftsforschung).

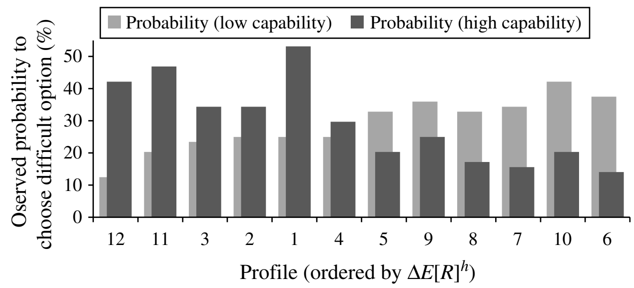
The same research assistant recruited participants from the University of Cologne subject pool and conducted all sessions. Participants were told that the experiment would be conducted in English, and only one person withdrew based on the language requirement. Each session started with participants reading a set of written instructions (available in the online appendix). After this, the research assistant answered any questions participants had about the rules of the game. Questions were always answered in private. Following the questions, the 48 rounds of the game were conducted. Upon completion of the session, participants were paid their earnings from the game, again in private. Earnings, paid in euros, were proportional to the earnings in experimental currency and were converted at a preannounced exchange rate. Participants also earned a €5 participation fee for arriving on time.

5. Results

5.1. Agent Behavior

5.1.1. Do Highly Capable and Less Capable Agents React to Expected Reputational Gain? We compare the probabilities of choosing the difficult

Figure 1 **The Probability of Choosing the Difficult Option in the Unobservable Condition**



option in the unobservable condition for different profiles and agent types in Figure 1. It is clear from the figure that, consistent with Hypothesis 1(a), the different types of agents have very different probabilities of choosing the difficult option. We tested Hypothesis 1(a) formally by estimating a random effects probit model using the unobservable condition data, with the dependent variable equaling 1 if an agent chose the difficult option and 0 if he chose the easy option. The independent variables were period number, to control for a linear trend over time, and fixed effects for the 12 different profiles for each of the two agent types. The model converged ($\chi^2_{df=24} = 103.38$, $p \leq 0.01$). The period number was significant and positive ($\beta = 0.006$, $z = 2.02$, $p = 0.04$), indicating that participants became slightly more likely to choose the difficult option over time. We then tested whether an average highly capable agent and an average less capable agent have the same overall propensity to choose the difficult option. This null hypothesis was rejected ($\chi^2_{df=12} = 83.84$, $p \leq 0.01$), which is consistent with Hypothesis 1(a).

Hypothesis 1(b) states that the gain in reputation from choosing the difficult option should influence the observed probability of choosing this option. Because the profiles in Figure 1 are ordered by the expected reputation gain of choosing the difficult option for the highly capable agent (and therefore reverse ordered for the same value for the less capable agent), one can also see in Figure 1 that there is an overall correspondence between the expected reputation gain from choosing the difficult option and the estimated probability that the agent will choose that option. Specifically, the sequence of dark grey columns is (on average) decreasing, whereas the sequence of light grey columns is (on average) increasing. The probability of choosing the difficult option is high when the expected reputational gain of the difficult option is high, for both highly capable and less capable agents.

Interestingly, we observed unexpectedly high probabilities of choosing the difficult option in profile 1 for highly capable agents, and to a lesser extent in profile 10 for both types of agents. This may be because, as we can see from columns labeled Δp^h and Δp^l in Table 2, the absolute difference between the difficult option and easy option success probabilities in these profiles is low (5%–6%) compared to all other profiles (average of 34%). This structural difference may lead to more randomness in respondent behavior, and therefore to an observed likelihood of choosing the difficult option that is closer to 50% than the theoretical value of that difficult option would predict.

We tested Hypothesis 1(b) by reestimating the probit model for the unobservable condition, replacing the fixed effects for profiles and agent types with the value of choosing the difficult option (in terms of expected reputational gain, that is, $\Delta E[R]^c$) for each decision as an explanatory variable. Because the magnitude of $\Delta E[R]^c$ is much higher in profiles 11 and 12 than in the other profiles, we added an interaction variable between $\Delta E[R]^c$ and an indicator variable for profiles 11 and 12. We further added control variables for the absolute levels of the two success probabilities of the difficult and easy options, the difference in variance of the outcomes between the two choices, and the indicator variable for the highly capable agent type. The results of this analysis are reported in Table 3.

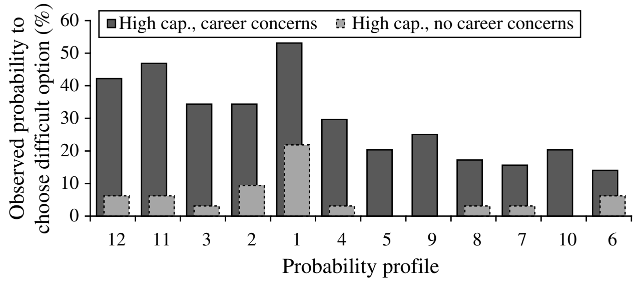
For an average participant, the propensity to choose the difficult option increased in the expected reputational gain of the difficult option, which is consistent with Hypothesis 1(b). There was also evidence that this effect decreases as the magnitude of the gain increases, because it is smaller in profiles 11 and 12 than in the other profiles, though still positive and significant ($\beta = 3.63$, $p \leq 0.01$). We also observed that the absolute level of the success probability of an agent's difficult option had a significant effect on his behavior, whereas the absolute level of his easy option had no significant effect on his behavior. This may indicate that the success probability of the difficult option acts as an anchor when determining behavior. Finally, the difference in variance between the two options had little effect on behavior, indicating that

Table 3 **Propensity to Choose the Difficult Option**

Independent variable	Coefficient	Std. error
Choice no. ($\times 10^{-2}$)	0.54*	(0.003)
Expected reputational gain ($\Delta E[R]^c$)	18.16**	(3.524)
$\Delta E[R]^c \times$ (*profile* 11 or 12)	−14.54**	(3.427)
Success probability of difficult option (p_d^c)	1.13**	(0.332)
Success probability of easy option (p_e^c)	−0.09	(0.472)
Variance difference ($\Delta V[o]^c$)	−1.15†	(0.672)
Agent type (*highly capable*)	−0.74*	(0.380)
Constant	−0.94**	(0.361)
N	1,536	
χ^2	90.12**	

$^{*}p \leq 0.05$; $^{**}p \leq 0.01$; $^{\dagger}p \leq 0.10$.

Figure 2 **The Probability of Choosing the Difficult Option With and Without Reputation Concerns**



risk aversion seems less of a concern for the agent. Agent type, though, had a significant effect on behavior, with highly capable agents being, ceteris paribus, less likely to choose the difficult option. Controlling for p^c and $\Delta V[o]^c$ in this analysis showed that $\Delta E[R]^c$ had an effect on behavior above and beyond what differences in probability levels and differences in variance between profiles can explain.

5.1.2. Do Reputation Concerns Matter? To test whether these effects were the result of reputation concerns, we compared the agents' estimated choice patterns in the unobservable condition to the choice patterns in the no-reputation-concerns condition. Unfortunately, it was impossible to estimate a random effects probit model using these data, because in numerous profiles within the no-reputation-concerns condition, no participant chose the difficult option at all. Figure 2 compares the observed probabilities to choose the difficult option with and without reputation concerns for highly capable agents (for less capable agents, there were only 21 choices of the difficult option out of the 768 total choices, so the comparison for the low types looks even more extreme). Clearly, reputation concerns are a driving motivation to choose the difficult option.

An overall t-test of the difference between the choices with and without reputation concerns revealed a significant difference between the two groups ($t = 9.84$, $p \leq 0.01$ for highly capable agents, and $t = 12.33$, $p \leq 0.01$ for less capable agents). This is consistent with Hypothesis 2. Notice that even though agents gained no expected benefit from choosing the difficult option in the no-reputation-concerns condition, still quite a few highly capable agents chose this option. This effect is most pronounced in profile 1, where 22% of the highly capable agents chose the difficult option despite having no expected gain in reputation for doing so.

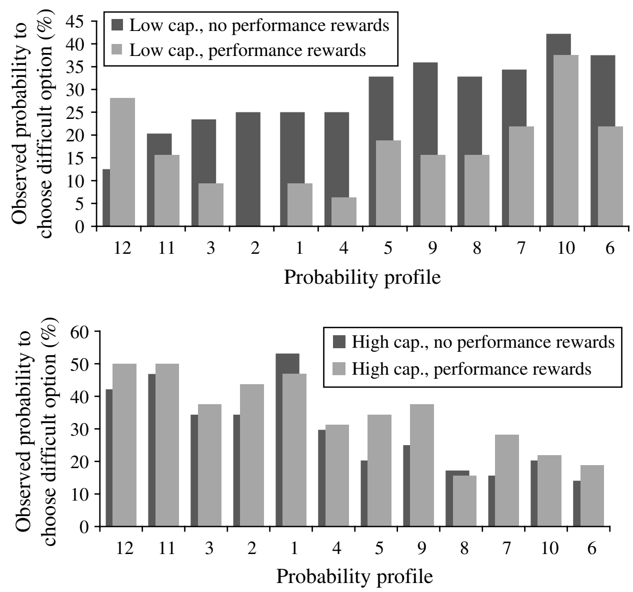
5.1.3. Do Less Capable Agents Mimic Highly Capable Ones if Choices Are Observed? To analyze whether the observability of choice can influence the agent's decision, we estimated our model including the data from the unobservable and the observable conditions. Fixed effects for profile-by-agent types were included in the estimation to allow for different intercepts in all profile/agent condition combinations. The model converged ($\chi^2_{df=48} = 240.63$, $p \leq 0.01$), and the time trend variable was positive and significant ($\beta = 0.009$, $p \leq 0.01$). Hypothesis 3(a) states that making the choice set observable should not alter the behavior of highly capable agents, and our data are consistent with this hypothesis. Highly capable agents did not change their behavior between the two conditions ($\chi^2_{df=12} = 15.11$, $p = 0.24$).

Hypothesis 3(b) predicts that if the choice set becomes observable, less capable agents will attempt to mimic highly capable agents. Statistically, less capable agents behave differently in the two conditions ($\chi^2_{df=12} = 44.01$, $p \leq 0.01$). We illustrate this effect in Figure A.1 in the appendix. However, an overall test of whether less capable agents in the observable condition act like highly capable agents in the unobservable condition was rejected ($\chi^2_{df=12} = 42.35$, $p \leq 0.01$). Similarly, an overall test of whether less capable agents in the observable condition act like highly capable agents in the Observable condition was rejected as well ($\chi^2_{df=12} = 58.93$, $p \leq 0.01$). We therefore rejected Hypothesis 3(b). Although less capable agents clearly recognized that the observability of their decision should influence their behavior, they did not in fact perfectly resemble highly capable agents in their decision patterns.

We do, however, emphasize that the change in behavior of less capable agents induced in the observable condition is in the expected direction. As can be seen in Figure A.1, less capable agents in the unobservable condition chose the difficult option only 22% of the time when it had a high $\Delta E[R]^h$ value (profiles 12, 11, 3, 2, 1, and 4), and 36% of the time when it had a low $\Delta E[R]^h$ value (profiles 5, 9, 8, 7, 10, and 6), a difference that is positive and significant ($p \leq 0.01$). Less capable agents in the observable condition, however, inversed this trend by choosing the difficult option 28% of the time when it had a high $\Delta E[R]^h$ value, and only 22% of the time when it had a low $\Delta E[R]^h$ value, a difference that is negative and significant ($p \leq 0.05$). In other words, without perfectly imitating highly capable agents, behavior of less capable agents in the observable condition became more like the behavior of highly capable agents.

5.1.4. Do Performance Rewards Help? Finally, we tested the effects of performance rewards on the agent's choice. In this experimental condition we awarded agents a bonus for succeeding, which, as we detail in Table A.1 in the appendix, lowers the value of choosing the difficult option. Therefore, and according to Hypothesis 4, directly rewarding performance should lower the agents' propensity to choose the difficult option. To test this hypothesis,

Figure 3 Performance Rewards vs. No Performance Rewards



we estimated a probit model including data from the unobservable and performance rewards conditions. We had to exclude profile 2 from this probit estimation, since no less capable agent in this profile chose the difficult option. The model converged ($\chi^2_{df=44} = 160.36$, $p \leq 0.01$), and the time trend variable was positive and significant ($\beta = 0.007$, $p \leq 0.01$). Note that as can be seen in Table A.1 in the appendix, the effect of providing these incentives is asymmetric for highly capable and less capable agents. Although directionally both agents should have a lower tendency to choose the difficult option, the incentive effect is different in magnitude for each profile and agent type, and we therefore allow for different effects for each profile and agent type in our analysis.

As can be seen in Figure 3, less capable agents, on average, show a decreased tendency to choose the difficult option under performance rewards ($\chi^2_{df=11} = 22.70$, $p \leq 0.05$). This decreased tendency provides support for Hypothesis 4 among less capable agents. However, the same is not true for highly capable agents: statistically, the average highly capable agent did not alter his propensity to choose the difficult option when receiving performance rewards ($\chi^2_{df=11} = 4.17$, $p = 0.96$). We provide an overview of this behavior in Figure 3. Thus, Hypothesis 4 was rejected for highly capable agents.

5.2. Performance Implications

The previous subsection supports the idea that, within our experiment, the agents' induced desire to convince a principal of their capability systematically influences their decisions to select more difficult options for their tasks. In this section, we briefly explore whether such behavior has implications for performance within the confines of our experiment. Performance has two dimensions: the likelihood of the agent succeeding in the task and the principal's ability to correctly differentiate highly capable from less capable agents when assigning promotions. We emphasize that, in practice, the agent's choice for a more difficult solution may have other performance implications, such as more complex product designs than necessary, but further exploring such other implications is beyond the scope of the present study.

We need to point out one important caveat. Because we have already shown that agents in the unobservable condition are more likely to choose the difficult option than agents in the no-reputation-concerns condition, productivity of agents in the unobservable condition has to be lower than productivity of agents in the no-reputation-concerns condition, because more difficult options have a lower likelihood of succeeding by definition. We report statistical tests for such comparisons for completeness only, because their outcome is a foregone conclusion. We do, however, have other comparisons where we do not have a strong result for the direction of an effect. For example, we know that less capable agents behaved different in the observable condition when compared to the unobservable condition, but the direction of that effect is not constant for all profiles (see Figure A.1 in the appendix). We report those statistical tests to show the effect of behavior on productivity.

To measure differences in productivity, we compared the observed proportions of successes within each experimental condition, conditional on agent type. The performance benchmark here was the no-reputation-concerns condition, where theoretically agents should have no incentive to choose the difficult option and, therefore, the highest likelihood of success. All significance tests were made using two-sample tests of proportion in Stata. Highly capable agents in this condition succeeded in 89% of all cases; less capable agents succeeded in only about 58% of all cases. In the unobservable condition, our baseline condition with reputation concerns, this performance decreased to 83% for highly capable agents and to 44% for less capable agents.

To test whether the managerial interventions proposed in our study, that is, making choice observable and giving performance bonuses, reduce these detrimental effects of reputation concerns on performance in our experiment, we tested whether performance increased in the observable or performance rewards conditions, compared to the unobservable condition. The success probability of highly capable agents improved in neither the observable condition (82%, $p = 0.63$) nor the performance rewards condition (83%, $p = 0.91$). This is consistent with our finding that the behavior of highly capable agents does not change in either condition. The success probability of less capable agents, however, improved both in the observable condition (52%, $p \leq 0.01$) as well as in the performance rewards condition (53%, $p \leq 0.01$). This is consistent with our evidence that the behavior of the less capable agent changes in both conditions.

To test whether principals can successfully differentiate highly capable from less capable agents (and whether the treatments in our study improve performance along these lines) we estimated a random effects interval regression to predict the principal's promotion in all conditions (except the no-reputation-concerns condition). As independent variables we used (1) the choice number (to control for learning), (2) a dummy variable that captured whether the agent actually was highly capable (equal to 1) or not, and (3) a dummy variable that captured whether the agent chose the more difficult option (equal to 1) or not (to test for possible signaling effects). If principals were able to distinguish the two types of agents successfully from each other, highly capable agents should have received higher promotions.

As Table 4 shows, although principals were generally able to provide higher promotions to more capable agents, none of our experimental treatments improved the principal's performance in these regards. This result runs counter to our intuition for the observable condition. In the observable condition, less capable agents are in theory forced to a strategy that creates outcome signals that are most informative about their true type. This would improve the principal's ability to separate highly capable from less capable agents in that condition, and lead to the prediction that the principal can allocate higher promotions to highly capable agents in that condition. That such performance improvements are not visible can probably be explained by the fact that, in the same condition, the principals attempt to interpret choice. The effect of "option chosen" is significant in the "observable" condition. Although theoretically agents should make similar decisions, principals assign a higher promotion to those agents that choose the difficult solution.

Table 4 Promotion Decisions Predicted by Agent Type

	Unobservable		Observable		Performance rewards	
	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
Choice no.	−0.003**	(0.001)	−0.001	(0.001)	−0.002†	(0.001)
Highly capable	0.159**	(0.020)	0.117**	(0.017)	0.157**	(0.033)
Option chosen	0.028	(0.024)	0.039*	(0.020)	.038	(0.039)
Intercept	0.445**	(0.038)	0.377**	(0.031)	0.456**	(0.069)
N	1,536		1,536		768	
χ^2	76.25		51.79		28.77	

*$p \leq 0.05$; **$p \leq 0.01$; †$p \leq 0.10$.

6. Conclusions

We subjected to empirical scrutiny the ideas proposed by Siemsen (2008) and found some support for that theoretical model. Furthermore, we identified several important phenomena that this model cannot explain. In our laboratory setting, reputation concerns did indeed lead subjects to choose more difficult solutions to their tasks, and the estimates generated from the present study provide a useful demonstration that the phenomenon exists and can be quite detrimental. Our data were fully consistent with Hypotheses 1 and 2. Agents in our experiment selected more difficult solutions to enhance their reputation with a principal. The expected gain in reputation an agent can receive from choosing a difficult option was a clear predictor of his actual tendency to do so. Therefore, highly capable agents within our context showed a preference for moderately more difficult task solutions, whereas less capable agents exhibited a preference for highly difficult task solutions.

We further demonstrated that if the principal can interpret the agent's choice, less capable agents change their behavior. However, contrary to Siemsen (2008), they do not fully mimic highly capable agents. Although the data are consistent with Hypothesis 3(a), they are not consistent with Hypothesis 3(b). We do, however, see that the behavior of less capable agents in this context becomes more like that of highly capable agents. As a result, we did find that when the principal is informed, less capable agents are significantly more likely to ultimately succeed. We also provide evidence that in our experiment, performance incentives lower the tendency of less capable agents to choose more difficult tasks and, therefore, also increase their probability of success. These performance incentives, though, seem to have no effect on the behavior of highly capable agents. Hypothesis 4 was therefore only partially supported.

Our research is not without limitations. First and foremost, our experimental design emphasized internal validity over external validity. The setting we used in our experiment was by design very close to the theoretical setting in Siemsen (2008). It was not specifically linked to the day-to-day work context that R&D professionals typically face. Thus, although the results of our experiment support Siemsen's (2008) theory, the experiment should be viewed as a first step toward testing the model's applicability in the R&D context. Future empirical research that tests this theory should put more emphasis on external validity. For example, one direction for future research would be to replicate our experiments using a participant pool of engineering students who are instructed to work on an actual design task for which they can choose different solutions. The use of electronic event sampling (Amabile et al. 2005) would also allow the theory presented here to be tested in the field, for instance, by comparing design decisions in highly career-oriented organizations with similar decisions in organizations that place less emphasis on career incentives.

Another important limitation of our study is that it cannot be used to test the model in its full generality, but only in the specific experimental implementation we chose. In that sense, the experiment cannot demonstrate that the model is correct, but can only show where the model fails in its predictions. When our experiment finds that the data are different from the model's predictions, this is strong evidence that the model is wrong. However, if the experiment shows that the data are consistent with the model, it is weaker evidence that the model is right, because it is only right for the specific experimental parameters and our specific implementation, and it is possible that the model fails in its predictions for other parameters. Although constructing the 12 different profiles allowed us to control for some other profile-related differences, like changes in the underlying variance of the outcome or absolute probability levels, it is possible that other factors of these profiles that were not analyzed influenced our results.

Our research contributes to a better understanding of the decentralized product development process. The handling of complex modern product-development projects requires a certain degree of decentralization of decision rights. This, in turn, implies that a crucial managerial challenge in these projects is the coordination of development activities. As Loch and Terwiesch (2007, p. 340) noted, "An important part of the coordination challenge lies in incentives, where much work is needed." The present study addresses this need by showing that when reputation concerns are present, decentralization, when combined with asymmetric information and limited performance signals, may create incentives for R&D professionals to choose more difficult solutions to their tasks. In other words, if employees are given the autonomy to choose the way to approach their organizational tasks, they can use this autonomy to further their own careers, which can lead to lower productivity and decisions that are not aligned with market requirements. This finding contributes to the growing literature on incentives in R&D (Mihm 2010, Chao et al. 2009, Sauermann and Cohen 2010, Hutchison-Krupat and Kavadias 2010).

A finding of particular interest to incentive theory is our observation that performance incentives, in our experiment, have a strong effect on the behavior of less capable agents, whereas they have little effect on the behavior of highly capable agents. It may well be that if people strongly believe in their capability, their long-term drive to establish their reputation is in no way influenced by the more short-term consideration of earning a bonus. The performance incentives condition adds an extrinsic motivation for success. Less capable agents are receptive to this extrinsic manipulation, because they otherwise have little opportunity to satisfy their intrinsic need for recognition. The average expected promotion they can obtain—even if they follow an optimal strategy—is only 0.43. In other words, principals will on average see them as less capable, rather than highly capable. Highly capable agents may not be as receptive to this manipulation, because their intrinsic need for recognition can be satisfied in the experiment. The average expected reputation they can obtain following an optimal strategy is 0.61. In other words, they can expect to be recognized as highly capable. This expectation, combined with their intrinsic and extrinsic motivation for recognition, may ultimately overpower the added extrinsic motivation to succeed in the task.

It is also curious that Hypothesis 3 was rejected. In some sense, this finding was not completely unexpected, because Hypothesis 3 relies on more in-depth second-order reasoning, and therefore provided a stronger cognitive challenge for our subjects. However, there are alternative ex post interpretations of this finding.[4] First, the decision profiles in which observed behavior was most different from predicted behavior were profiles 1 and 10. As detailed earlier, the difficult and easy options in these profiles have very similar success probabilities, and therefore maybe lacked adequate distinctiveness, leading subjects to more random decisions. Second, as also detailed earlier, we have evidence that principals interpret decisions in this context as a signal of capability, with subjects choosing the difficult option receiving a promotion that was, on average, four percentage points higher. Signaling attempts were not futile. This may further explain why less capable agents did not fully act like highly capable ones.

From a managerial perspective, our research highlighted the possible detrimental effect of reputation concerns. We also proposed and tested several interventions that help improve performance. Projects and tasks can potentially suffer from unnecessarily difficult solutions and the negative performance implications that such detrimental incentives may have for organizations. Overall, our data showed that the productivity loss due to reputation concerns leads to tasks in our experiment having, on average, a 10 percentage point lower likelihood of success. Although this number does not translate directly into practice,

[4] We emphasize that these interpretations are post hoc. They are made in reaction to the data, and serve as avenues for future research, rather than as established facts.

it shows that, at least in our experiment, these performance implications were not trivial. Furthermore, in our data, the productivity losses due to less capable agents selecting highly difficult tasks were higher than those due to highly capable agents selecting moderately more difficult tasks.

To counter this productivity loss, our study offered two ways to induce less capable agents to select less difficult options. One intervention that proved successful for less capable agents in our experiment was to make the principal more informed. Having knowledgeable principals evaluate individual capability leads to an increase in the likelihood of succeeding of about eight percentage points for less capable agents. The second intervention was to introduce a small bonus for achieving task success. This bonus changed the less capable agents' behavior fairly dramatically, increasing their likelihood of succeeding by nine percentage points. It is, however, important to emphasize that the clear provision of performance bonuses is not always feasible in R&D organizations, because task outcomes can be multidimensional, intangible, delayed in effect, and difficult to assess. Our research points to outcome related bonuses being a way to reduce the potential detrimental effects of reputational concerns only in situations where the clear provision of such bonuses is feasible. We hope that further research will explore how to overcome the adversity of genius if outcomes are more difficult to assess.

7. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

Acknowledgments

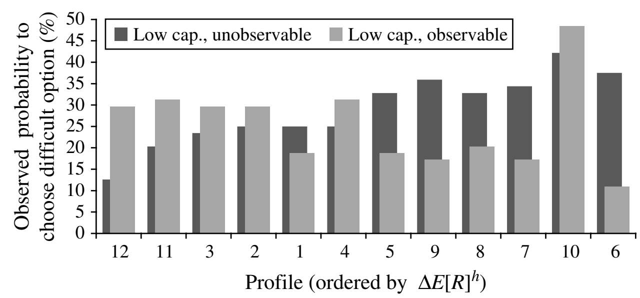
The authors acknowledge the support of the Campus Research Board of the University of Illinois for funding this research. They thank Axel Ockenfels and the Deutsche Forschungsgemeinschaft for financial support through the Leibniz-Program. E. Katok gratefully acknowledges support from the National Science Foundation, Penn State's Smeal College of Business, and the Center for Supply Chain Research at the Smeal College of Business through the Smeal Summer Grants program. The authors also thank seminar participants at the European School of Management and Technology, National University of Singapore, Georgia Tech, INSEAD, London Business School, Harvard University, the University of Minnesota, Emory University, and the University of Michigan for their insightful comments.

Appendix

Table A.1 Change in Expected Payoff for Choosing the Difficult Solution

	Unobservable		Performance rewards	
Profile	$c=h$	$c=l$	$c=h$	$c=l$
1	2.13	−2.13	1.63	−3.73
2	2.45	−2.45	0.95	−5.45
3	3.32	−3.32	0.82	−7.52
4	1.95	−1.95	−1.65	−6.65
5	1.27	−1.27	−2.83	−5.97
6	−0.45	0.45	−4.85	−3.85
7	−0.29	0.29	−4.39	−3.61
8	−0.19	0.19	−3.49	−2.91
9	−0.10	0.10	−2.30	−2.00
10	−0.41	0.41	−1.01	−0.09
11	16.67	−16.67	14.67	−21.67
12	19.55	−19.55	18.55	−24.05

Figure A.1 The Effect of Knowledgeable Principals on Less Capable Agents



References

Amabile, T. M., S. G. Barsade, J. S. Mueller, B. M. Staw. 2005. Affect and creativity at work. *Admin. Sci. Quart.* **50**(3) 367–403.

Autor, D. H., F. Levy, R. J. Murnane. 2003. The skill content of recent technological change: An empirical exploration. *Quart. J. Econom.* **118**(4) 1279–1333.

Bendoly, E., K. Donohue, K. L. Schultz. 2006. Behavior in operations management: Assessing recent findings and revisiting old assumptions. *J. Oper. Management* **24**(6) 737–752.

Chao, R., S. Kavadias, C. Gaimon. 2009. Revenue-driven resource allocation: Funding authority, incentives, and new product development portfolio management. *Management Sci.* **55**(9) 1556–1569.

Coburn, P. 2006. *The Change Function*. Penguin Group, New York.

Fama, E. F. 1980. Agency problems and the theory of the firm. *J. Political Econom.* **88**(2) 288–307.

Fischbacher, U. 2007. z-Tree: Zurich toolbox for ready-made economic experiments. *Experiment. Econom.* **10**(2) 171–178.

Holmström, B. 1999. Managerial incentive problems: A dynamic perspective. *Rev. Econom. Stud.* **66**(1) 169–182.

Hopp, W. J., S. M. R. Iravani, F. Liu. 2009. Managing white-collar work: An operations-oriented survey. *Production Oper. Management* **18**(1) 1–32.

Hutchison-Krupat, J., S. Kavadias. 2010. Compensation challenges for cross-functional. Working paper, Georgia Institute of Technology, Atlanta.

Irlenbusch, B., D. Sliwka. 2006. Career concerns in a simple, experimental labor market. *Eur. Econom. Rev.* **50**(1) 147–170.

Koch, A. K., A. Morgenstern, P. Raab. 2009. Career concerns incentives: An experimental test. *J. Econom. Behav. Organ.* **72**(1) 571–588.

Loch, C., C. Terwiesch. 2007. Coordination and information exchange. C. Loch, S. Kavadias, eds. *Handbook of New Product Development Management*. Butterworth Heinemann, Boston, 315–343.

Mihm, J. 2010. Incentives in new product development projects and the role of target costing. *Management Sci.* **56**(8) 1324–1344.

Rust, R. T., D. V. Thompson, R. W. Hamilton. 2006. Defeating feature fatigue. *Harvard Bus. Rev.* **84**(2) 98–107.

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

Siemsen, E. 2008. The hidden perils of career concerns in R&D organizations. *Management Sci.* **54**(5) 863–877.