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Delegating Innovation Projects with Deadline: Committed vs. Flexible Stopping

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Abstract. In many contexts such as product design and development, advertising, and scouting for technical solutions, clients seek the expertise of external providers to generate innovative solutions for their business problems. Because innovation projects are beset with uncertainty, they often require multiple iterations of ideation and evaluation. Although some clients make a commitment to take the first feasible solution from the provider, other clients retain the flexibility to seek more solutions until they decide to stop the project. Which of these policies is the better way to delegate an innovation project? To answer this question, we develop game-theoretic models that capture two salient aspects of delegated innovation projects: a deadline for the project and dynamic effort adjustment by the provider. We show that the flexible stopping policy, despite its intuitive appeal, may not always benefit the client. Specifically, the committed stopping policy is optimal when the provider is highly capable of generating solutions and when the client's cost of evaluating solutions is in an intermediate range. In such situations, the committed stopping policy provides a stronger incentive to the provider to exert costly effort early on, which improves the quality of initial solutions. Considering endogenous payments, we show that the committed policy not only mitigates the provider's tendency to postpone effort but also does so with a smaller payment.

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Keywords: delegation • innovation • project management • stopping policy • game theory

1. Introduction

Firms often seek the expertise of external entities to find innovative solutions to their business problems. Those solution experts—or providers—are delegated by clients to generate ideas in many business contexts such as product design and development, advertising, architecture, and scouting for technical solutions. The importance of delegating innovation in the economy can be witnessed in the consistent growth of concept-generating agencies (Johnson 2015, Vanhemert 2015). For instance, there are more than 25,000 design and advertising agencies in the United States, and in 2018 alone, the aggregate revenue generated by these firms exceeded \$60 billion (Statistica 2019b, U.S. Census Bureau 2019). More broadly, providers of consulting, engineering, and analytical services recorded more than \$250 billion in revenue from their clients in 2018, with a projected growth of at least 5% per year (Statistica 2019a).

Although delegating innovation is increasingly prevalent, a common collection of factors combines to add complexity to delegated innovation projects. First, clients who delegate innovation operate under

tight deadlines to implement ideas (Project Management Institute 2008, Hughes 2017). For instance, when Xerox wanted to produce a multifunction printer, it delegated the task of designing the facsimile hardware to California-based Jetfax (Jetfax has since been renamed eFax). To enable Xerox's timely entry into the market, Jetfax had to identify a solution within three rounds of concept generation and evaluation (Electronic Data Gathering, Analysis, and Retrieval (EDGAR) 1994). Clients are also known to operate under a "very tight schedule" in the realm of architecture and graphic design (American Institute of Graphic Arts 2013, p. 13). Indeed, in our survey of innovation professionals, most of the respondents reported that their project had strict deadlines "often" or "always" (see Section B.1 of Online Appendix B).

Second, because the client himself or herself may not be an expert in the provider's ideation and concept-generation process, he or she typically has limited insight into and control of the amount and timing of the provider's effort (Wu et al. 2014, Hutchison-Krupat and Kavadias 2016). As the project's deadline approaches, the provider may increase

the intensity of its effort or expand the scope of its search for a solution (Gersick 1988). This is driven by the inherent uncertainty regarding the value of a new concept, which is resolved only after the client evaluates it. In practice, providers can modify their effort levels during the course of a project by changing their technical approach or by adding different skills or more members to the team (Birnberg 1992, chapter 13; also see Section B.2 of Online Appendix B).

Naturally, given the need to identify the best possible solution before the deadline, clients desire to see a rapid succession of outstanding solutions from the provider. However, with profits as their ultimate objective, clients also seek the best possible solution to their problem (Girotra et al. 2010). Thus, clients may desire the flexibility to decide when to stop the project. This is especially common in industries such as product design, architecture, and advertising (Terwiesch and Loch 2004). For example, when PayPal engaged Workstage to design a new corporate office, the contract allowed PayPal to request new designs during the project even if submitted designs were feasible (i.e., compliant with regulations and needs; EDGAR 2002). Similar flexibility in stopping policy can be observed in Bechtel's contract to design Webvan's distribution centers (EDGAR 2001).

However, such contracts are not ubiquitous in practice. In many industries, such as hardware, electronics, and electrical design, clients delegate innovation with less flexibility. In this setup, which we refer to as the *committed* stopping policy, the client agrees to end the project when a feasible solution that meets the acceptance criteria is identified. In other words, the client cedes the right to continue the project after a feasible solution is identified. As an illustration, when Xerox delegated the task of designing the facsimile hardware to Jetfax, it committed to implementing the first design that passed the "acceptance test procedures" administered by Xerox (EDGAR 1994, p. 7). This type of committed stopping policy is also observed in other delegated projects of integrated hardware design (EDGAR 2005) and biological research and development (EDGAR 2000).

Although the differences between the flexible and committed stopping policies may appear to be obvious for the client, these policies also have different repercussions for the provider's concept-generation activities. The overall impact of this choice on the outcome of the project is not well understood. Addressing this gap is the primary objective of this paper. Intuition favors the flexible stopping policy when the client is seeking the best possible solution. As the examples illustrate, however, clients do not always seek such flexibility in practice. This raises our first research question: Is the flexible stopping policy always optimal? In other words, can the client ever

benefit through the committed stopping policy? Using a model-based inquiry, we find that the answer to the latter question is "Yes." To further our understanding of the drivers, we also ask, why and when does the committed stopping policy benefit the client?

To answer these questions, we develop game-theoretic models that capture the interactions between a provider and a client in a delegated innovation project under the flexible and committed stopping policies. At the core of our model is a client that is delegating concept generation to a provider, with the goal of implementing the best (feasible) concept. Concept generation is inherently uncertain because the quality of a solution cannot be known before the solution is evaluated by the client. In the flexible stopping policy, the client retains the right to seek additional solutions until it decides to stop the project; by contrast, the committed stopping policy effectively ends the project as soon as a feasible solution is delivered. Motivated by practical observations and a survey of innovation professionals, our model jointly considers three important factors in delegated innovation: the client adopts the best feasible concept for the opportunity, the client faces a deadline for implementation and must conclude the project within a finite number of rounds, and finally and most important, the provider has the autonomy to determine the optimal level of effort to exert in each round. The provider delivers one solution to the client at the end of each round. The solution's quality is stochastic and depends on the capability of the provider and the intensity of its effort (which is costly). The client evaluates solutions at the end of each round and decides whether to stop the project or continue to another round of concept generation.

Intuition suggests that the client would always benefit from the flexible stopping policy because it allows the client to seek higher-quality solutions by extending the project; however, we show that this holds true only if deadlines do not exist or if the provider's effort is constant. However, when these salient factors of delegation are accounted for, the flexible stopping policy is not unequivocally better; the primary reason is that the flexible policy can demotivate the provider from exerting high effort in the earlier rounds of the project. We also consider a setting where the provider is able to build on previously submitted solutions in subsequent rounds; the committed policy remains a robust mechanism to elicit higher provider efforts even in such a setting. Moreover, our analysis identifies specific scenarios under which the client should adopt the committed stopping policy to delegate an innovation project. The committed stopping policy is optimal when the provider is highly capable (e.g., through experience or know-how) in generating solutions and when the

client's cost of evaluating solutions is in an intermediate range.

We extend the model and analysis to situations where the client can employ the optimal payment as an additional lever. We find that the optimal payment under the committed policy never exceeds the optimal payment under the flexible policy. This result further underscores the value of the committed policy as an efficient mechanism to conduct a delegated innovation project with an autonomous provider. A large-scale numerical analysis also reveals that when the committed policy is optimal, choosing the flexible policy could result in significant performance degradation for the client (even more than when the flexible policy is optimal and the committed policy is chosen). Finally, we find that the committed policy is ideal for scenarios where the provider's capability or costs of effort drive up the optimal payment for the project.

The rest of this paper is organized as follows. We review the related literature in the next section and present the model of flexible and committed stopping policies in Section 3. We then present in Section 4 the analysis of the two stopping policies and discuss why and when the committed policy benefits the client. In Section 5, we characterize and compare endogenous payments under the two policies. We present our conclusions in Section 6. All proofs and technical details are gathered in Online Appendix A.

2. Literature Review

The challenges faced by organizations in managing innovation projects have been extensively documented and studied in many contexts (Kavadias and Ulrich 2020). Innovation projects are beset with uncertainty (Fleming 2001, Sommer et al. 2009, Loch et al. 2011) and often require multiple iterations of ideation and evaluation (Krishnan et al. 1997, Kavadias et al. 2000). Several approaches have been proposed to manage iterations in these highly uncertain projects; they include implementing trial-and-error learning (Sommer and Loch 2004), enabling better coordination between designers (Mihm et al. 2003), and including diverse domains in the research and development process (Oraiopoulos and Kavadias 2014). Although this paper also focuses on improving the execution of innovation projects, it is closer to the literature that examines the challenges involved in delegating innovation projects to another firm.

One key challenge for firms (clients) in delegating their innovation projects is the misalignment of their objectives with those of their solution providers (Holmström 1982, Hutchison-Krupat and Kavadias 2016, Basu and Bhaskaran 2018). There exists a large literature on designing incentives to mitigate the inefficiencies of delegated engagements because of

misaligned actions (e.g., Manso 2011, Wu et al. 2014, Crama et al. 2018, Zorc et al. 2019). In addition to (or instead of) incentive mechanisms, clients can use other (operational) levers to improve project performance. For instance, the client can influence the provider's effort by imposing deadlines (Zhang 2016), modulating its own participation in the project (Rahmani et al. 2017), or implementing better monitoring of the provider (Roels et al. 2010). This paper complements this stream of research by studying how the client's employment of decision rights—as it relates to stopping policy—can influence the provider's effort.

The literature on managing delegated innovation can be categorized in two groups based on their consideration of the client's stopping policy: one group of studies has focused on committed stopping policy, where the client stops the project as soon as a feasible solution is found (Zhang 2016, Crama et al. 2018, Rahmani et al. 2018). In these papers, all feasible solutions yield the same value; therefore, finding any feasible solution is sufficient and effectively ends the project. A different group of studies has considered the flexible stopping policy (Weitzman 1979, Terwiesch and Loch 2004), where the project does not end automatically when a feasible solution is found. This set of papers considers scenarios in which the existence of an even better solution cannot be ruled out; accordingly, the project reward depends on the quality of the best outcome. However, these papers do not address the question of which stopping policy is optimal and under what circumstances. Addressing this gap is the focal point of this paper.

The model we propose to address this gap is closest to that of Terwiesch and Loch (2004), who also consider sequential interactions between a client and a provider. A key distinction of our model is that we account for two salient aspects of delegated innovation (observed in our anecdotal examples and the survey): the importance of deadlines (which most clients face) and the provider's autonomy (which manifests as a dynamic choice of effort). Specifically, Terwiesch and Loch (2004) consider situations where the provider incurs a constant cost to generate a solution, and the distribution of the solution quality is not affected by the provider's actions. Yet, in practice, the provider can improve the quality of solutions through the intensity of its effort (resources, labor, etc.). We advance their model by considering the case where the cost to generate a solution and the distribution of the solution quality depend on the provider's effort. In addition, we account for the project deadline. From a practical standpoint, a deadline is a reality and a key restriction in many projects (Project Management Institute 2008). As such, we close an extant gap in the literature by showing how the

provider's autonomy and the project's deadline can impact the optimality of different stopping policies.

This paper is also related to an adjacent stream of research that studies how a proposer should make offers to a responder, who might be searching for a job or a house (e.g., Morgan 1983, Morgan and Manning 1985, Lippman and Mamer 2012). Given this context, this literature has generally assumed that the responder receives offers that are identically and independently distributed (Tang et al. 2009, Hu and Tang 2021, Zorc and Tsetlin 2020). A notable exception is Zorc et al. (2019), who study optimal contracts to delegate search to a risk-averse agent. However, Zorc et al. (2019) consider search without recall; that is, a solution proposed in a particular round ceases to be available in subsequent rounds. Although these assumptions are appropriate for a job hunt or a search for a house, they are less applicable in the context of innovation projects. When delegating innovation, it is crucial to take into account that the quality of solutions depends on the provider's effort (which can change dynamically) and that previously submitted solutions remain available to clients (Terwiesch and Loch 2004).

All in all, our paper contributes to the literature on delegating innovation in the following ways. First and foremost, we compare the performance of the committed and flexible stopping policies, which to the best of our knowledge has not been studied in prior research. In addition, we account for both the project deadline and the provider's effort provision. This study therefore advances the literature on delegated innovation by not only capturing those salient aspects but, more important, by generating insights on how the client's choice of stopping policy can impact the quality of solutions and, ultimately, the client's profit.

3. Model

We consider a client that has delegated an innovation project to an external provider. The provider generates one solution in each round with quality $v_t \geq 0$. The quality v_t is a unidimensional construct that captures the overall economic value the client will obtain by implementing the solution. Because of the innovative nature of the project, there is uncertainty about the quality of solutions. Indeed, the provider's solution may turn out to be infeasible or worthless for the client (i.e., it is possible to obtain $v_t = 0$).¹ We denote the quality of the best solution received by round t by \bar{v}_t ; accordingly, $\bar{v}_t = \max(v_i)$ for $i \leq t$. We assume that v_t is drawn from a distribution function $\Phi_{\mu_t}(\cdot)$, which depends on the intensity of the provider's effort in that round (μ_t ; specifically, $\Phi_{\mu_t}(\cdot)$ decreases with μ_t). Importantly, the provider can change the intensity of its effort in each round. In

practice, the provider may add or remove resources from the project, explore new solution domains, or use different tools for conducting research.² Thus, the distribution of the solution quality changes from one round to the other. We denote the provider's cost of effort to generate a solution in each round by $c(\mu_t)$, where $c'(\mu_t) > 0$.

The client evaluates the quality of each submitted solution and decides whether to implement the best feasible solution received thus far. We denote the client's cost of evaluating each submitted solution by c_l . Clients may incur this cost for a combination of reasons, including the direct cost of solution evaluation (such as prototyping and destructive testing) and/or administrative costs incurred to organize meetings or communicate with the provider. Evaluation costs tend to be lower in contexts where concepts can be tested virtually and significantly higher where concepts have to be tested using comprehensive prototypes (Thomke 2003). For instance, consider a client that receives a television commercial proposal from an advertising agency; the client evaluates the concept by testing its prototype (generally, a low-budget skit) with focus groups of future consumers. In a different context, when an automotive original equipment manufacturer receives a concept for a new door from a provider, the concept is evaluated using destructive crash tests on a full-scale prototype. In both cases, the evaluation cost can be obtained by combining the administrative and direct costs of prototyping and testing the concept.

The project is stopped when one of the following situations arises: (1) when the client chooses to stop or (2) when the project reaches its deadline, denoted by T . After the project is stopped, the client pays a fixed payment p to the provider only if a feasible solution is found ($\bar{v}_t > 0$). If no solution is found by the deadline (i.e., $\bar{v}_T = 0$), the project is stopped, and no payment is made to the provider.³ In Section 4, we analyze the problem for a given payment p ; subsequently, we extend our analysis to the case where the client optimally chooses p in Section 5.

The client can consider one of the two stopping policies: (1) flexible stopping policy, where the client retains the decision right to stop or continue the project upon receiving each solution, and (2) committed stopping policy, where the client commits to stop the project as soon as a feasible solution is found (i.e., $v_t > 0$). We next present models of the two stopping policies.

3.1. Models of Stopping Policies

3.1.1. Flexible Stopping Policy (F). Under the flexible stopping policy, the client retains the decision right to continue the project to future rounds. If the client stops the project after any round $t - 1$, it will

implement the best solution unearthed until that point, which bears a value of \bar{v}_{t-1} . Under this policy, in each round, the client determines whether to continue the project by comparing its present expected payoff from continuation with its profit from choosing the best solution found until that round. We denote the client's payoff when $\bar{v}_{t-1} > 0$ by $\Pi_t^{F+}(\bar{v}_{t-1})$ and when $\bar{v}_{t-1} = 0$ by Π_t^{F-} . Accordingly,

$$\Pi_t^{F+}(\bar{v}_{t-1}) = \max \left\{ (\bar{v}_{t-1} - p), -c_I + \int_{\bar{v}_{t-1}}^{+\infty} \Pi_{t+1}^{F+}(v) D\Phi_{\mu_t}(v) + \Phi_{\mu_t}(\bar{v}_{t-1}) \Pi_{t+1}^{F+}(\bar{v}_{t-1}) \right\}, \quad (1)$$

$$\Pi_t^{F-} = -c_I + \int_0^{+\infty} \Pi_{t+1}^{F+}(v) D\Phi_{\mu_t}(v) + \Phi_{\mu_t}(0) \Pi_{t+1}^{F-}, \quad (2)$$

$$\Pi_{T+1}^{F+}(\bar{v}_T) = \bar{v}_T - p \text{ and } \Pi_{T+1}^{F-} = 0. \quad (3)$$

The terminal conditions in Equation (3) capture the concept that when the project reaches its deadline, the client takes the best feasible solution (if any) and pays the provider.

The client's payoff depends on the effort exerted by the provider in each round. Furthermore, the provider consciously chooses the optimal effort level in each round based on the current state of the project, represented by t and \bar{v}_t . We denote the provider's efforts when $\bar{v}_{t-1} > 0$ by μ_t^{F+} and when $\bar{v}_{t-1} = 0$ by μ_t^{F-} ; this distinguishes scenarios in which a feasible solution has already been discovered from scenarios in which no feasible solution has been identified. The client's decision in Equation (1) results in a threshold policy, which determines continuation into the next round (we formally characterize this threshold in Proposition 2). Let us denote this stopping threshold by $v_{s,t}^F$ for $t < T$; that is, the client will stop the project at the end of round t if $\bar{v}_t \geq v_{s,t}^F$ and continues the project otherwise. Although the endogenous stopping threshold $v_{s,t}^F$ is not set in advance, the provider anticipates the client's stopping criteria and chooses its effort in each round t by maximizing its own payoff to go as follows:

$$\mu_t^{F+} = \arg \max_{\mu_t} -c(\mu_t) + (1 - \Phi_{\mu_t}(v_{s,t}^F)) \cdot p + \Phi_{\mu_t}(v_{s,t}^F) U_{t+1}^{F+}, \quad (4)$$

$$\mu_t^{F-} = \arg \max_{\mu_t} -c(\mu_t) + (1 - \Phi_{\mu_t}(v_{s,t}^F)) \cdot p + (\Phi_{\mu_t}(v_{s,t}^F) - \Phi_{\mu_t}(0)) U_{t+1}^{F+} + \Phi_{\mu_t}(0) U_{t+1}^{F-}, \quad (5)$$

where U_{t+1}^{F+} denotes the provider's expected payoff to go when $\bar{v}_t > 0$, and U_{t+1}^{F-} denotes the provider's expected payoff to go when $\bar{v}_t = 0$. Specifically,

$$U_{t+1}^{F+} = -c(\mu_{t+1}^{F+}) + (1 - \Phi_{\mu_{t+1}^{F+}}(v_{s,t+1}^F)) \cdot p + \Phi_{\mu_{t+1}^{F+}}(v_{s,t+1}^F) U_{t+2}^{F+}, \quad (6)$$

$$U_{t+1}^{F-} = -c(\mu_{t+1}^{F-}) + (1 - \Phi_{\mu_{t+1}^{F-}}(v_{s,t+1}^F)) \cdot p + (\Phi_{\mu_{t+1}^{F-}}(v_{s,t+1}^F) - \Phi_{\mu_{t+1}^{F-}}(0)) U_{t+2}^{F+} + \Phi_{\mu_{t+1}^{F-}}(0) U_{t+2}^{F-}, \quad (7)$$

with $U_{T+1}^{F+} = p$ and $U_{T+1}^{F-} = 0$.

3.1.2. Committed Stopping Policy (C). Under the committed stopping policy, the client abdicates the decision right to continue and commits to stop the project and pay the provider as soon as the first feasible solution is found (i.e., $v_t > 0$ for any $t < T$). In this case, the client's payoff is $\Pi_t^C = v_{t-1} - p$ if $v_{t-1} > 0$, and

$$\Pi_t^C = -c_I + \int_0^{+\infty} (v - p) D\Phi_{\mu_t}(v) + \Phi_{\mu_t}(0) \Pi_{t+1}^C \quad \text{if } v_{t-1} = 0, \quad (8)$$

$$\Pi_{T+1}^C = v_T - p \text{ if } v_T > 0 \text{ and } \Pi_{T+1}^C = 0 \text{ otherwise.}$$

The provider chooses its effort by maximizing its expected payoff to go as follows:

$$\mu_t^C = \arg \max_{\mu_t} -c(\mu_t) + (1 - \Phi_{\mu_t}(0)) \cdot p + \Phi_{\mu_t}(0) U_{t+1}^C, \quad (9)$$

where U_{t+1}^C denotes the provider's expected payoff to go under the committed stopping policy such that

$$U_{t+1}^C = -c(\mu_{t+1}^C) + (1 - \Phi_{\mu_{t+1}^C}(0)) \cdot p + \Phi_{\mu_{t+1}^C}(0) U_{t+2}^C, \quad (10)$$

with $U_{T+1}^C = 0$. The committed stopping policy may appear to be a subset of the flexible stopping policy, but it is indeed not the case. In our setting, where the provider is an independent agent that chooses its effort by maximizing its own payoff in any round, the two stopping policies can induce different strategic reactions by the provider and therefore lead to different outcomes, as we show in Section 4.1.

3.1.3. The Client's Choice of Stopping Policy. At the start of the project, the client chooses between the flexible and committed stopping policies by maximizing

its total expected profit. We denote the client choice of stopping policy by $S^* \in \{C, F\}$ such that

$$S^* = \arg \max \left\{ \Pi_1^F(\mu^F), \Pi_1^C(\mu^C) \right\}$$

Subject to (s.t.) $\mu^F = (\mu_1^F, \dots, \mu_T^F)$ are the provider's optimal efforts under the flexible stopping policy,
 $\mu^C = (\mu_1^C, \dots, \mu_T^C)$ are the provider's optimal efforts under the committed stopping policy. (11)

3.2. Specifics of the Model

In order to generate insights and solve the problem in closed form, we consider that the solution quality follows an exponential distribution (i.e., $\Phi_{\mu_t}(x) = 1 - P_{\mu_t}(v \geq x) = 1 - \mu_t e^{-x/k}$). This probability distribution has desirable properties: (1) it allows the possibility of generating a better solution than an existing feasible solution because it does not bound from above the quality of solutions (i.e., $v_t \in \mathbb{R}^+$), (2) the expected quality of solutions is $k\mu_t$, which is increasing in the provider's effort (μ_t) and in its capability level (k), and (3) for any effort $0 \leq \mu_t \leq 1$ and capability level $k > 0$, the probability of finding a feasible solution lies in the unit interval. The capability factor (k) represents the provider's expertise in the problem domain. Considering the client's decision at the end of round t , the probability of finding a solution that has a higher quality than \bar{v}_t is equal to $P_{\mu_{t+1}}(v \geq \bar{v}_t) = \mu_{t+1} e^{-\bar{v}_t/k}$, which is decreasing in \bar{v}_t and increasing in the anticipated future effort level μ_{t+1} . This implies that as the quality of previously submitted solutions (\bar{v}_t) increases, the likelihood of finding an even better solution becomes smaller (for a given effort). In Section 4.3, we also extend the model and analysis to situations where the provider can build on previously generated solutions to produce new concepts.⁴

In any round where the client seeks a solution from the provider, the provider can choose to exert effort $\mu_t \in \{\mu_l, \mu_h\}$ to generate a solution. Without loss of generality, we assume that $(\mu_l, \mu_h) \in (0, 1)$, with $\mu_h > \mu_l$. Specifically, the solution quality generated by effort μ_h has first-order stochastic dominance over the solution quality generated by effort μ_l . Accordingly, we consider the provider's cost of effort to be $c(\mu_l) = c_l$ and $c(\mu_h) = c_h$, with $c_h > c_l$. In line with prior research, we also assume that the marginal cost of improving solution quality increases with the effort level, i.e., $c_h/\mu_h \geq c_l/\mu_l$ (e.g., see Bhaskaran and Ramachandran 2011). This assumption is not restrictive and holds for many cost functions, including linear and convex.

3.3. Benchmark Scenarios

In this section, we consider two benchmark models considered in the prior literature (Terwiesch and

Loch 2004, section 5): (1) the project has no deadline (i.e., the client has an infinite number of rounds to find a solution), and (2) the provider does not adjust its effort over the course of the project (i.e., the distribution of the solution quality remains the same from one round to the next). Although these assumptions are not consistent with the context we study, they provide useful benchmarks to understand how our results are driven by the context.

3.3.1. Scenario 1: Infinite Rounds. Suppose that the client does not face a deadline for concept selection (i.e., $T \rightarrow \infty$).

Lemma 1. *When the project can continue for an infinite number of rounds, the client always benefits from adopting the flexible stopping policy rather than the committed stopping policy.*

The intuition behind Lemma 1 is as follows: because there is no limit to the number of rounds that the project can continue, the provider only exerts low effort through the multiple rounds of the project (even if it has the option to adjust its effort from round to round), and the provider's effort is also the same under both stopping policies. As a result, the committed stopping policy becomes a subcase of the flexible stopping policy, because the only difference between them is that under the flexible stopping policy the client chooses the stopping thresholds. Hence, the flexible policy (weakly) dominates the committed policy.

3.3.2. Scenario 2: Fixed Provider Effort. Suppose that the project can continue for only a finite number of rounds, but the provider does not adjust its effort over the course of the project (e.g., $\mu_t = \mu_l \forall t$).

Lemma 2. *When the provider's effort is the same in all rounds, the client always benefits from adopting the flexible stopping policy rather than the committed stopping policy.*

Lemma 2 shows that desiring flexibility is indeed optimal when the provider is not strategic. That is, because the provider's effort is constant throughout the project (i.e., it has no impact on the distribution of the solution quality), the only difference between the two models is the client's stopping threshold. Hence, given that under the flexible stopping policy the client optimally chooses the stopping thresholds, the flexible policy (weakly) dominates the committed policy.

4. Results

Although the flexible stopping policy is theoretically dominant in the aforementioned stylized settings, the committed policy is commonly observed in practice. In this section, we show how accounting for the project deadline and dynamic adjustment of the

provider's effort could make the flexible stopping policy suboptimal.

Proposition 1. *When the project can continue for only a finite number of rounds and the provider can adjust its effort dynamically over the course of the project, the client can benefit from adopting the committed stopping policy rather than the flexible stopping policy.*

Proposition 1 shows that the flexible stopping policy can be a suboptimal approach for a client that faces a deadline. This result may seem counterintuitive at first because one might think the committed stopping policy is a subcase of the flexible stopping policy (similar to the benchmark scenarios). However, this is not the case here because of the effort adjustment of the provider. In the remainder of this section, we show why and when the committed stopping policy can benefit the client in a project with a finite number of rounds.

We first answer the why question by characterizing equilibrium choices of the client and the provider under the two stopping policies in Section 4.1 and then answer the when question by comparing the client's total expected profit under the two stopping policies in Section 4.2. In order to simplify the exposition and generate more insights, in the remainder of this paper, we focus our analysis on a project with two rounds (i.e., $T = 2$).⁵ In addition, to avoid trivial cases, we focus on situations where the project payment p is neither too high nor too small; this ensures that both the client and the provider have incentives to participate in the project (see details in Lemma A-1 in Online Appendix A).

4.1. Why Does the Committed Stopping Policy Benefit the Client?

The next two propositions characterize the client's and provider's equilibrium choices under the committed and flexible stopping policies. Because under the committed policy the client stops the project as soon as a feasible solution is found (i.e., $v_t > 0$), the client's choice of stopping threshold only arises in the flexible stopping policy. Specifically, solving Equation (1), the client determines whether to continue the project by comparing its present expected payoff from continuation with its profit from choosing a received feasible solution, which we characterize next.

Proposition 2 (Client's Stopping Threshold). *Under the flexible stopping policy, there exists a unique threshold $v_s^F \geq 0$ such that*

- The client stops the project and takes the first submitted solution if $v_1 \geq v_s^F$, or*
- The client continues the project and seeks another solution if $v_1 < v_s^F$.*
- In addition, v_s^F is nondecreasing in k , and it is nonincreasing in c_l .*

Proposition 2 shows that the client stops the project only if the first solution is feasible and of considerably high quality ($v_1 \geq v_s^F$). When the first solution is feasible but unimpressive ($v_1 < v_s^F$), the next solution from the provider has a high probability of outperforming this incumbent solution. As a result, the client finds it worthwhile to proceed to the second round. In addition, the stopping threshold is higher when the client's evaluation cost (c_l) is low or the provider's capability (k) is high. When the evaluation cost c_l is low, continuing the project to another round is inexpensive for the client, making it optimal to seek another solution even if the probability of receiving a better solution is lower. Similarly, when the provider's capability is high, there is a higher likelihood that it could find a better solution in the second round than the one offered in the first round. Thus, continuation of the project would be worthwhile from the client's perspective.

The threshold v_s^F operationalizes the client's optimal usage of the flexible stopping policy. It is when $v_s^F > 0$ that the flexible policy is especially appealing for the client because it gives the client recourse when it receives feasible solutions with limited value. However, the client's optimal decisions impact the provider's effort, which we characterize in the next proposition.

Proposition 3 (Provider's Efforts). *There exist thresholds \underline{p} , \bar{p}^C , and \bar{p}^F such that*

- Under the committed stopping policy,*

$$(\mu_1^C, \mu_2^C) = \begin{cases} (\mu_l, \mu_l), & \text{if } p < \underline{p}, \\ (\mu_l, \mu_h), & \text{if } \underline{p} \leq p < \bar{p}^C, \\ (\mu_h, \mu_h), & \text{if } \bar{p}^C \leq p. \end{cases}$$

- Under the flexible stopping policy, $\mu_2^{F+} = \mu_l$. In addition,*

$$(\mu_1^F, \mu_2^{F-}) = \begin{cases} (\mu_l, \mu_l), & \text{if } p < \underline{p}, \\ (\mu_l, \mu_h), & \text{if } \underline{p} \leq p < \bar{p}^F, \\ (\mu_h, \mu_h), & \text{if } \bar{p}^F \leq p. \end{cases}$$

- The thresholds are such that $\bar{p}^C \leq \bar{p}^F$. In addition, $\bar{p}^F - \bar{p}^C$ is nondecreasing in k , and it is nonincreasing in c_l .*

The first part of Proposition 3 shows that under the committed stopping policy, the provider's effort escalates over the two rounds: that is, the provider may choose to exert low effort in the first round and increase its effort only in the second round; this particularly happens when $\underline{p} \leq p < \bar{p}^C$. It is important to note that in our model, the escalation in the provider's effort is not a result of psychological factors that have been discussed in the prior literature (e.g., see Wu et al. 2014). Rather, it is a rational decision for the provider to exert less effort in the first round because

it can increase its effort level in the second round (if it cannot find a feasible solution in the first round).

This effort escalation may also occur under the flexible policy if the first round is not fruitful (Proposition 3(b)). In particular, if $\underline{p} \leq p < \bar{p}^F$ and the provider cannot find a feasible solution in the first round, it increases its effort in the second round. If the provider finds a feasible solution in the first round, it has no incentive to exert high effort in the second round. Although the effort variation predicted by our model is consistent with empirical evidence (Gersick 1988), prior literature on delegated innovation with flexible stopping has generally ignored intertemporal variation in the provider's efforts.

Finally, part (c) of Proposition 3 shows that the payment threshold above which the provider exerts high effort in the first round is smaller under the committed stopping policy than under the flexible stopping policy. Figure 1 illustrates this result and shows that the region where the provider exerts high effort in both rounds of the flexible stopping policy is smaller than the same under the committed stopping policy. This answers our question of why the committed stopping policy can benefit the client. When the client uses the committed policy, the provider's expected benefit from the first-round effort is higher because delivering a feasible solution is enough to be immediately rewarded. Specifically, for any $p \in [\bar{p}^C, \bar{p}^F]$, the committed stopping policy provides higher incentives to the provider to exert high effort early on.

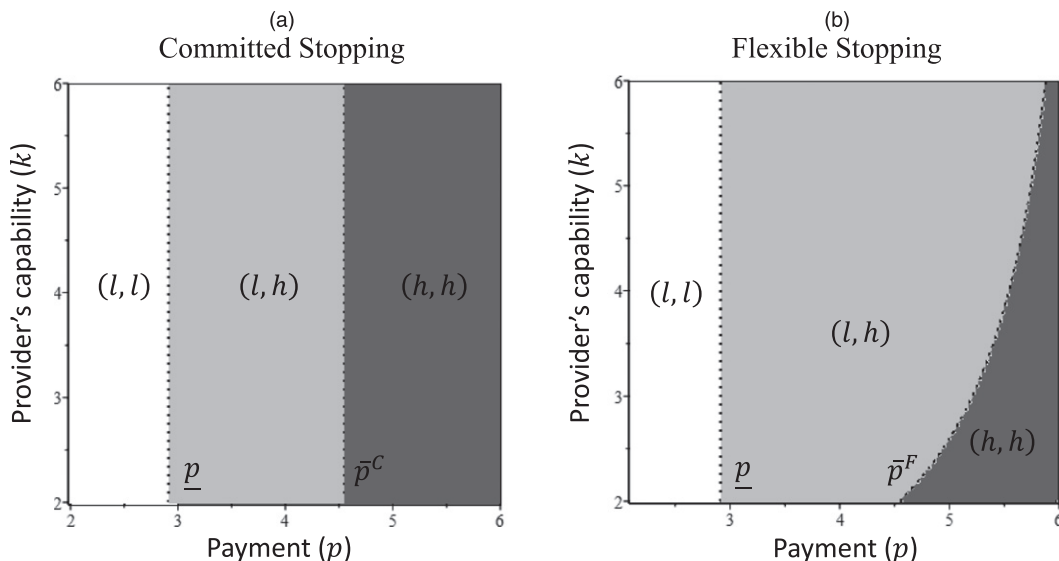
As a result of this higher first-round effort from the provider in this region, the committed policy results in a higher probability of yielding a feasible solution in the first round, as well as a higher expected quality of the first solution. As a result, the two policies behave differently, and from the client's perspective, the committed stopping policy is no longer a subcase of the flexible stopping policy. By providing the incentive for early action by the provider, the committed policy mitigates the provider's tendency to postpone effort until the deadline is imminent. The deadline effect on the provider's effort—and the committed stopping policy's ability to mitigate it—can be observed for any finite deadline $T < \infty$ (see details in Section A.1 of Online Appendix A).

It is important to note that the lower early effort of the provider in the flexible stopping policy does not automatically imply that the flexible stopping is less efficient because retaining flexibility gives the client the option to seek additional solutions. This is the essence of the client's trade-off in comparing these two policies. In the next section, we turn our attention to when the committed stopping policy can benefit the client.

4.2. When Does the Committed Stopping Policy Benefit the Client?

In this section, we compare the client's total expected profit under the committed and flexible stopping policies by solving (11) while anticipating the provider's

Figure 1. Provider's Efforts Under Committed Stopping Policy (μ_1^C, μ_2^C) and Flexible Stopping Policy (μ_1^F, μ_2^F)



Notes. Parameters: $\mu_h = 0.8$, $\mu_l = 0.25$, $c_h = 2$, $c_l = 0.4$, and $c_l = 0.5$. Note that the ratio of μ_l/μ_h is close to the average reported by survey respondents in Section B.2 of Online Appendix B.

optimal efforts in each round of the project and under each stopping policy (as characterized in Proposition 3). In order to isolate the effect of the client's choice of stopping policy on its total expected profit from the delegated project, we consider situations where the client has a fixed budget and cannot alter the provider's payment depending on the stopping policy. In Section 5, we generalize our model and analysis to the case where the client can optimally choose the payment for each stopping policy.

Proposition 4 (When Is Commitment Optimal?). *There exist two thresholds $\hat{c}_I(k)$ and $\bar{c}_I(k)$ such that*

- The client benefits from adopting the committed stopping policy rather than the flexible stopping policy if and only if $\hat{c}_I(k) < c_I < \bar{c}_I(k)$ and $p \geq \frac{c_h - c_l}{\mu_h - \mu_l}$.*
- In addition, $\hat{c}_I(k)$ is nonincreasing in k , and $\bar{c}_I(k)$ is nondecreasing in k .*

Proposition 4 shows that the committed stopping policy benefits the client, particularly when the provider's capability is high and the client's cost of evaluation is in an intermediate range. Figure 2 illustrates this result.

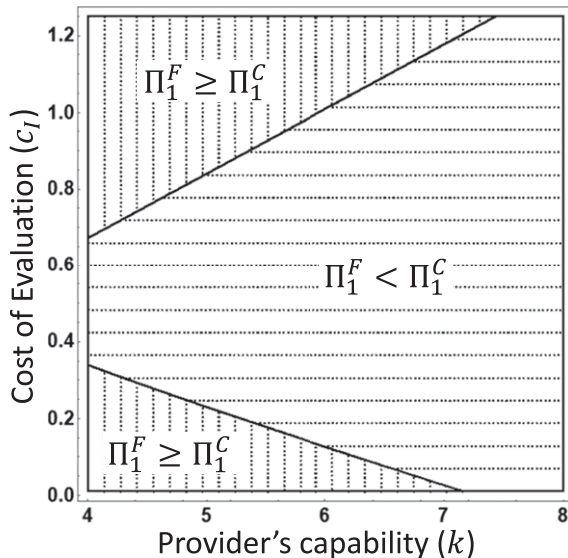
To understand this result, first consider the case where the provider's capability k is very high. Suppose that the client adopts the flexible approach in such a scenario: because of the high capability of the provider, it is very likely to generate a feasible solution in the first round itself, and this feasible solution is likely to be of high quality. Given the high expected quality of the first solution, both the client and the provider anticipate that the provider will not have the incentive to exert a high effort in the

second round. Therefore, the option to continue into the second round is unlikely to be exercised. More important, the flexible stopping policy would discourage the provider's effort in the first round (Proposition 3), which could result in a lower-quality first solution without adding a meaningful second round of effort. As a result, when k is high, it is simply better to adopt the committed stopping policy.

When the provider's capability is low, the answer is less clear. Here the provider's effort in the first round is less likely to produce a feasible solution, and the expected quality of the solution is also lower. Therefore, the client would value the option to extend the project to the second round even if a feasible solution is found. However, this is optimal only as long as the cost of the flexible stopping policy is sufficiently low. The direct cost of the flexible policy is low when the evaluation cost c_I is sufficiently low ($c_I < \hat{c}_I$). By contrast, the indirect cost of flexibility is low if the provider's effort in the first round is not distorted by the choice of the stopping policy. When $c_I > \bar{c}_I$, it is not optimal for the client to extend the project unless the first solution is barely feasible (v_s^F is small); this encourages the provider to exert the same effort under both policies, thus eliminating the indirect cost of flexibility for the client. As a joint consequence of these direct and indirect costs, the flexible stopping policy is optimal when c_I is either sufficiently high or sufficiently low.

In the next section, we explore a comparison between the committed and flexible stopping policies in situations where the provider can leverage the previously generated solutions in producing new solutions.

Figure 2. Comparison of Committed and Flexible Stopping Policies



Note. Parameters are the same as in Figure 1 with $p = 5.2$.

4.3. Building on Previous Solutions

In this section, we consider situations where the provider can build on its previously generated solutions in producing new concepts. We consider a parsimonious functional form to capture the relationship between past and new solutions; specifically, $v_{t+1} = \alpha \bar{v}_t + \hat{v}_{t+1}$, where \hat{v}_{t+1} is drawn from a distribution function $\mu_{t+1(\cdot)}$, and $\bar{v}_t = \max\{v_i\}$ for $i \leq t$. The parameter $\alpha \in [0, 1]$ captures the degree at which the best current solution (\bar{v}_t) can improve the quality of the next solution (v_{t+1}). We refer to α as the *dependency* between successive solutions. Will the provider's ability to build on prior solutions favor the committed or flexible stopping policy? If the provider exerted the same fixed effort in each period, the inclusion of α would enhance the value of the flexible policy; however, the answer is less clear when the provider chooses its efforts optimally. The next proposition characterizes the effect of dependency between solutions (α).

Proposition 5 (Effect of Dependency of Solutions (α)). For any $\alpha \in [0, 1]$, there exist two thresholds $\hat{c}_l(\alpha)$ and $\bar{c}_l(\alpha)$ such that

- The client benefits from adopting the committed stopping policy rather than the flexible stopping policy if and only if $\hat{c}_l(\alpha) < c_l < \bar{c}_l(\alpha)$ and $p \geq \frac{c_h - c_l}{\mu_h - \mu_l}$.
- In addition, $\hat{c}_l(\alpha)$ and $\bar{c}_l(\alpha)$ are nondecreasing in α .

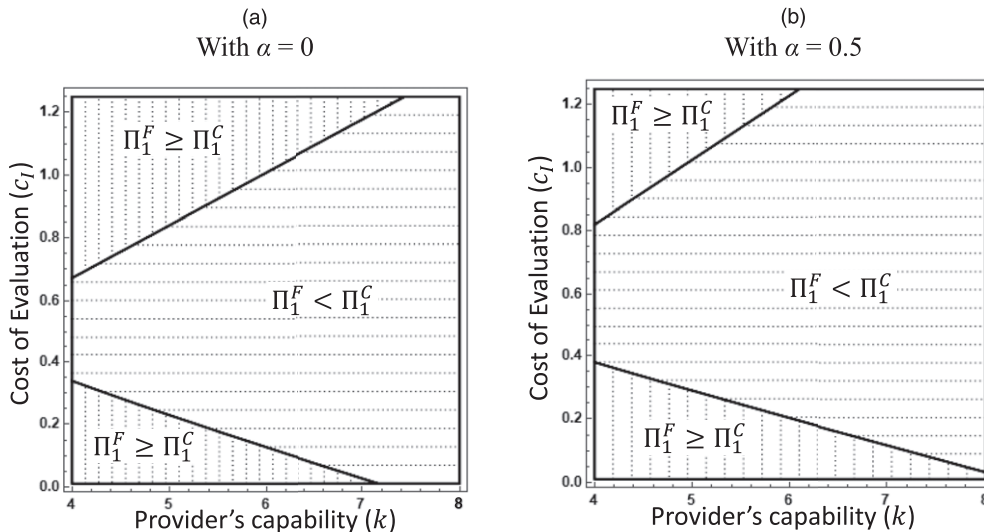
Proposition 5 shows that even in situations where the provider can build on the previously generated solution in producing a new solution, the committed stopping policy can benefit the client. To understand how the dependency between successive solutions (by itself) affects the choice between flexible and committed policies, we consider how the parameter α affects the thresholds \hat{c}_l and \bar{c}_l . Proposition 5(b) shows that both thresholds increase when the provider's ability to leverage the previously generated solution (α) increases. This implies that the dependency between solutions favors the flexible stopping policy when the cost of evaluation is low but enhances the benefit from the committed stopping policy when the cost of evaluation is high.

To understand this result, Figure 3 illustrates a comparison of the committed and flexible policies when solutions are and are not dependent. The immediate observation from Figure 3(b) is that the committed policy continues to be optimal for the client in many scenarios (region with $\Pi_1^C > \Pi_1^F$). However, comparing Figure 3(a) with Figure 3(b), it can be seen that both thresholds are higher when $\alpha > 0$. The increase in the lower threshold is because of the fact that a higher α increases the expected quality of subsequent solutions, which makes continuation more desirable for the client. Then the question is why this effect does not persist when the cost of evaluation is high.

We answer this question by examining how the dependency between solutions affects the provider's optimal efforts, specifically under the flexible stopping policy. Note that if the provider's effort was fixed (as in Lemma 2), a higher α could only make the flexible stopping policy more beneficial for the client; this is because both the expected quality of the second solution and the likelihood of finding a better solution in the second round increase in α . However, when the provider dynamically adjusts its effort, a higher α may not always improve the performance of the flexible policy. Naturally, a higher α increases the expected quality of the second solution, hence enticing the client to continue the project even when a high-quality solution is delivered in the first round (i.e., $v_s^F(\alpha)$ increases in α). The client's stronger tendency to continue the project when α is high demotivates the provider from exerting high effort in the first round of the flexible policy (see Lemma A-2 in Online Appendix A). Hence, even though the second solution improves with α , the first solution's quality may decline. As a result, the client may have to incur two rounds of evaluation costs before a high-quality solution is obtained. This particularly affects the performance of the flexible policy when the evaluation cost is high.

Overall, our analyses in Section 4 show that the client's own stopping policy can be an important lever in managing a delegated innovation project. A key takeaway is that the common practice of the flexible stopping policy can be suboptimal because it can discourage the provider from exerting high effort early on and therefore lead to lower-quality solutions. In the next section, we explore the payment to the provider as an additional lever for the client in managing delegated innovation.

Figure 3. Comparison of Committed and Flexible Stopping Policies with $\alpha \geq 0$



Notes. Parameters are the same as in Figure 2.

5. Endogenous Payments

In this section, we extend our analysis by considering situations where the client can optimally choose the payment p under each stopping policy while anticipating the provider's choices of effort. We first derive the optimal payments for each stopping policy and subsequently compare the two policies. For any stopping policy S , the client chooses the optimal payment at the start of the project, denoted by p^{*S} , by maximizing its total expected profit as follows:

$$\begin{aligned} p^{*S} &= \arg \max_p \Pi_1^S(\mu_1^S(p), \mu_2^S(p)) \\ \text{s.t. } &(\mu_1^S(p), \mu_2^S(p)) \text{ are the provider's optimal} \\ &\text{efforts under the stopping policy } S \in \{C, F\}, \\ &U_1^S(\mu_1^S(p), \mu_2^S(p)) \geq 0, \end{aligned} \quad (12)$$

where the first constraint ensures that the provider's efforts in the two rounds are optimal given the payment p (characterized in Proposition 3). As before, we focus our attention on the interesting cases where the provider does have an incentive to participate, which is ensured by the second constraint. In Propositions 6 and 7, we characterize the optimal payments and the provider's equilibrium efforts under the committed and flexible stopping policies, respectively.

Proposition 6 (Optimal Payments Under Committed Stopping). *Consider the committed stopping policy. There exist thresholds k_1^C and k_2^C (with $k_2^C \geq k_1^C$) such that*

a. *It is optimal for the client to offer the following payments and extract corresponding efforts:*

$$(\mu_1^C, \mu_2^C, p^{*C}) = \begin{cases} (\mu_l, \mu_l, p_{ll}^{*C}), & \text{if } k < k_1^C, \\ (\mu_l, \mu_h, p_{lh}^{*C}), & \text{if } k_1^C \leq k < k_2^C, \\ (\mu_h, \mu_h, p_{hh}^{*C}), & \text{otherwise,} \end{cases}$$

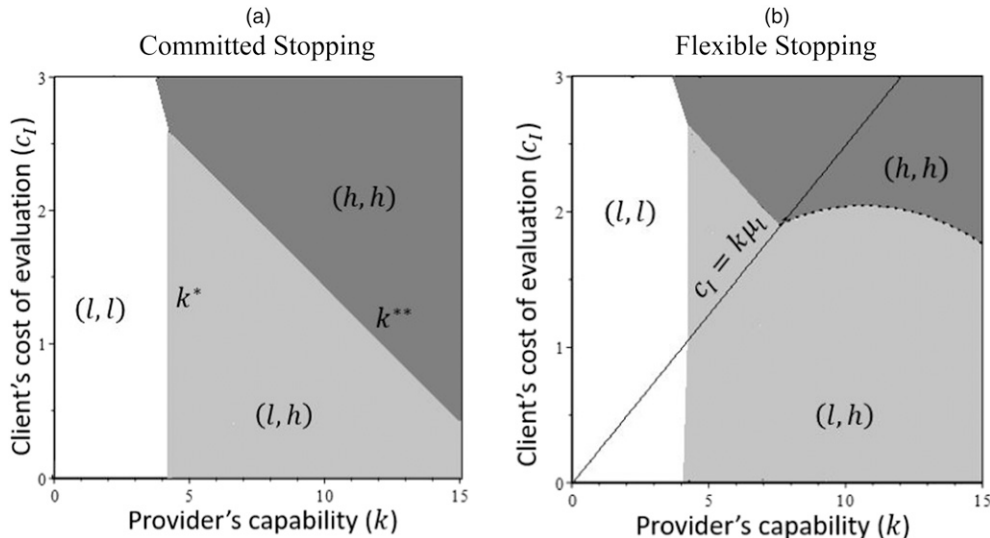
where $p_{ll}^{*C} \doteq \frac{c_l}{\mu_l}$, $p_{lh}^{*C} \doteq \frac{c_h - c_l}{\mu_h - \mu_l}$, and $p_{hh}^{*C} \doteq \frac{c_h - c_l - c_h(\mu_h - \mu_l)}{(1 - \mu_h)(\mu_h - \mu_l)}$; and

b. *The optimal payments are such that $p_{hh}^{*C} \geq p_{lh}^{*C} \geq p_{ll}^{*C}$. Further, k_1^C and k_2^C are nonincreasing in c_l .*

Proposition 6 characterizes how the client's payment to the provider depends on the capability of the provider. The additional effort by the provider is more valuable for the client when the provider is more capable; this is because capability compounds the value of effort in improving the expected quality of a solution (in any round). Therefore, Proposition 6(a) shows that the client induces greater effort from the provider if the provider's capability is higher—first by inducing a high effort in the second round (when $k > k_2^C$) and later by inducing high efforts in both rounds (when $k > k_1^C$). In order to induce these higher efforts, the client offers a higher payment p^{*C} as the capability k increases.

Proposition 6(b) reveals further insights by identifying the relationships between the provider's capability thresholds and the client's evaluation cost c_l . We illustrate this via Figure 4(a), which shows the provider's equilibrium choices of effort induced by the client under the committed stopping policy (note that the second-round effort is irrelevant if a feasible solution is generated in the first round itself). The combined message from Proposition 6(b) and Figure 4(a) is that the client is keen on inducing greater efforts from the provider when the evaluation cost is higher and even more so when the provider is more capable. This is because when c_l and k are both high, the need to minimize evaluation (because of high c_l) and the opportunity to generate high-quality solutions (because of high k) make it valuable to draw higher efforts from the provider in both rounds.

Figure 4. Provider's Efforts Under Committed and Flexible Stopping Policies with Endogenous Payments



Notes. Parameters are the same as in Figure 1.

We next characterize the client's optimal choices of payment and the provider's equilibrium efforts under the flexible stopping policy.

Proposition 7 (Optimal Payments Under Flexible Stopping). *Consider the flexible stopping policy. There exist thresholds k_1^F , k_2^F , and k_3^F (with $k_1^F \leq k_2^F \leq k_3^F$) such that*

- If $c_l \geq k\mu_l$, the optimal payments and efforts are the same as in Proposition 6.*
- If $c_l < k\mu_l$, then it is optimal for the client to offer the following payments and extract corresponding efforts:*

$$(\mu_l^F, \mu_h^F, p^{*F}) = \begin{cases} (\mu_l, \mu_l, p_{ll}^{*F}), & \text{if } k_1^F < k \leq k_2^F, \\ (\mu_l, \mu_h, p_{lh}^{*F}), & \text{if } k_2^F \leq k < k_3^F, \\ (\mu_h, \mu_h, p_{hh}^{*F}) & \text{otherwise,} \end{cases}$$

where $p_{ll}^{*F} \doteq \frac{c_l}{\mu_l} \left(\frac{2k-c_l}{k(2-\mu_l)} \right)$, $p_{lh}^{*F} \doteq \frac{c_h-c_l}{\mu_h-\mu_l}$, and $p_{hh}^{*F} \doteq \frac{c_h-c_l-c_h(\mu_h-\mu_l)}{(1-\mu_h)(\mu_h-\mu_l)} + \frac{c_l(k\mu_l-c_l)}{k\mu_l(1-\mu_h)}$.

When the evaluation cost is significantly high (i.e., $c_l \geq k\mu_l$), it is optimal for the client to stop the project on receiving the first feasible solution (i.e., $v_s^F = 0$). Therefore, the flexible and committed policies are identical to each other. However, when the evaluation cost is low (i.e., $c_l < k\mu_l$), the client's stopping threshold is positive, which drives differences in efforts and payments between the two policies. Figure 4(b) illustrates the results in Proposition 7. We observe that the provider's capability has two counteracting effects on the equilibrium efforts in the flexible policy. First, as k increases, the provider is more inclined to exert low effort in the first round because even low effort can produce a high-quality solution. As a result, the client needs to offer a higher payment to extract high efforts in both rounds, leading to an increase in the size of the (l, h) region. However, when the provider's capability is very high, extracting high effort in the first round can lead to a significantly higher-quality first solution. This justifies a higher payment required to induce high efforts in both rounds, leading to an increase in the size of the (h, h) region.

5.1. Comparison of Stopping Policies with Endogenous Payments

As shown in Figure 4, the region where the client extracts high efforts in both rounds is smaller when the client adopts the flexible stopping policy. This implies that even when the client optimally chooses payments under the two stopping policies, the committed policy can still provide higher incentives for early effort by the provider. The next proposition shows not only that the committed policy mitigates the provider's tendency to postpone effort but that it does so with a smaller optimal payment.

Proposition 8 (Optimal Payments Comparison). *Comparing the optimal payments under the two policies,*

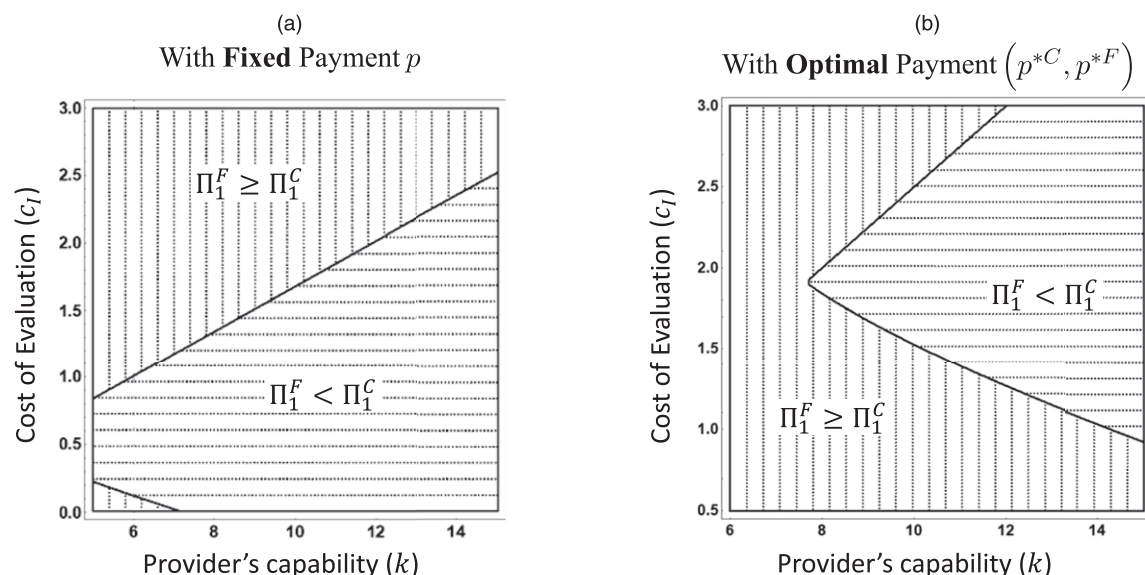
$p_{ll}^{*F} \geq p_{ll}^{*C}$, $p_{lh}^{*F} = p_{lh}^{*C}$, and $p_{hh}^{*F} \geq p_{hh}^{*C}$. In addition, $p_{hh}^{*F} - p_{hh}^{*C}$ is nonincreasing in c_l and nondecreasing in k .

Proposition 8 establishes that the optimal payments are always (weakly) smaller when the client adopts the committed policy, reiterating the idea that it is easier to extract greater first-round effort from the provider under the committed policy. This result also suggests that the client ends up paying a premium in order to use the flexible policy because of the provider's autonomy. It is worth noting that this premium has not been identified in the prior literature, where the flexible policy has been considered to be the norm. The proposition also reveals that this flexibility premium is higher when c_l is low and k is large. Why? When the evaluation cost c_l is high, the provider infers that the client is unlikely to exercise the option to continue after a feasible solution is delivered, hence closing the gap between the optimal payments. By contrast, when k is high, the client will continue the project into the second round unless a solution of remarkably high quality is discovered in the first round; the provider understands the client's incentive, which makes it more difficult to incentivize the provider's efforts under the flexible policy.

Figure 5 illustrates a comparison of committed and flexible stopping policies with and without endogenous payments (using the same example from Figure 2). The immediate observation from Figure 5(b) is that the committed policy continues to be optimal for the client in many scenarios (region with $\Pi_1^C > \Pi_1^F$). Further, consistent with the case in which the payment is fixed, the committed policy is optimal when the provider is more capable and evaluation costs are in an intermediate range. Interestingly, we find that when the payment p is chosen optimally by the client, the committed policy might become optimal even in scenarios where the flexible policy might have been optimal for a fixed p . For instance, this occurs in our illustration in the particular case where $c_l = 2.5$ and $k = 12$. This can be attributed to the flexibility premium (Proposition 8). In such cases, the client is able to efficiently induce higher efforts in both rounds by giving up its flexibility.

In order to generate additional insights on the optimality of the committed policy with endogenous payments, we conduct a large-scale numerical analysis in which the client selects the optimal payment to the provider under each policy (by solving the problem in Equation (12)) and then chooses the optimal stopping policy with endogenous payments. We randomly generated 10,000 sets of problem parameters within ranges depicted in Table 1. Naturally, we only admitted parameter sets in which $c_l < c_h$ and $\mu_l < \mu_h$. Further, to ensure that the provider's cost was increasing and convex in its effort, we consider that

Figure 5. Comparison of Committed and Flexible Stopping Policies with Endogenous Payments



Notes. Parameters are the same as in Figure 2.

$c_h/\mu_h > c_l/\mu_l$ in all problem sets. The optimal payments characterized in Propositions 6 and 7 allow us to solve the problems efficiently. In the rest of this section, we summarily present the key insights from the generated optimal solutions as they pertain to the central question of the optimal stopping policy.

Across the broad range of parameters, the performance of the committed and flexible stopping policies is summarized in Table 2. From the 10,000 problems, Table 2 shows the number of instances (and, correspondingly, the fraction of instances) in which each policy was found to be optimal. The “Gain, %” column in Table 2 shows the average improvement in the client’s profit as a result of choosing the optimal policy (relative to the alternative policy). For example, if a client could obtain a profit of $\Pi_1^F = 2$ and $\Pi_1^C = 3$ from the flexible and committed policies, respectively, we attribute 50% of the gain to selecting the correct stopping policy. Overall, when the deadline and the provider’s effort provision are taken into account, the results show that the committed policy is profitable for the client in a significant number of scenarios. Furthermore, the results suggest that when the committed policy is optimal, choosing the flexible policy could result in heavy performance degradation

for the client (even more than when the flexible policy is optimal and the committed policy is chosen).

We now consider how the optimal payment varies between different scenarios. Looking at the two policies separately, the average optimal payments in the committed and flexible policies are 1.95 and 2.08, respectively. However, somewhat surprisingly, we find that the average optimal payment is higher when the committed policy is optimal (column (3) of Table 3), and the optimal payment is also a higher multiple of the high effort μ_h when the committed policy is optimal (column (4) of Table 3). Does this imply that commitment is not efficient after all? No. What we observe is a selection effect rather than a treatment effect. To understand this, column (5) of Table 3 shows the optimal payment that the client would have paid if the wrong optimal policy had been chosen. This shows that the optimal payment would, on average, be lower under the committed policy (3.24 when committed is optimal and 1.39 when it is not). Furthermore, combined with the discussion, we can conclude that the committed policy is optimal when other factors, such as the provider’s capability

Table 1. Parameter Ranges for Numerical Study

Parameter	μ_l	μ_h	c_l	c_h	c_l	k
Range	(0, 1]	(0, 1]	(0, 1]	(0, 3]	(0, 3]	[1, 15]
Other limits	$\mu_l < \mu_h$		$c_h > c_l \mu_h / \mu_l$			

Note. All distributions were uniform.

Table 2. Performance of Stopping Policies and Client’s Profit

Policy	Optimal, no.	Optimal, %	Gain, %
Committed	1,841	18.41	10.32
Flexible	6,183	61.83	7.64
Both (tie)	1,976	19.76	N/A

Note. N/A, not applicable.

Table 3. Optimal Payments

Policy	Optimal, %	$E[p^*]$	$E[p^*/\mu_h]$	$E[p^{NO}]$
Committed	18.41	3.238	8.805	3.404
Flexible	61.83	1.562	2.895	1.388
Both (tie)	19.76	2.512	5.150	2.512

or costs of effort, conspire to make the optimal payment high under the flexible policy.

6. Conclusions

Clients who face challenging problems in many realms delegate their innovation projects to external providers that offer greater expertise, better access to talent, and a fresh perspective (Hughes 2017). This has resulted in the remarkable growth in the ranks and revenues of concept-generating agencies such as advertising, product design, and industrial design firms (Statistica 2019b, U.S. Census Bureau 2019). In such delegated projects, intuition suggests that clients will benefit from retaining the flexibility—specifically, in terms of decision rights—to determine when to end the project. We challenge this idea in this paper and demonstrate that renouncing flexibility can be valuable in delegated innovation projects. Our findings explain seemingly puzzling practical instances where clients agree to conclude the project immediately after the first feasible solution is delivered. In this paper, we explain that such a policy of commitment can indeed outperform a flexible approach when the project's deadline and the dynamic effort adjustment of the provider are considered jointly.

Our model-based analysis shows that although flexibility is appealing to the client, it demotivates the provider during the early stages of the project. Conversely, the committed stopping policy can induce the provider to exert costly effort early on, which results in a higher probability of yielding a feasible solution, as well as a higher expected quality of initial solutions. The committed policy is most valuable when the expertise of the provider is high or when the client's cost of evaluating solutions is moderate. In addition, the committed policy is optimal when factors, such as provider's capability and costs of effort, conspire to make the optimal payment high under the flexible stopping policy. In these circumstances, not using the committed policy (when it is optimal) could also lead to a significant reduction in the client's profit.

At a broader level, our paper joins an emergent chorus of research that questions whether the pursuit of flexibility is always justifiable, especially in innovative contexts. For example, Adner and Levinthal (2004) argue that flexibility based on a real-options

logic can result in underperformance if abandonment criteria are unclear. The value attributed to flexibility may just as easily be gained by disciplined reallocation of resources (Klingebiel and Adner 2015). Our analysis reveals a previously unexplored threat to the value of flexibility: the unintended effects of flexibility on the enthusiasm of providers. As such, we caution managers of innovation projects to be judicious about seeking flexibility while delegating innovation.

Future research can extend our exploration of delegated innovation in several interesting directions. First, in some of the business-to-business contexts we study, clients such as device manufacturers face competition. Second, providers themselves may subcontract some work, studying which offers significant opportunities for supply chain researchers. Third, clients may also be able to influence providers by coupling optimized acceptance criteria with more sophisticated and dynamic incentive schemes. Finally, additional empirical tests and experiments would be necessary to understand how norms have emerged across different industries and cultures when it comes to delegating innovation.

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Endnotes

¹ This feasibility threshold is exogenous and can depend on factors such as market conditions, incumbent solutions, and implementation capability. The main insights from this paper continue to hold when the model is extended to accommodate a nonzero feasibility threshold (i.e., a solution is feasible when $v_t > A$). See details in Section A.2 of Online Appendix A.

² Figures A-6 and A-7 in Section B.2 of Online Appendix B show that providers regularly vary their effort in practice, making this not only a valid assumption but a necessary relaxation of previous models in the literature (e.g., Terwiesch and Loch 2004).

³ The main insights from this paper continue to hold when the model is extended to situations where in addition to the payment p , the client also pays the provider a wage per round (w). See details in Section A.2 of Online Appendix A.

⁴ For ease of exposition, we assume that the provider's capability is apparent to the client and that it cannot be modified in the short run (Argote and Hora 2016). However, our central findings hold even in a setting where the provider's capability improves from one round of

the project to the next. See details in Section A.2 of Online Appendix A.

⁵See Wu et al. (2014), Zhang (2016), and Crama et al. (2018) for a similar assumption of projects with two rounds. Although $T = 2$ suffices to draw our main results, the key insights hold for any $T < \infty$.

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