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Team Composition and Incentive Design in Collaborative Product Development

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Abstract

Choosing the right development team is crucial for companies. We investigate how project collaboration requirements and uncertainty levels affect the choice between "specialists" with higher levels of task-specific abilities and "generalists" with higher levels of collaboration skills. We also examine how these factors affect optimal team incentives. In addition to performance-enhancing helping, we consider another type of collaboration that has received less attention in the incentive literature: information-sharing, which can reduce uncertainty and lead to more compatible design decisions. In the case of helping, we show that if uncertainty is high then specialists might be preferred in order to reduce risk exposure—even if their task-specific abilities are only slightly better. Conversely, if information-sharing can significantly reduce uncertainty then generalists may be favored even if their task-specific abilities are much lower. Our study also reveals that task and collaboration incentives can be either complements or substitutes depending on the type of collaboration and level of project uncertainty: in projects that benefit from helping, firms will always substitute task incentives for collaboration incentives when selecting a team of specialists (rather than a team of generalists), yet this need not be the case with information-sharing. In such projects, it can be optimal to offer higher task incentives and also higher collaboration incentives to a team of specialists (than to a team of generalists) even though specialists' collaboration skills are relatively lower.

Keywords

Team Composition, Product Development, Specialists/Generalists, Collaboration Incentives

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Imagine that you are responsible for setting up a product development team in your company. Whom should you include on your team? Should you choose specialists with a high level of expertise and skills for a specific set of tasks, or generalists who may have less expertise for such tasks but whose general knowledge facilitates their collaboration on problems outside their main skill set? As Epstein (2019) puts it, should you prefer a "Tiger Woods-style" person who has devoted his entire life to mastering a particular skill set or instead a "Roger Federer-type" who tried out several alternatives before focusing on a specific domain?

The literature suggests that the verdict is still out. Epstein (2019) argues that generalists are more adaptable to uncertain information; along the same lines, Bajic (2013) makes the case for hiring generalists who are more flexible in early-stage start-ups. Other research (e.g., Teodoridis et al., 2018, 2019) advocates specialists for any fast-changing environment because they can more easily keep up with quickly changing technical developments. We explore the dilemma of choosing between specialists and generalists by considering the *type of collaboration* that is needed for a particular development project.

We consider two types of projects, as described next.

1. Projects requiring collaboration in the form of "helping"—that is, projects in which team members have similar skill sets and are asked to help each other by carrying out parts of the task assigned to the other team members.
2. Projects requiring collaboration in the form of "information-sharing"—that is, complex projects in

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which team members are asked to share information about their design choices with other team members working on different but interdependent components; such information sharing reduces the uncertainty and leads to more compatible design decisions.

These two types of collaboration are not mutually exclusive, but they do often transpire in different settings and/or among different team members. Helping usually takes place between members who carry out related tasks and have similar skill sets but who might, nevertheless, have different skill levels pertaining to a specific assigned task. Consider, for example, two team members working on an IT project and helping each other to debug code or to write new code. If one of them has written a similar code for another project in the past, she would probably be more efficient (i.e., has greater ability to carry out this particular programming task) than another team member who has worked on very different tasks before and hence cannot draw on the same relevant prior experience. In contrast, information-sharing typically occurs in cross-unit teams—that is, among team members from different departments who carry out very different tasks but whose decisions influence which choices are the most effective for the other team members (e.g., Mihm et al., 2003; Peng et al., 2014; Terwiesch et al., 2002).

We study the impact of these collaboration types on project performance in terms of the quality of the obtained solution;[1] at the same time, we consider the optimal team composition (viz., hiring specialists vs. generalists). In theory, collaboration efforts can have two fundamental effects on the quality of the project: they can improve the *expected* quality of the project, or they can *reduce the uncertainty* about the obtained quality of the project. Following the literature, we model the impact of helping efforts as an improvement in expected performance (Auriol et al., 2002; Siemsen et al., 2007). Here one team member's collaboration efforts substitute for another member's task efforts and directly improve the expected outcome quality.[2] Information-sharing ensures the compatibility of team members' design decisions, thereby reducing the uncertainty about project outcome quality and also heightening the expected quality levels because information sharing minimizes performance gaps due to design incompatibilities (see Section 3).

Hansen (2009) points out that, whereas "internal collaboration is almost universally viewed as good for an organization" (p. 83), collaboration remains difficult and employees "resent taking on extra work if they don't get additional recognition or financial incentives" (p. 87). The need for such incentives has been widely recognized in the literature, and there is a growing body of research in management that uses principal–agent theory to study how firms should incentivize collaboration within teams (e.g., Caldieraro and Coughlan, 2009; Chan et al., 2014; Crama et al., 2019; Kretschmer and Puranam, 2008). We build on this literature and assume that, for any chosen form of team composition, the firm will set optimal incentives. Our paper's contribution to this research is to describe how the choice of team composition (generalists vs. specialists) affects the optimal incentive design for projects requiring different types of collaboration.

Our analysis reveals that the required type of collaboration strongly affects not only the optimal choice of team members but also the optimal incentives. Moreover, we show that project uncertainty and team characteristics can affect these decisions differently depending on the type of collaboration involved.

The rest of this article proceeds as follows. After reviewing the related literature in Section 1, we describe our basic model setup in Section 2. Next, Section 3 provides details about the two types of collaboration and the optimal incentive design. In Section 4, we derive analytical insights concerning (a) the optimal team composition for the different types of collaboration and (b) the effect of team composition on the optimal incentive plan. Section 5 employs numerical analysis to investigate further how team and project characteristics affect the optimal team composition and the optimal incentive plan. We conclude in Section 6, with a summary of our findings and suggestions for further research.

1 Related Literature

Our article is motivated by the literature on team composition choices, which studies their impact on team interactions and performance outcomes. This study contributes also to the incentive design literature, which examines how incentive mechanisms affect team efforts.

Team Composition Decision

A key consideration when choosing team members involves the task-specific skills or expertise of the chosen team members. Studies have repeatedly shown that team members' task-specific abilities improve team performance (Bell, 2007; Faraj and Sproull, 2000; Stewart, 2006; Tessarolo, 2007; for a review of this literature, see Mathieu et al., 2014) and that specialists with more in-depth knowledge are more successful and productive (Conti et al., 2014; Leahey et al., 2017).

However, the individual team members' task abilities are not the only source of improved team performance. A second critical characteristic identified in the literature is the team members' collaboration skills. There is ample evidence that higher collaboration skills improve team effectiveness (e.g., Bell, 2007; Hirschfeld et al., 2006; Stewart, 2006; again see Mathieu et al., 2014, for a review) and that collaboration and communication improve team performance (Cooper and Kleinschmidt, 1994; Faraj and Sproull, 2000; Gardner et al., 2012; Hoegl et al., 2004; Peng et al., 2014).

Task-specific abilities and collaboration skills have been shown to improve outcomes, but *both* characteristics are seldom found in a given team member. Bajaj et al. (2004) emphasized that, when designing complex products, highly specialized individuals tend to focus on subsystems and not on the system as a whole. Studies have similarly shown that team members with non-overlapping knowledge find it difficult to share information and engage in discussions (Postrel, 2002; Rulke and Galaskiewicz, 2000; Stasser and Stewart, 1992; Stasser and Titus, 1987).

Hence the question arises: Under what circumstances are task-specific abilities or collaboration skills more important? Or, in other words, when should you choose team members with high domain-specific knowledge and expertise, thereby forgoing collaboration skills, and when should you build a team of generalists with better collaboration skills, thus forgoing more specialized expertise? The literature suggests that frequent communication and close collaboration are especially important (a) when tasks are highly interdependent (Espinosa et al., 2007; Mihm et al., 2003; Van de Ven et al., 1976) or executed almost concurrently (Loch and Terwiesch, 1998) and (b) when tasks are outsourced (Parker and Anderson Jr, 2002) or performed by globally distributed teams (Anderson Jr and Parker, 2013). Huckman and Staats (2011) reported that generalists with a diverse and overlapping knowledge-base perform better in fast-changing environments than do specialists with a narrower and less overlapping knowledge base; other studies suggest the opposite, namely that task-specific abilities are more valuable in such environments (Teodoridis et al., 2019) and for adopting complex technological breakthroughs throughout a firm's life cycle (Tzabbar and Margolis, 2017). In a laboratory experiment requiring a model assembly (K'NEX), Reagans et al. (2016) showed the need for task-specific *and* collaboration skills, and find that—in their context's trade-off—collaboration skills are more important. Another stream of literature confirms the positive effect of combining different specialized knowledge domains on creativity—although only to the extent that this diversity does not severely diminish team members' communication and collaboration (Hoisl et al., 2017; Somech and Drach-Zahavy, 2013; Taylor and Greve, 2006).

In summary, despite there being strong evidence for the value of specialized expertise and collaboration skills, few scholars have addressed the choice of team members should a trade-off be required between these team member characteristics. Our paper further explores this trade-off and contributes to the discussion by examining the influence of two project characteristics: its uncertainty and the type of collaboration it requires. While considering these parameters, we identify the circumstances under which either collaboration skills or specialized expertise dominates.

Incentive Design

In light of the recognized benefits of collaboration, there is a growing body of research that uses principal–agent theory to study how firms should incentivize such collaboration within teams. Drago and Turnbull (1988) presented one of the first studies that explicitly addresses incentives for collaboration and how rewards based on individual or group performance affect an individual's cooperation behavior. More recent papers discuss, for example, the use of group incentives to avoid sabotage or shirking when there are repeated interactions between teams (Che and Yoo, 2001), to ensure better resource allocation across projects (Schlapp et al., 2015), and to encourage timely execution of projects (Crama et al., 2019).

One part of our work builds closely on the "helping" model introduced by Itoh (1992); he shows that incentives for collaboration in the form of helping are generally beneficial when the costs are additively separable, which is the setting that we consider here. Auriol et al. (2002) and Siemsen et al. (2007) both build on Itoh's basic helping setup. Auriol et al. showed how the firm's commitment to a salary path can ensure the focal agent's helping behavior in a multi-period setting. Siemsen et al. (2007) compared the optimal incentives in the helping setting to those in different settings, such as the case of performance correlations applicable to sales representatives or assembly line workers—settings that we do not consider because our context is characterized by collaborations between development team members who work on the same project.

When we consider the basic helping model as one form of collaboration between team members, the focus of our analysis differs from the literature cited previously in that we explore how team composition choices affect the incentives offered. Moreover, we compare the helping type of collaboration to another form of collaboration frequently observed in development settings: information-sharing intended to ensure compatible design decisions (Mihm et al., 2003; Terwiesch et al., 2002).

The idea of studying incentive contracts for information-sharing is not a new one. Many papers, especially in the supply chain setting, study contracts that allow for the sharing of asymmetric information between a principal and an agent (e.g., Corbett, 2001; Corbett and Tang, 1998; Shen et al., 2019). Schlapp et al. (2015) do so in a *multi-agent* product development context; they study the effect of incentives on the acquisition and sharing of information about alternative projects with a principal in order to enable better project selection decisions. Unlike these papers, however, we are interested in horizontal information sharing between agents that can reduce their payoff uncertainty and ensure compatible design decisions. Gershkov et al. (2016) and Rothenberg (2015) also considered horizontal information sharing between agents. In this previous research, agents choose whether to (costlessly) share private information about the productivity of their task-related efforts and so the focus is on incentives for the truthful revelation of asymmetric information. In contrast, our attention is directed toward providing incentives that can motivate risk-averse agents to exert costly efforts to share information; such sharing will help ensure that design decisions are more compatible and performance outcomes less uncertain. We show how the team composition decision influences the optimal incentives a firm should provide in this information-sharing setting as compared with the helping setting.

2 The Setup

Consider a development project for which the firm needs to engage two experts. Focusing on just two experts allows us to explore the basic trade-offs while maintaining expositional simplicity and, to a large extent, analytical tractability. In addition to working on their own tasks, the firm wants these experts to collaborate. We consider two possible types of projects: those in which firms want experts to help each other with their respective tasks (the helping setting), and complex projects in which firms want experts to share information with each other so that they make better-informed decisions when working on their own development tasks (the information-sharing setting). Thus the required type of collaboration is one of the project characteristics known to the firm.

Both employees i ($i \in \{1,2\}$) will exert effort to develop a solution, which contributes value P_i^x ($x \in \{I,H\}$) to overall project performance P^x; superscripts I and H correspond (respectively) to the information-sharing and helping types of collaboration. We assume that the overall project performance is simply the sum of the individual performance contributions: $P^x = P_1^x + P_2^x$—an additive form that is commonly assumed in the principal–agent literature (Auriol et al., 2002; Gibbons, 1998). This assumption is also consistent with the one that underlies conjoint analysis: overall product value is estimated as the sum of the individual value contributions of the different product features or attributes; this approach approximates the value of many new products reasonably well.[3]

Each employee i can exert two types of efforts: effort directed toward his own tasks, denoted e_i; and effort directed toward collaboration with the other employee, denoted e_{ij} for $j = 3 - i$. To simplify the analysis, we normalize the minimum required effort levels to zero. The agents' minimum effort level will ensure the delivery of some solution to the principal. This solution creates overall value $P_i^x(e_i^x = 0, e_{ji}^x = 0) = v_i + \epsilon_i^x$ ($i \in \{1,2\}, j = 3 - i, x \in \{I,H\}$) for the firm, where v_i is a constant and represents the expected value of the solution obtained, if agent i exerts only the minimum effort. $\epsilon_i^x \sim \mathcal{N}(\mu_i, \sigma_i^2)$ captures the uncertainty of the value of this minimum effort solution, as explained in more detail in Section 3. When exerting additional task-related efforts e_i or collaboration efforts e_{ij}, employees can improve their performance contributions P_i^x at a cost C_i^T. We make the fairly standard assumption of convex but additively separable costs in order to capture the decreasing returns of efforts and to ensure that collaboration is indeed desirable from the firm's perspective: $C_i^T = C_i(e_i^2 + e_{ij}^2)/2$.

The effect of employees' efforts on P_i^x depends on their respective characteristics and on the type of collaboration required for this project. We will discuss the detailed assumptions and derive performance functions for both types of collaboration in Section 3. With regard to employee characteristics, we capture the effectiveness of a task-related effort e_i directed toward employee i's own task performance P_i^x with the parameter a_i, or employee i's *task ability*; we capture the effectiveness of the effort e_{ij} exerted by employee i when collaborating with employee j with the parameter k_j, or employee j's *collaboration skills*.

The literature on team composition leads us to identify two aspects that are frequently mentioned as differentiating highly specialized team members from the so-called generalists. In particular: highly specialized team members typically have (i) a greater depth of knowledge, which improves their effectiveness when working on their specialized task, yet (ii) a lesser effectiveness or willingness to collaborate with other team members or to understand and use their inputs. Thus, by "specialists" we refer to team members with relatively greater task abilities a_i and lesser collaboration skills k_i and by "generalists" we mean team members with greater collaboration skills k_i but lesser task abilities a_i.[4]

Because much of the work in a development project involves knowledge-intensive tasks with uncertain performance outcomes, employees' efforts (beyond the minimum level required to deliver a solution) are non-observable. Therefore, ensuring that employees exert more effort (than this minimum level) requires the firm to offer performance-based incentives to motivate the two individuals—both to improve their own performance and to collaborate with each other.[5] As in most of the literature, our setup presumes that individual performance contributions are observable.[6] More specifically, we assume that the firm offers employee i a linear wage contract W_i that depends in part on employee i's individual performance contribution P_i^x and in part on employee j's performance contribution P_j^x. This wage contract is defined as $W_i = w_i + \alpha_i(P_i^x - v_i) + \beta_i(P_j^x - v_j)$;[7] here w_i denotes the fixed-wage component, and α_i and β_i are (respectively) the task incentive and collaboration incentive for performance improvements. More complex contracts could theoretically be optimal; however, linear incentive contracts are not only easier to implement but also more robust (Holmström and Milgrom, 1987).

Each employee chooses how much effort to exert in a way that maximizes his utility derived from the wage contract. We are interested in how uncertainty affects the optimal incentives and optimal team composition, so we must take into consideration that most employees are risk averse. Employee i's utility is modeled by a negative exponential utility function with an Arrow–Pratt measure of risk aversion r_i; thus, $U_i = -\exp(-r_i(W_i - C_i^x)), x \in \{I,H\}$ (Gibbons, 2005). Substituting into the wage contract W_i specified previously, we can formulate employee i's utility maximization problem—or, equivalently, the maximization of the certainty equivalent

CE_i^x—as follows:

$$\max_{e_i,e_{ij}} \mathrm{CE}_i^x = \max_{e_i,e_{ij}} \Big\{ w_i + \alpha_i \mathbb{E}[P_i^x - v_i] + \beta_i \mathbb{E}[P_j^x - v_j] - C_i^T - \frac{1}{2} r_i V[W_i] \Big\}, \quad (1)$$

for $i \in \{1,2\}$, $j = 3 - i$, and $x \in \{I, H\}$; in this expression, $V[W_i]$ is the variance in wages for individual i.

Finally, we assume that the firm is risk neutral and maximizes its expected value, $\Pi = \mathbb{E}[P^x - W_1 - W_2]$, by choosing the wage contracts W_i and W_j—which is to say, by setting the incentive parameters α_i, α_j, β_i, and β_j as well as the fixed-wage components w_i and w_j. While doing this, the firm must ensure that the employees will accept the contract; hence the certainty equivalents CE_i^x, $i \in \{1,2\}$, must be no less than the employees' outside options M_i: $\mathrm{CE}_i^x \geq M_i$ (individual rationality constraint, IR). We assume that M_i is large enough that the probability of the realized wages being negative is negligible. In other words, the fixed-wage component exceeds the incentive component by enough to preclude negative wages. Of course, the employees' outside options $M_1 + M_2$ must be considerably lower than the expected value of the overall project $\mathbb{E}[P^x]$ to the firm, for otherwise this development opportunity would not be worth pursuing. This implies that the expected value $(v_i + v_j)$ for the agents' minimum efforts needs to be sufficiently large. Furthermore, the firm supposes that each employee i chooses his task-related efforts e_i^x and collaboration efforts e_{ij}^x so as to maximize the certainty equivalent CE_i^x (incentive compatibility constraint, IC). Hence, for $x \in \{I, H\}$, the firm's profit maximization problem is

$$\begin{aligned} &\max_{\alpha_1,\alpha_2,\beta_1,\beta_2,w_1,w_2} \Pi \\ &= \max_{\alpha_1,\alpha_2,\beta_1,\beta_2,w_1,w_2} \mathbb{E}[P^x - W_1 - W_2] \\ &= \max_{\alpha_1,\alpha_2,\beta_1,\beta_2,w_1,w_2} \big(v_1 + v_2 + (1 - \alpha_1 - \beta_2)\mathbb{E}[P_1^x - v_1] \\ &\quad + (1 - \alpha_2 - \beta_1)\mathbb{E}[P_2^x - v_2] - w_1 - w_2 \big) \end{aligned} \quad (2)$$

subject to

$$\mathrm{CE}_i^x \geq M_i \text{ for } i \in \{1,2\}, \quad \text{(IR)}$$
$$e_i^x, e_{ij}^x = \arg\max \mathrm{CE}_i^x \text{ for } i \in \{1,2\} \text{ and } j = 3 - i. \quad \text{(IC)}$$

In the next section, we derive the optimal effort levels and incentives for the two different types of collaboration before turning to the optimal team composition decision.

3 Optimal Incentive Contracts

3.1 Collaboration in the Form of Information-Sharing

As discussed in the Introduction, information-sharing is a common type of collaboration in large, *complex* development projects where experts work on different parts of the project. In such projects, individuals must frequently share information about their design decisions to ensure the integrity and compatibility of various parts and to converge quickly on a satisfactory overall performance (e.g., Mihm et al., 2003; Peng et al., 2014; Terwiesch et al., 2002). This form of collaboration reduces uncertainty and eliminates incorrect perceptions regarding the design choices of other employees.

Information sharing has been studied extensively in the literature on concurrent engineering, which provides guidelines for the optimal extent of concurrency (Krishnan et al., 1997; Loch and Terwiesch, 1998; Roemer and Ahmadi, 2004), for the type of information to exchange (Terwiesch et al., 2002), and for the frequency of the information exchange and of joint decision making more generally (Loch and Terwiesch, 2005; Mihm et al., 2003; Mitchell and Nault, 2007; Özkan-Seely et al., 2015; Rahmani et al., 2017; Sting et al., 2021). Yet to the best of our knowledge, the incentive literature has paid scant attention to horizontal information sharing among team members for the purpose of ensuring compatible decisions. So that we can focus on the incentive aspects, we abstract from details about the information exchange and model only the overall effect of information exchange on employees' performance contributions.

We begin by defining specifications for the information-sharing type of collaboration. Then we solve the problem backwards, first determining the employees' optimal effort choices and then the optimal incentive parameters for the contract set by the firm.

Performance Contribution P_i^I in the Information-Sharing Setting

In the information-sharing setting, collaboration reduces the uncertainty each employee faces regarding the *other* employee's design choices, resulting in designs that are more compatible. We capture the impact of information exchange on the total performance contribution of employee i with a linear decreasing error term, ϵ_{ij}: $P_i^I = v_i + a_i e_i + \max(1 - k_i e_{ji}, 0)\epsilon_{ij} + \epsilon_{i,\text{ext}}$ with $\epsilon_{ij} \sim \mathcal{N}(\mu_i, \tau_i \sigma_i^2)$; here $\mu_i < 0$ reflects the expected performance gap (due to lack of information) that results in lower design compatibilities, and $\tau_i \in (0,1]$ stands for the proportion of the uncertainty σ_i^2 in the performance estimation that can be reduced by information sharing. For information-sharing to be relevant, we assume τ_i to be significantly larger than zero.[8] In the absence of information sharing ($e_{ji} = 0$), employees must base their design decisions solely on their initial perceptions regarding other design choices—for example, on initial specifications or similar past designs. The random performance effect ϵ_{ij} stemming from these design interactions can be reduced by sharing relevant information ($e_{ji} > 0$). However, a proportion $1 - \tau_i$ of the overall uncertainty σ_i^2 is likely the result of external factors (e.g., market uncertainty) that cannot be resolved until later: during or after development of the project. We use $\epsilon_{i,\text{ext}}$ to denote the performance impact due to external factors and assume that it is normally distributed with a mean of zero: $\epsilon_{i,\text{ext}} \sim \mathcal{N}(0, (1-\tau_i)\sigma_i^2)$. In the absence of information sharing ($e_{ji} = 0$), this results in an overall performance impact due to both internal and external factors of $\epsilon_i \sim \mathcal{N}(\mu_i, \sigma_i^2)$, which corresponds to the uncertainty in the value of the minimum effort solution, as specified in the basic setup in Section 2.

We can now specify the certainty equivalent in equation (1) for the information-sharing setting:

$$\begin{aligned}\mathrm{CE}_i^I = {} & w_i + \alpha_i\big(a_i e_i + \max(1-k_i e_{ji}, 0)\mu_i\big) \\ & + \beta_i\big(a_j e_j + \max(1-k_j e_{ij}, 0)\mu_j\big) - \frac{C_i}{2}(e_i^2 + e_{ij}^2) \\ & - \frac{1}{2} r_i \Big(\alpha_i^2 \sigma_i^2 \big((\max(1-k_i e_{ji}, 0))^2 \tau_i + (1-\tau_i)\big) \\ & + \beta_i^2 \sigma_j^2 \big((\max(1-k_j e_{ij}, 0))^2 \tau_j + (1-\tau_j)\big)\Big). \qquad (3)\end{aligned}$$

This expression for CE_i^I clearly shows the two ways in which e_{ji} affects performance: it reduces the average performance gap resulting from the initial specification's incorrect assumptions to $\max(1 - k_i e_{ji}, 0)\mu_i$; and it reduces the uncertainty stemming from design interactions to $\big(\max(1-k_i e_{ji}, 0)\big)^2 \tau_i \sigma_i^2$. Thus information sharing reduces a project's risk by reducing the variance and by shifting upward the distribution of the performance.

Optimal Effort Choice in the Information-Sharing Setting

Solving the principal–agent problem backwards, we begin with employees' effort choices under an incentive wage contract offered by the firm. Each employee chooses an effort level that maximizes his respective utility—or the certainty equivalent thereof, as given in equation (3). The utility-maximizing optimal efforts of employee i in the information-sharing setting are denoted e_i^I and e_{ij}^I for $i \in \{1, 2\}$ and $j = 3 - i$:

$$e_i^I = \frac{\alpha_i a_i}{C_i}, \quad e_{ij}^I = \min\left(\frac{k_j \beta_i (\beta_i r_i \tau_j \sigma_j^2 - \mu_j)}{C_i + k_j^2 \beta_i^2 r_i \tau_j \sigma_j^2}, \frac{1}{k_j}\right). \qquad (4)$$

(See Proof 1). All derivations and proofs are given in the online Supplemental Appendix EC-1.

Here we can make an interesting observation if $e_{ij}^I < 1/k_j$, that is, if the collaboration efforts have an interior solution: for projects with higher reducible uncertainty $\tau_j \sigma_j^2$ or a larger expected performance gap μ_j, employee i would choose to make greater collaboration effort (see Proof 1) in order to reduce the effect of this uncertainty or of design incompatibilities on their performance—even if the collaboration incentive β_i remained unchanged. It is clear that, with higher k_j, employee i's collaboration efforts e_{ij} become more effective; also, beyond a certain amount of information-sharing effort $e_{ij}^I = 1/k_j$, additional effort does not reduce the risk any further.

Optimal Incentives in the Information-Sharing Setting

Recall that choosing the optimal incentive contract requires the principal to maximize equation (2). If we now replace e_i and e_{ij} with the employees' optimal effort choices for information-sharing e_i^I and e_{ij}^I (to ensure that equation's (2) IC constraint is met). If we set w_i so as to ensure that equation's (2) IR constraint is satisfied, then the firm's profit-maximization problem in the information-sharing setting can be restated as follows:

$$\begin{aligned}\max_{\alpha_1,\alpha_2,\beta_1,\beta_2} \Pi^I = \max_{\alpha_1,\alpha_2,\beta_1,\beta_2} \sum_{\substack{i=\{1,2\}\\ j=3-i}} \Big(& v_i + (a_i e_i^I + \max(1-k_i e_{ji}^I, 0)\mu_i) \\ & - \frac{1}{2} r_i \alpha_i^2 \sigma_i^2 ((\max(1-k_i e_{ji}^I, 0))^2 \tau_i + (1-\tau_i)) \\ & - \frac{1}{2} r_i \beta_i^2 \sigma_j^2 ((\max(1-k_j e_{ij}^I, 0))^2 \tau_j + (1-\tau_j)) \\ & - \frac{C_i}{2}({e_i^I}^2 + {e_{ij}^I}^2) - M_i \Big). \qquad (5)\end{aligned}$$

Solving equation (5) for α_i and β_j, we derive the optimal incentive contract described in our first proposition.

PROPOSITION 1. *Let $A_j = \beta_j^2 k_i^2 r_j \tau_i \sigma_i^2$, $B_j = C_j + \beta_j k_i^2 \mu_i$, and $D_j = \beta_j r_j \tau_i \sigma_i^2$.*

(i) There are unique nonnegative values of α_i^I and β_j^I that satisfy the following equations:

$$\alpha_i = \frac{a_i^2}{a_i^2 + \sigma_i^2 r_i \left(1 - \tau_i + \left(\frac{B_j}{A_j + C_j}\right)^2 \tau_i\right) C_i}; \qquad (6)$$

$$\begin{aligned} 0 = {} & r_j \beta_j \sigma_i^2 \left(1 - \tau_i + \frac{B_j^2 \tau_i}{(A_j + C_j)^2}\right) \\ & + \frac{k_i^2}{A_j + C_j}\left(\frac{(D_j - \mu_i)(A_j - C_j)}{A_j + C_j} + D_j\right) \\ & \times \left(\frac{C_j \beta_j (D_j - \mu_i)}{A_j + C_j} + \mu_i - \frac{\sigma_i^2 B_j \tau_i (\alpha_i^2 r_i + \beta_j^2 r_j)}{A_j + C_j}\right). \qquad (7)\end{aligned}$$

(ii) If $\max(1 - k_i e_{ji}^I, 0) = 0$ for the α_i^I and β_j^I found in part (i) then the optimal incentive parameters are instead as follows:

$$\alpha_i^I = \frac{a_i^2}{a_i^2 + \sigma_i^2 r_i (1-\tau_i) C_i}, \quad \beta_j^I = -\frac{C_j}{\mu_i k_i^2}. \qquad (8)$$

Although we do not derive closed-form solutions, we can make several relevant observations. First, both α_i^I and β_j^I are always strictly positive; this means that the firm will always offer task incentives to team members to motivate their task-related efforts and will offer collaboration incentives to motivate their collaboration efforts. Focusing first on the interior solutions—part (i) of the proposition—an interesting point is that employee i's collaboration skill k_i affects not only the collaboration incentive but also the task incentive the firm should offer to employee j. The reason is as follows. The employee's collaboration skill influences the effectiveness of the collaboration efforts, which in turn reduces some of the reducible uncertainty $\tau_i\sigma_i^2$ faced by the risk-averse agent. This reduction of uncertainty allows the firm to offer greater task incentives to risk-averse agents (i.e., to increase α_i), as shown formally in Proof 4. In a similar manner, greater individual task abilities a_i not only make higher task incentives attractive to the firm (Proof 5) but also result in higher collaboration incentives (Proof 6). The reason is that higher task incentives increase the employees' risk exposure, and the firm should balance this dynamic by increasing the incentives for uncertainty-reducing collaboration.

The impact of collaboration skills on collaboration incentives is more subtle and depends critically on the extent to which uncertainty $\tau_i\sigma_i^2$ can be reduced via information sharing (see Proof 7). For lower levels of reducible uncertainty $\tau_i\sigma_i^2$, the firm should increase the incentives for collaboration as those increased skills make the collaboration more effective. However, if the reducible uncertainty $\tau_i\sigma_i^2$ is sufficiently high then the firm need not offer high collaboration incentives to increase collaboration in response to higher collaboration skills. Since the collaboration efforts e_{ji}^I can now reduce a large part of the negative effect of uncertainty on performance, employee i's higher collaboration skills are sufficient to motivate employee j to collaborate more. In other words: the greater the collaboration skills, the more effective the collaboration effort will be at high levels of reducible uncertainty, and the lower the need for collaboration incentives to achieve a high level of collaboration. The effect of a performance gap μ_i on the collaboration incentive is similarly contingent on the level of reducible uncertainty $\tau_i\sigma_i^2$ (see Proof 8). In situations where the reducible uncertainty $\tau_i\sigma_i^2$ is relatively low, β_j is small to begin with; hence, if the performance gap increases then the firm will raise the collaboration incentives (β_j) and thereby increase employee motivation to reduce this larger performance gap. Yet in cases characterized by high reducible uncertainty, the optimal β_j is already high. Because a larger performance gap (μ_i) itself now provides additional collaboration benefits (i.e., incentives for employees to collaborate), the firm can reduce the collaboration incentives and thus lower the risk exposure of risk-averse employees.

The effect of overall uncertainty (σ_i^2) on the collaboration incentives is also nonlinear. First, as the overall σ_i^2 increases, the optimal collaboration incentives decrease for risk-averse agents—as expected. (this is also the case for task incentives). With an increase in σ_i^2, however, the reducible uncertainty $\tau_i\sigma_i^2$ increases as well and so, beyond the threshold $\underline{\tau_i\sigma_i^2}$, incentive β_j^I increases with uncertainty σ_i^2. In these circumstances, it is worthwhile for the firm to offer a higher collaboration incentive because doing so will further motivate individuals to collaborate and will lessen the reducible part of this high uncertainty $\tau_i\sigma_i^2$; the result will be the improved effectiveness of task incentives (Proof 9).

Finally, we briefly consider the border condition—that is, part (ii) of Proposition 1. When the condition holds, employee i's collaboration skills are so high that a relatively small collaboration effort of employee j can completely eliminate the reducible uncertainty and any potential performance gap. Hence the firm will choose the minimum collaboration incentive required to induce this level of collaboration, in which case the optimal collaboration incentive no longer depends on the reducible task uncertainty $\tau_i\sigma_i^2$ or on the performance gap. It is important to note that, for the rest of the discussions in the article, we focus on the case where incentives are interior solutions (in other words, it is too difficult and hence costly to resolve *all* the uncertainty, and $\max(1 - k_i e_{ji}^I, 0) > 0$).

In what follows, we contrast these observations with results from the helping type of collaboration.

3.2 Collaboration in the Form of Helping

The second form of collaboration that we study is helping. By helping employee i with his tasks, employee j's collaboration efforts act as a substitute for i's task-related effort and thus directly improve employee i's performance. This form of collaboration has been extensively studied in the incentive literature. Even though our model closely resembles the basic models in some of the earlier papers (e.g., Auriol et al., 2002; Itoh, 1992), we provide the full derivations of the optimal effort levels and the optimal incentive parameters on this page and the following page for completeness and ease of comparison.

Performance Contribution P_i^H in the Helping Setting

Much as in the research previously cited, we assume that the effects of both task-related and collaboration efforts on performance are linear: $P_i^H = v_i + a_i e_i + k_i e_{ji} + \epsilon_i$, with $\epsilon_i \sim \mathcal{N}(\mu_i, \sigma_i^2)$.[9] We can now restate employee i's certainty equivalent in the helping setting, CE_i^H, for $i \in \{1,2\}$ and $j = 3 - i$:

$$\mathrm{CE}_i^H = w_i + \alpha_i(a_i e_i + k_i e_{ji} + \mu_i) + \beta_i(a_j e_j + k_j e_{ij} + \mu_j) - \frac{1}{2}C_i(e_i^2 + e_{ij}^2) - \frac{1}{2}r_i(\alpha_i^2\sigma_i^2 + \beta_i^2\sigma_j^2). \tag{9}$$

Optimal Effort Choice in the Helping Setting

We begin once again with the employee's effort choice under the incentive wage contract offered by the firm. Maximizing employee i's certainty equivalent in equation (9) allows us to derive individual i's optimal effort levels in the helping setting, which we denote as e_i^H and e_{ij}^H:

$$e_i^H = \frac{\alpha_i a_i}{C_i}, \qquad e_{ij}^H = \frac{\beta_i k_j}{C_i} \quad \text{for } i \in \{1,2\}, j = 3-i. \quad (10)$$

It is clear that positive incentives will always encourage employees to exert both types of effort in the helping setting. And unlike in the information-sharing setting, neither uncertainty (σ_i^2) nor the size of the average performance gap (μ_i) influence employees' efforts—provided the incentives remain unchanged and the IR constraint is met (i.e., as long as the employees participate).

Optimal Incentives in the Helping Setting

After setting $e_i = e_i^H$, $e_{ij} = e_{ij}^H$, and w_i, $i \in \{1,2\}$—to ensure that the IC and IR constraints in equation (2) are met—we can rewrite the firm's profit maximization problem in the helping setting as follows:

$$\begin{aligned}\max_{\alpha_1,\alpha_2,\beta_1,\beta_2} \Pi^H &= \max_{\alpha_1,\alpha_2,\beta_1,\beta_2} \sum_{\substack{i=\{1,2\}\\ j=3-i}} \Big(v_i + a_i e_i^H + k_i e_{ji}^H + \mu_i \\ &\quad - \frac{1}{2} C_i \Big(e_i^{H2} + e_{ij}^{H2} \Big) - \frac{1}{2} r_i \Big(\alpha_i^2 \sigma_i^2 + \beta_i^2 \sigma_j^2 \Big) - M_i \Big). \quad (11)\end{aligned}$$

Now solving equation (11) for the incentive parameters α_i and β_j yields, for the helping setting, the optimal incentive plan described in our next proposition.

PROPOSITION 2. *The optimal incentive plan in the helping setting is given by the following equation:*

$$\begin{aligned}\alpha_i^H &= \frac{a_i^2}{r_i \sigma_i^2 C_i + a_i^2}, \\ \beta_j^H &= \frac{k_i^2}{r_j \sigma_i^2 C_j + k_i^2}, \quad \text{for } i \in \{1,2\}, j = 3-i. \quad (12)\end{aligned}$$

In the helping setting, it is again always optimal to provide both task and collaboration incentives. More interestingly, the relative strength of these incentives depends mainly on the relative size of the parameters capturing the employees' task ability and collaboration skills, a_i and k_i. Of course, employee i's (task) ability to influence his own performance contribution P_i^H should normally be greater than the effectiveness of employee j's helping efforts e_{ji}: $a_i > k_i$ (Auriol et al., 2002). It follows that, for otherwise identical agents (same risk aversion and same cost function), the firm should provide more incentives for employee i's more effective task-related effort e_i than for employee j's helping effort e_{ji} (so that typically $\alpha_i^H > \beta_j^H$).

Comparing the incentives in the helping setting with those in the information-sharing setting reveals some notable differences. As expected, the average performance gap μ_i does not influence the optimal incentives in the helping setting. More importantly, collaboration skills do not affect task incentives in this setting and neither do individual task abilities affect collaboration incentives. Thus, in the helping setting, the firm offers collaboration incentives solely to lower its overall costs and not to improve task-related efforts.

Another interesting difference is the impact of uncertainty. Because employees are risk averse, firms must compensate employees for this risk exposure; hence higher uncertainty always results in lower task *and* collaboration incentives in the helping setting. Also, uncertainty plays no differentiating role in the effects of collaboration skills on collaboration incentives: in the helping setting, collaboration incentives always increase with k_i. This outcome contrasts with the information-sharing setting, where firms might be able to reduce the collaboration incentives for higher levels of k_i if the reducible part of the uncertainty ($\tau_i \sigma_i^2$) is very high. The reason is that in the information-sharing setting employees who are more efficient require less incentive to exert greater effort toward reducing the high level of uncertainty that they face.

The need (and capacity) to provide incentives drives the firm's labor costs and therefore affects the optimal team composition choice. We, therefore, summarize the differences in the effects of task ability, collaboration skills, and uncertainty between the helping versus the information-sharing setting in the following three lemmas.

LEMMA 1. *The firm should offer higher collaboration incentives to employees collaborating with team members who have higher task abilities a_i if and only if the collaboration is in the form of information-sharing: $\partial \beta_j^H / \partial a_i = 0$ and $\partial \beta_j^I / \partial a_i \geq 0$.*

LEMMA 2. *The firm should offer higher collaboration incentives to employees collaborating with members who have higher collaboration skills k_i—unless (a) the collaboration is in the form of information-sharing and (b) a considerable part of the uncertainty can be reduced through collaboration: $\partial \beta_j^H / \partial k_i \geq 0$ and $\partial \beta_j^I / \partial k_i < 0$ if $\tau_i \sigma_i^2 > \widehat{\tau_i \sigma_i^2}$, and $\partial \beta_j^I / \partial k_i \geq 0$ otherwise; here $\widehat{\tau_i \sigma_i^2}$ is a unique threshold.*

LEMMA 3. *If the project's uncertainty increases then the firm should offer lower collaboration incentives unless (a) the collaboration is in the form of information-sharing and (b) a considerable part of the project's uncertainty can be reduced through collaboration: $\partial \beta_j^H / \partial \sigma_i^2 < 0$ and $\partial \beta_j^I / \partial \sigma_i^2 \geq 0$ if $\tau_i \sigma_i^2 \geq \underline{\tau_i \sigma_i^2}$, and $\partial \beta_j^I / \partial \sigma_i^2 < 0$ otherwise; here $\underline{\tau_i \sigma_i^2}$ is a unique threshold.*

4 Team Composition Choice and Its Effects on Collaboration Incentives

4.1 Optimal Team Composition

We now turn to the firm's team composition decision. When should a firm prefer hiring a team of specialists, and when should it instead choose a team of generalists? We compare the performance obtained by firms that hire these respective types of teams and assume that, in each case, the firm adjusts the incentives optimally. We also assume that both types of employees (specialists and generalists) have the same outside options (i.e., they are equally valued in the labor market and hence have the same outside option M). Asymmetric outside options would simply have the obvious effect of favoring the less expensive employees over a larger range of task abilities and/or collaboration skills.

In this subsection, we consider homogeneous teams—that is, $k_i = k_j$ and $a_i = a_j$. Thus, the firm chooses between these two team compositions: (i) a homogeneous team of generalists who have higher collaboration skills than do specialists, $k_g > k_s$; and (ii) a homogeneous team of specialists who have higher task abilities than do generalists, $a_s > a_g$. Similarly, we consider that the two tasks carried out by employees i and j face the same random performance effect stemming from design interactions, that is, $\epsilon_{ij} \sim \mathcal{N}(\mu, \tau\sigma^2)$ and $\epsilon_{ji} \sim \mathcal{N}(\mu, \tau\sigma^2)$.

Proposition 3 summarizes the conditions under which a profit-maximizing firm should favor a team of specialists over a team of generalists.

PROPOSITION 3. *Recall that specialists have a lower level of collaboration skills than generalists ($k_s < k_g$) but a higher level of task ability ($a_s > a_g$), where $a_s = a_g + \Delta a$ and $\Delta a > 0$. The firm should hire a team of specialists if $\Delta a \geq \hat{\Delta}^x$, $x \in \{I, H\}$, where $\hat{\Delta}^x$ is a unique threshold below which a team of generalists would be preferred and where the following statements hold.*

- *$\hat{\Delta}^I$ increases with higher $\tau\sigma^2$ if $\tau\sigma^2 \geq \underline{\tau\sigma^2}$; there might exist a threshold $\tau\sigma^2 > \overline{\tau\sigma^2}$ beyond which generalists are always preferred.*
- *$\hat{\Delta}^H$ decreases with higher σ^2 if $\sigma^2 > \underline{\sigma^{2,H}}$ unless $k_s^4 \geq (a_g^2 - k_g^2)(k_g^2 + k_s^2)$.*

The effect of a larger Δa in the employee's task ability has an obvious effect in both the information-sharing setting and the helping setting—namely, that specialists are preferred only if this difference is sufficiently large (i.e., greater than a unique threshold $\hat{\Delta}^x$, $x \in \{I, H\}$). The impact of uncertainty is more interesting: the effects are opposite in the two collaboration settings. In the helping setting, beyond a certain threshold of σ^2, greater uncertainty σ^2 typically results in preferring specialists over generalists even at a lower level of Δa.[10] But in the information-sharing setting, higher uncertainty favors generalists even at higher levels of Δa (provided the reducible part of the uncertainty $\tau\sigma^2$ is large enough). For helping, this result is driven by high uncertainty preventing the firm from setting high incentives for risk-averse agents, which makes the more effective task-related efforts even more important; hence a smaller Δa suffices to favor specialists. For information-sharing also, high overall uncertainty increases the cost of incentives for task-related efforts. Yet in situations where a large part of the overall uncertainty can be reduced by collaborating ($\tau\sigma^2 \geq \underline{\tau\sigma^2}$), the firm is more likely to mitigate these costs by hiring generalists because they require relatively lower incentives to reduce the uncertainty (i.e., $\hat{\Delta}^I$ increases; see also Lemma 2 and the discussion in Section 3.1). Finally, there may be a threshold $\overline{\tau\sigma^2}$ beyond which $\hat{\Delta}^I$ might not exist. In that case, it could *always* be optimal to employ a team of generalists.

Finally, we would like to note that the boundary conditions in Proposition 3 for both helping and information-sharing are *sufficient* (but not necessary) conditions for the results to hold. In Section 5, we explore the cases where we lack clear analytical results —along with the impact of other parameters on team composition choices—using numerical methods. For now, we examine analytically how the choice of team composition affects optimal incentive design.

4.2 The Effect of Team Composition Choices on Optimal Incentive Design

So far, we have shown that the required type of collaboration has a strong effect on the optimal composition of teams. Now we focus on how the firm should optimally adjust the incentive depending on (a) the chosen team composition (generalists or specialists) and (b) the type of collaboration required by the project. If a firm chooses a team of specialists instead of a team of generalists, should it offer stronger incentives to encourage more collaboration or rather simply give up on collaboration? And how does the answer to that question depend on the type of collaboration required? A different team composition will affect individuals' task abilities as well as their collaboration skills, so we must consider the *joint* impact—of a change in task abilities and also collaboration skills—on the optimal incentives.

PROPOSITION 4. *Let $\beta_{j,s}^X, \alpha_{i,s}^X$, and $\beta_{j,g}^X, \alpha_{i,g}^X$ denote (respectively) the optimal collaboration and task incentives for specialists and generalists, where $X \in \{H, I\}$. The incentives a firm should offer to a team of specialists compare as follows to the optimal incentives for a team of generalists:*

- *If the collaboration is in the form of information-sharing specialists receive: higher collaboration incentives ($\beta_{j,s}^I \geq \beta_{j,g}^I$) if $\widetilde{\tau_i\sigma_i^2} \leq \tau_i\sigma_i^2 \leq \approx\!\!\!\!\widetilde{\tau_i\sigma_i^2}$ (otherwise, $\beta_{j,s}^I < \beta_{j,g}^I$) and higher task incentives ($\alpha_{i,s}^I \geq \alpha_{i,g}^I$) if $\Delta a \geq \check{\Delta}$ (otherwise, $\alpha_{i,s}^I < \alpha_{i,g}^I$).*
- *If the collaboration is in the form of helping specialists receive: lower collaboration incentives ($\beta_{j,s}^H \leq \beta_{j,g}^H$) and higher task incentives ($\alpha_{i,s}^H \geq \alpha_{i,g}^H$).*

Proposition 4 shows that, when adjusting the incentives to the chosen team composition, the firm should carefully consider the type of collaboration required by the project. The result for the case of collaboration in the form of helping follows directly from our discussion of Proposition 2: the optimal task incentives are affected only by (and are increasing in) the task ability a_i, whereas the optimal collaboration incentives are affected only by (and are increasing in) the collaboration skills k_j; see also Lemmas 1 and 2. A team of specialists should therefore receive higher task incentives and lower collaboration incentives than a team of generalists, which is to say that task and collaboration incentives act as *substitutes*. This substitution makes sense because, in a team of specialists, less efficient collaborative helping efforts can be replaced—at least in part—by more efficient task-related efforts (efficiency levels as compared with a team of generalists).

For information-sharing, if a_i is larger and k_j is smaller then the overall effect on task and collaboration incentives is less obvious. From our discussion of Lemmas 1 and 2, we know that the optimal task incentives increase with increasing task abilities a_i and decrease with declining collaboration skills k_j, whereas the optimal collaboration incentives increase with the task ability a_i yet may increase or decrease with the collaboration skills k_j—that is, depending on the extent to which information sharing can reduce uncertainty (see Lemma 2). Proposition 4 establishes that, unlike the case of helping, task and collaboration incentives in the case of information-sharing are not always substitutes. Instead, a team of specialists might receive higher task incentives *and* higher collaboration incentives; in other words, there might exist a region $\widetilde{\tau_i\sigma_i^2} \leq \tau_i\sigma_i^2 \leq \widetilde{\widetilde{\tau_i\sigma_i^2}}$ and a $\Delta a \geq \breve{\Delta}$ such that task and collaboration incentives could be *complements*. In scenarios characterized by low levels of reducible uncertainty ($\tau_i\sigma_i^2 < \widetilde{\tau_i\sigma_i^2}$), the effort and cost required to motivate specialists with lower collaboration skills to collaborate outweigh the potential (small) benefits. A similar situation prevails when the reducible uncertainty reaches very high levels ($\tau_i\sigma_i^2 > \widetilde{\widetilde{\tau_i\sigma_i^2}}$); in that case, offering high collaboration incentives to specialists with less collaboration skills becomes prohibitively expensive for the firm, leading it to essentially give up on collaboration. Yet there might be an intermediate range of reducible uncertainty within which the firm's optimal choice involves providing greater collaboration incentives to specialists, thereby encouraging collaboration despite their comparatively lower collaboration skills.

Note that Proposition 4 presents the optimal incentive design for a given team composition *without* verifying whether the "given" team composition is itself optimal. For collaboration in the form of information-sharing, this shortcoming raises the question of whether task and collaboration incentives can be complementary after one accounts for the results of Proposition 3 (i.e., the optimal team composition). Because the thresholds of Propositions 3 and 4 cannot be compared analytically, we explore this question numerically in Section 5.3. We shall prove by example that a region in which task and collaboration incentives are complements can exist, even when we take the optimal team composition into account.

5 Numerical Results

5.1 Numerical Results for the Team Composition Decision

In this section, we create a number of scenarios to derive further insights into how employee and project characteristics affect the optimal team composition. For each scenario, we solve the incentive optimization problem and calculate the firm's profits for each team composition; we then determine the profit-maximizing team composition.

5.1.1 Scenario Description. In line with Section 4 analysis, we continue to focus on homogeneous teams (teams of two specialists or teams of two generalists). In the Appendix, we consider a mixed team (one generalist and one specialist) while assuming an intermediate level of collaboration skills k. Figure A1 illustrates that, as expected, the mixed team dominates around the cut-off lines between the two homogeneous teams discussed here.

In this section's figures, we generate the following scenarios for the *team member characteristics*. We fix the generalists' collaboration skills at $k_g = 0.65$ and the generalists' task abilities at $a_g = 0.7$; this choice of parameters ensures that, for the helping setting, we are consistent with our assumption that employees are typically more effective at their own job than is the help received from a colleague. Then we vary the specialists' advantage in their task ability, Δa (plotted on the x-axis), from 0 to 0.5 in increments of 0.001. We show two levels of collaboration skills for the specialists as cut-off lines in each panel of Figure 1: for information-sharing, $k_s = 0.59$ and $k_s = 0.4$ in all panels; for helping, $k_s = 0.59$ and $k_s = 0.4$ in Panel D and $k_s = 0.15$ and $k_s = 0.4$ in Panel E. Finally, we assume that specialists and generalists are identical in terms of their risk aversion ($r = 0.5$) and marginal effort costs ($C = 0.8$).[11]

For this section's *problem characteristics*, we generate the following scenarios. First, we consider collaboration in the form of information-sharing (Panels A–C of Figure 1) and also in the form of helping (Panels D and E). Next, we vary the overall uncertainty (σ) from 0.05 to 5 for information-sharing and from 0.05 to 1.5 for helping.[12] In addition, we assume an average performance gap $\mu = -1.5$ and, for the information-sharing setting, three levels for the proportion τ of the uncertainty that can be reduced through information sharing: a large proportion, $\tau = 0.8$ (Panel A); a medium proportion, $\tau = 0.45$ (Panel B); and a very small proportion, $\tau = 0.05$ (Panel C).

5.1.2 Findings. Figure 1 illustrates the findings of Proposition 3. For both helping and information-sharing, the advantage in the specialists' task ability, Δa, must be large enough (relative to the difference between specialists' collaboration skills and generalists') for the firm to favor hiring a team of specialists, and the advantage Δa required for this choice in both cases

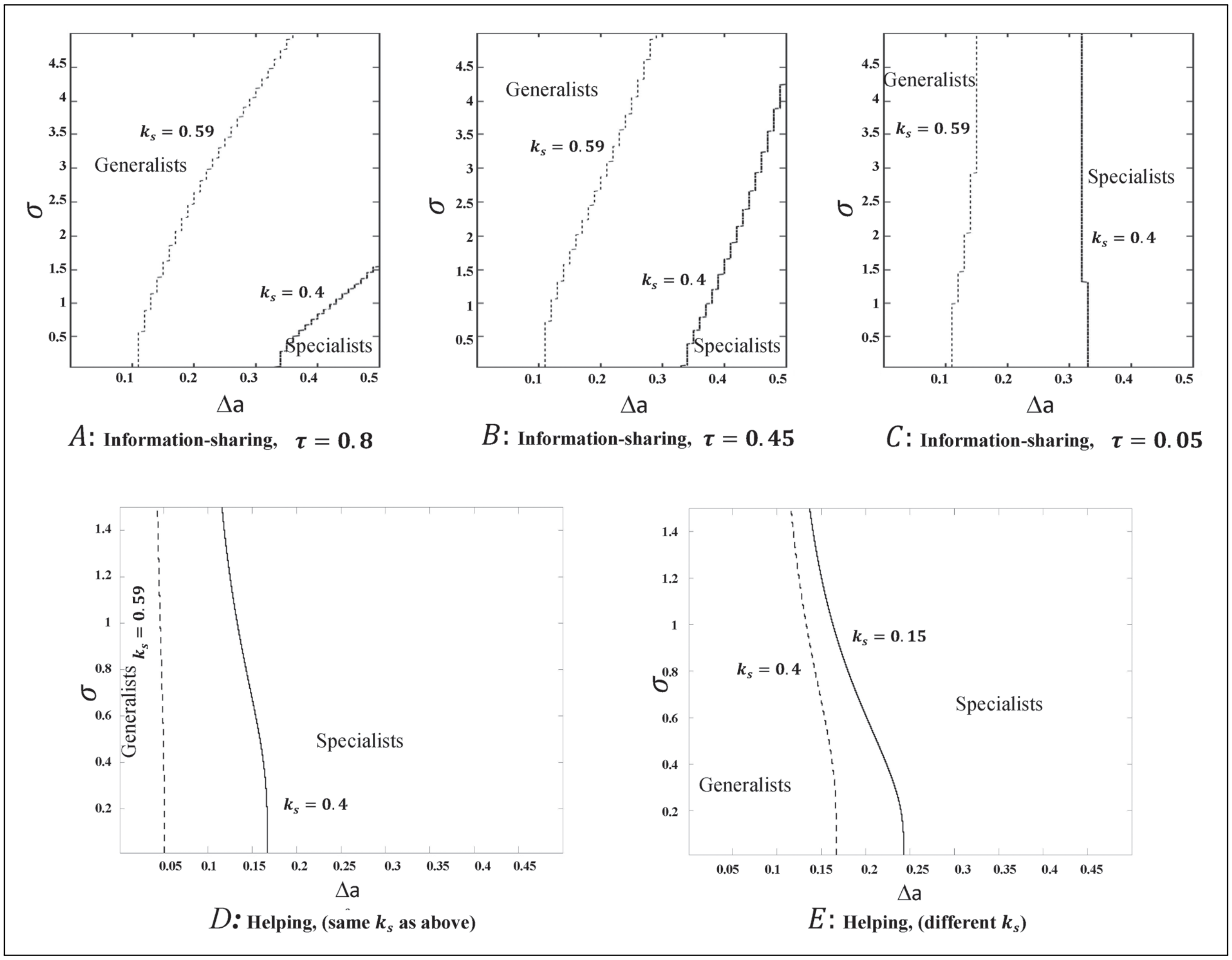

Figure 1. Optimal team composition ($a_g = 0.7$, $k_g = 0.65$, $\mu = -1.5$, $C = 0.8$, $r = 0.5$).

depends on the project uncertainty σ^2 (and, in the information-sharing setting, also on the proportion τ of the uncertainty that can be reduced).

The numerics show a marked difference in the sensitivity of the team composition decision to changes in team member characteristics. Panel D reveals that, in the case of helping, a small advantage Δa in the specialists' task ability might be enough to overcome a lower level of collaboration skills at any level of uncertainty; Panel E illustrates that specialists might still be preferred over a large range of Δa even if they have significantly lower collaboration skills than do generalists. For information-sharing, in contrast, a much larger advantage in task ability is required to compensate for lower collaboration skills. If collaboration skills are very small ($k_s = 0.15$) then the region where specialists remain optimal becomes extremely small, especially in Panels A and B (not shown in the graphs for the sake of readability).

Let us next turn to the impact of uncertainty (σ^2) on optimal team composition. For the helping setting, Panels D and E of Figure 1 again nicely illustrate Proposition 3 and how higher uncertainty σ^2 indeed lowers the threshold $\hat{\Delta}^H$ and favors specialists over a larger range of Δa. Our numerical analysis also sheds light on the situation at low levels of uncertainty ($\sigma < \underline{\sigma}$), where the sufficient condition of Proposition 3 might not hold. In all of the examined scenarios, we consistently observed that the threshold $\hat{\Delta}^H$ decreased with increasing σ^2, (though of course our numerical finding does not prove that this will always be the case).

In addition to illustrating Proposition 3, the numerics also demonstrate how the effect of a change in uncertainty on $\hat{\Delta}^H$ depends on the level of collaboration skills k_s. If the specialists' collaboration skills are not too low as compared with those of generalists ($k_s = 0.59$), then the uncertainty has only a marginal effect on the cut-off value for Δa. But if the specialists' collaboration skills are significantly lower ($k_s = 0.15$), then an increase in uncertainty results in an even larger increase in the range of Δa over which specialists are favored. Although we cannot prove this result analytically, the following explanation suggests that it might hold more generally. For high collaboration skills, the incentives for collaboration and for task-related efforts are both affected by an increase in uncertainty, and the effect does not differ much for generalist or specialist teams. In contrast, for very low collaboration skills, the collaboration incentives $\beta^H_{j,s}$—and hence the level of collaboration e^H_{ij}—are already very low for specialists (while they remain high for generalists). Therefore, uncertainty has little impact on the collaboration of specialists whereas it still has a strong effect on the collaboration efforts of generalists. It follows that a smaller increase in the task ability Δa suffices at higher levels of uncertainty (compared to lower levels) to shift the optimal team composition to specialists when they have low collaboration skills.

To examine how uncertainty affects information-sharing, we first consider only Panels A and B of Figure 1. These panels—and a comparison across them—again illustrate our finding in Proposition 3: a higher level of *reducible* uncertainty (higher τ or higher σ^2) favors generalists over a larger range of Δa. The numerics also show that a high enough amount of reducible uncertainty $\tau\sigma^2$ can indeed result in a team of specialists with low collaboration skills ($k_s = 0.4$) *never* being preferred over a team of generalists (at least, within our parameter range of Δa)—even if the advantage in their task abilities is high. This result follows because specialists with low collaboration skills are much less able (than are generalists) to reduce a high level of reducible uncertainty and so remain exposed to the high level of uncertainty. Because of that uncertainty exposure, the firm is unable to set task-related incentives for this team of specialists as high as it can for a team of generalists. The result is that the more able but less incentivized specialist team exerts less effort and delivers lower overall performance for the firm than would the generalist team.

Furthermore, our numerical analysis reveals the extent to which the effect of overall uncertainty σ^2 on the threshold $\hat{\Delta}^I$ depends on the values of k_s and τ. When τ is very large, effective collaboration efforts can substantially reduce the uncertainty. Therefore, if τ is larger, a low level of k_s results in a more pronounced disadvantage for specialists compared to scenarios with lower τ, when collaboration can resolve only a smaller fraction of the uncertainty $\tau\sigma^2$ in any case.

Finally, we consider what happens when τ is very small and so $\tau\sigma^2$ may fall below $\underline{\tau\sigma^{2,I}}$—possibly also for large values of σ^2. Consider first the impact on our model setup: as τ approaches zero, collaboration efforts no longer affect uncertainty and instead reduces only the average performance gap; hence we are approaching a scenario that no longer reflects the risk reduction of information sharing and instead more resembles the helping setting. This dynamic is evidenced by the plots in Panel C of Figure 1. If τ is very small and the collaboration skills of specialists are much lower than those of generalists ($k_s = 0.4$), then the optimal team composition decision (in the information-sharing setting but with only minimal risk reduction) resembles what we observed in the helping setting: as σ increases, specialists become the preferred choice over a broader range of Δa. The reason is the same as in the helping setting, namely, specialists with very low collaboration skills are already receiving very low incentives for collaboration and are therefore less affected (than are generalists) by an increase in uncertainty. This example demonstrates that increasing the reducible uncertainty $\tau\sigma^2$ can have the opposite effect on the team preference threshold, if the sufficient condition in Proposition 3 (viz., $\tau\sigma^2 \geq \underline{\tau\sigma^{2,I}}$) is not met. Yet this needs not always be the case: if the decline in collaboration skills is small ($k_s = 0.59$), then (a) σ^2's effect on collaboration incentives is similar for generalists and specialists, and (b) the optimal team composition choice aligns qualitatively with what was previously discussed for Panels A and B. So when σ^2 increases, generalists remain the preferred option across a (slightly) wider range of Δa.

Our main insights regarding the team composition decision remain valid for different parameter combinations in both the information-sharing and the helping settings, as confirmed in the online Supplemental Appendix (EC-2)—which also details further numerical results demonstrating the impact of changes in the risk aversion r, the effort costs C, or the performance gap/bias μ.

5.2 Numerical Results for the Effect of Team Composition on Optimal Incentive Design

Given the impossibility of analytically comparing the thresholds of Propositions 3 and 4, the question arises of whether it can be optimal for the firm to offer higher individual and higher collaboration incentives to a team of specialists (as compared with the incentives offered to a team of generalists) in any scenario where a team of specialists is the profit-maximizing choice. In other words, can incentives act as complements when it is optimal for the firm to hire a team of specialists? In this section, we address this question numerically.[13]

We begin by observing that, across all three panels presented in Figure 2, the regions where specialists constitute the optimal team composition consistently exhibit higher individual incentives: $\alpha^I_g < \alpha^I_s$ (although this is not explicitly annotated in this figure).[14]

Panel A in Figure 2 illustrates a scenario in which the firm should always offer higher task incentives and lower collaboration incentives to a team of specialists (as compared with the incentives offered to a team of generalists) whenever specialists are the preferred choice within our range of Δa. In this panel, specialists possess significantly lower collaboration skills than generalists and so choosing the former is optimal only when the level of reducible uncertainty ($\tau\sigma^2$) is low. At such low levels of reducible uncertainty, the additional cost to motivate specialists with limited collaboration skills is not justified; hence incentives act as substitutes, much as in the helping setting.

In Panel B of the figure we can see that, when the difference between specialists' and generalists' collaboration skills is less ($k_s = 0.55$ vs. $k_g = 0.65$), incentives can indeed be complements ($\alpha^I_s > \alpha^I_g$ and $\beta^I_s > \beta^I_g$)—especially when

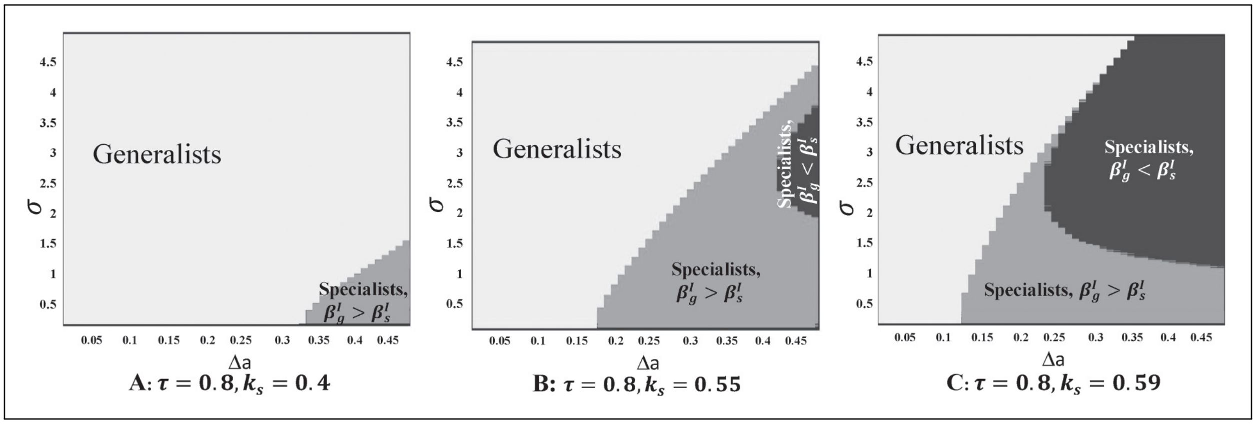

Figure 2. Optimal team composition and collaboration incentive ($a_g = 0.7$, $k_g = 0.65$).

reducible uncertainty is at an intermediate level. Yet if the firm still prefers specialists at higher levels of reducible uncertainty (i.e., owing to their significantly higher task abilities), then the optimal collaboration incentives are lower than what the firm would have offered to a team of generalists (under higher levels of reducible uncertainty); hence incentives are substitutes here as well. In this case, the reason is that it is more costly to motivate specialists to collaborate.

Panel C of Figure 2 plots results pertaining to an even smaller difference in collaboration skills ($k_s = 0.59$ vs. $k_g = 0.65$), which yields additional insights. For instance, the graph makes it more apparent that if Δa increases then incentives become complements over a wider range of uncertainty—encompassing both higher and lower levels of reducible uncertainty. This finding is consistent with Lemma 1. Also, a comparison of Panels B and C reveals that task and collaboration incentives are more likely to be complements for smaller differences between specialists' and generalists' collaboration skills; this observation is consistent with Lemma 2.

In sum, our numerical analysis proves by example that the two types of incentives can act as complements when a team of specialists is the preferred team composition for information-sharing. The numerical findings suggest that this holds when (a) reducible uncertainty is at an intermediate level and (b) choosing a team of specialists does *not* entail substantially lower collaboration skills than would choosing a team of generalists. With respect to the latter claim, we remark that the smaller the difference between specialists' and generalists' collaboration skills, the greater can be the level of reducible uncertainty at which specialists are preferred.[15]

6 Conclusion

In this article, we explore how the type of collaboration required for a development project and its level of uncertainty both affect the optimal team composition. More specifically, we consider a firm that must choose between a team of specialists with high task abilities to carry out their individual tasks and a team of generalists whose task abilities are lower than those of the specialists but who can more effectively collaborate because of their greater collaboration skills (Forman and Zeebroeck, 2012; Sosa et al., 2002). We assume that there are two team members and that the firm offers incentives to motivate these employees to increase their efforts at improving their individual performance and increasing their level of collaboration.

We distinguish two types of collaboration between the employees. We compare a type of collaboration considered in the incentive literature—namely, performance-enhancing helping—with a type of collaboration that has not received much attention in that literature: information-sharing. Information-sharing enables team members to make more informed and better-aligned design decisions, reducing performance uncertainty and reducing potential performance gaps caused by design incompatibilities.

Our findings indicate that the required type of collaboration plays an important role in the optimal team composition choice. Thus we contribute a crucial aspect to research on team composition, which discusses when to prioritize individual skills (task abilities) versus collaboration skills. We find in particular that, in the helping settings, *specialists'* advantage in individual task ability might easily overcome their lower collaboration skills—and even more so at high levels of uncertainty. In contrast, if information sharing can reduce a significant proportion of the uncertainty (high τ), then the firm might be better-off hiring *generalists* despite their disadvantage in individual task ability; this recommendation applies especially at higher levels of uncertainty and/or when the specialists' collaboration skills are significantly lower. The reason is that the firm is not able to set high task-related incentives for those specialists who are less able to reduce uncertainty through collaboration; as a result, the more able but less incentivized team of specialists expends less effort and delivers lower overall performance for the firm than would a team of generalists.

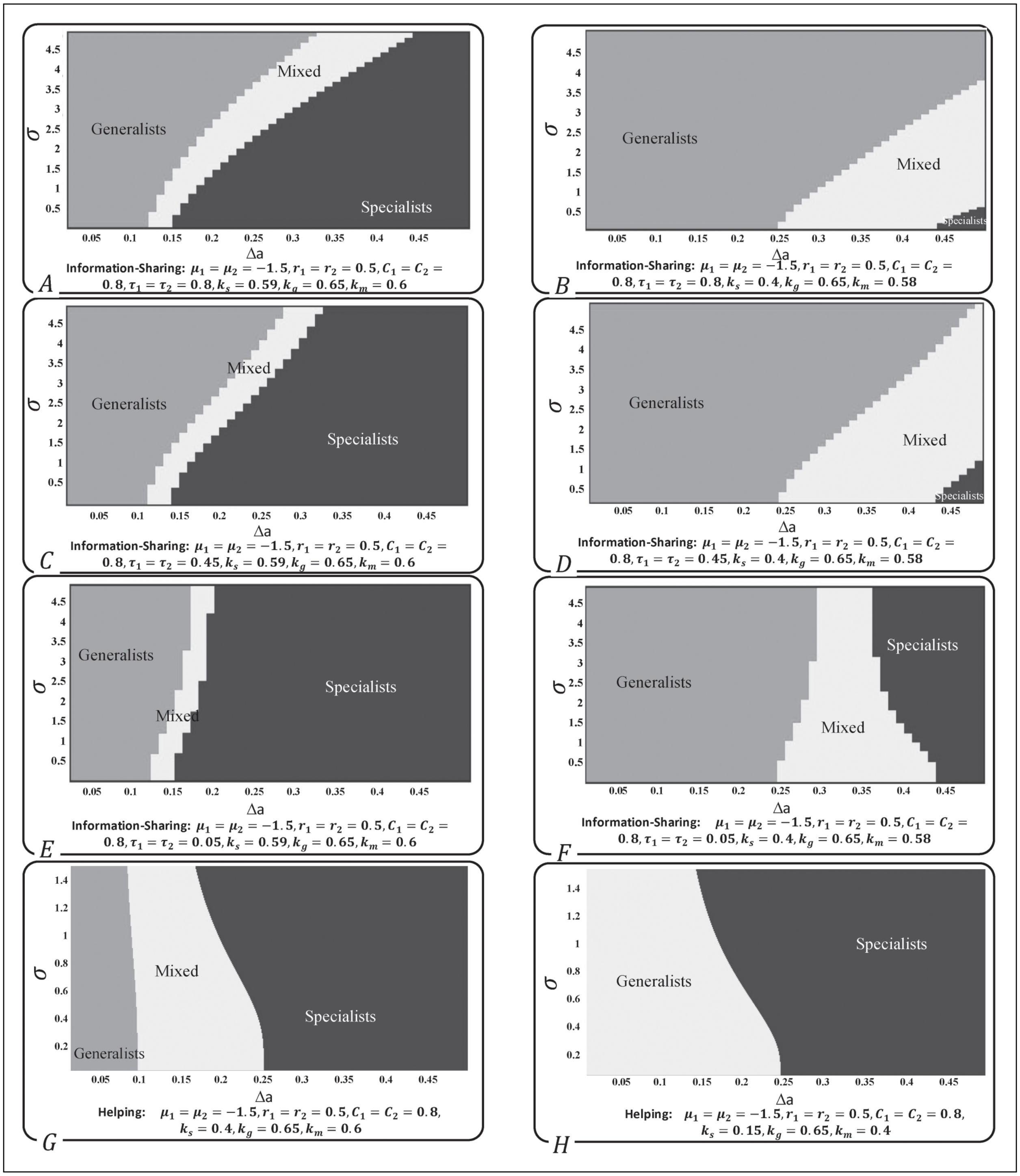

Figure A1. Optimal team composition including mixed teams ($a_g = 0.7, k_g = 0.65$).

We also demonstrate how the team composition choice (generalists or specialists) should influence the particular incentives offered by the firm and how the required type of collaboration plays again a critical role. For collaboration in the form of helping, a team of specialists should always receive higher task incentives and lower collaboration incentives than a team of generalists (i.e., task and collaboration incentives are substitutes). Yet in the information-sharing setting, it may be optimal for a team of specialists to receive both higher task incentives and higher collaboration incentives (i.e., here the two incentive types are complements). Our numerical analysis suggests that this circumstance arises when (a) the selection of a team of specialists does not lead to an extremely low level of collaboration skills compared to a team of generalists and (b) the uncertainty that can be reduced by information sharing is high enough for it to benefit the firm—but not so high that collaboration skills become more important than individual task abilities (in which case generalists would become the optimal choice) or that the cost of exposing specialists to risk outweighs the benefit of their uncertainty-reducing collaborations.

Our paper is not without some limitations. In order to obtain analytical results and to compare incentives in different settings, we make several simplifying assumptions. For example, we assume (as do most papers in the incentive literature) that the firm can observe the individuals' performance contributions. We also abstract from the details of the collaboration effort, which clearly takes place over time, and instead study a static model. In addition, it is certainly possible that the same project simultaneously requires different types of collaboration. In this study, we focus on each type separately in order to identify the differences in their effects on the optimal team composition and incentive decisions. We believe that the insights gained by our separate analyses would still be relevant if both types of collaboration are present in one project—as when helping is required from one subgroup (e.g., employees programming the project software) while information sharing is needed from a different subgroup (e.g., team leaders with a more managerial role). Still, exploring the interactions among several types of collaboration efforts or considering a more dynamic setting could be fruitful avenues for future research.

Appendix: Team Composition Decision With Mixed Teams

In Sections 4 and 5, we examined teams composed solely of specialists or generalists. However, in real-world scenarios, companies can form "mixed teams" that include both specialists and generalists. In this appendix, we extend our analysis to consider teams consisting of one specialist and one generalist.[16] We assume that the effectiveness of task-related efforts remains consistent with that observed in pure teams (same a_i). However, the introduction of mixed teams influences collaboration dynamics. For this simulation, we assume that the collaboration skills in mixed teams are superior to that of all-specialist teams but are not as effective as in all-generalist teams, that is, $k_s < k_m < k_g$. In the numerical simulations presented below, we set again $k_g = 0.65$, and denote the collaboration skills of mixed teams, $k_m = 0.6$ (when $k_s = 0.59$) and $k_m = 0.58$ (when $k_s = 0.4$), for the information-sharing setting. In the helping setting, we set $k_g = 0.65$, $k_m = 0.6$ (when $k_s = 0.4$) and $k_m = 0.4$ (when $k_s = 0.15$). All other parameters are kept the same as those used in the main body of the article.

Examination of Figure A1 reveals that, as expected, mixed teams are optimal at the boundary between the specialist and generalist regions identified in the body of the article. A closer comparison of the plots in Figure A1 with those for all-specialist or all-generalist teams reveals that the regions where mixed teams are optimal partially overlap with both the generalist and the specialist regions in our main analysis. Interestingly, in the helping setting, mixed teams might never be preferred if the level of collaboration skills for mixed teams is sufficiently low compared to all-generalist teams (as shown on the right-hand side of the panels). In this context, task-related and collaboration efforts act as substitutes in the performance function. As a result, the more efficient type of effort is favored, unless the mixed team offers sufficiently high collaboration skills, comparable to those of an all-generalist team, along with having the advantage of including a specialist with higher individual task ability.

Overall, this analysis indicates that the insights derived from pure-form teams remain relevant when considering the option of mixed teams.

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Notes

1. We acknowledge that collaboration can benefit product development in other ways. One frequently considered in the literature is the reduced time to market (Bodas Freitas and Fontana, 2018; Marion and Fixson, 2021). We do not model these time effects, but the model could capture the indirect effect on project performance resulting from first-mover advantages. Another possible benefit of collaboration is lowering the cost for a given quality of the obtained outcome. The results for cost-reducing collaboration are qualitatively similar to those for quality-enhancing collaborations and are available from the authors upon request.
2. In practice, helping could certainly also have a small effect on the variability of the outcome's quality. Yet the direction of this effect is not obvious: on the one hand, it could be argued that helping might slightly reduce the statistical dispersion because

other team members might detect mistakes; on the other hand, the variability might also increase because less experienced team members might make more mistakes. Since the ultimate impact is not clear and since risk reduction is not the goal of helping, we retain the literature's standard setup. This approach also allows the already well-studied helping setting to serve as a benchmark.

3. A few papers (see e.g., Kretschmer and Puranam, 2008) assume a multiplicative interaction between the different subunits' performance contributions. However, such a setup is not tractable when combined with risk-averse agents and so would prevent us from studying how a change in the level of uncertainty affects team incentives for risk-averse agents and hence team composition choices.
4. In the real world, there could be individuals who are good collaborators despite being highly specialized. In this article, however, we focus on the case where the firm must make a trade-off decision concerning these distinct attributes.
5. Note: For a performance-based incentive pay to be meaningful in a principal–agent models with moral hazard, both the uncertainty σ and the risk aversion coefficient r must be strictly positive; see Chapter 1 in (Tirole, 1988) for a discussion on the implications of $\sigma = 0$ and risk neutrality.
6. One exception is the work of Hutchison-Krupat and Kavadias (2016), who consider incentives for collaboration when only part of the individual performance contributions can be observed. Yet in that scenario, results can be derived only for team members who are risk neutral.
7. An alternative formulation of this problem is as a function of the total value P_i^x (rather than the performance improvement $P_i^x - v_i$) or even depending on P_i^x and the overall performance P^x. These setups are mathematically equivalent in theory, but the one we choose allows for simpler notation.
8. Another approach would be to model information-sharing as a signaling game (see e.g., Schlapp et al., 2015). Yet because our effort choices and payoffs are continuous and our agents risk averse, the result would be a complex updating equation in the certainty equivalent that would render the problem intractable. We therefore capture the performance impact of information sharing more directly while remaining consistent with the impact of such signals on performance.
9. The performance gap μ_i can be interpreted as the average under- or over-estimation of the performance contribution: a pessimism bias (for positive μ) or—what is likely more typical—an optimism bias (for negative μ) in the estimates for the performance contribution P_i^H. Using the more typical assumption that $\mu_i = 0$ does not alter our results.
10. We do not have results for high k_s, which, however, by our definition, is not (usually) the case, since it is always assumed to be significantly less than k_g or there is no real trade-off between generalists and specialists.
11. The values of M and v do not affect the cut-off lines in these two figures, but they do affect wages and firm profits. In the numerical simulations plotted here, wages and firm profits are each positive when, for example, $M = 1.2$ and $v = 4$.
12. The smaller range of σ for helping is purely for expositional purposes: it allows us to better zoom into the interesting parts of the figure's "helping" panels.
13. All parameter values remain consistent with those described for Panel A of Figure 1 *except* for an additional k_s value, which enables a more detailed discussion.
14. This has been the result for all the numerical examples we ran (including those not reported). However, because it is impossible to compare $\Delta\hat{a}^I$ and $\Delta\check{a}$ analytically, we cannot rule out the possibility that sometimes for small enough Δa, $\alpha_g^I > \alpha_s^I$.
15. Having proved by example that a region with complementary incentives can exist, we must concede that the description of this region is based only on numerical analysis and therefore does not constitute a proof that these conditions are either sufficient or jointly exhaustive.
16. In this comparison, we again assume that the firm sets optimal incentives for each team member. It is important to note that the different individual characteristics in mixed teams may necessitate different incentives for employees working on the same project, which could raise fairness concerns that we do not address in this article. Nonetheless, wage differences, including variations in fixed and incentive payments, are common among knowledge workers.

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