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Project managers' breadth of experience, project complexity, and project performance

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Abstract

Research has found that a project manager's experience is a driver of project performance. However, whether specialist or generalist project managers are more effective remains an open question to date. In this paper, we examine how project managers' breadth of experience influences project completion time under different levels of project complexity. Using longitudinal data from 9,765 enterprise resource planning (ERP) system projects executed by a software services organization, we find that managers' breadth of experience has a U-shaped impact on project completion time. We also find that while we can identify an optimal level of breadth of experience that minimizes project completion time on the U-curve, this optimal level becomes lower (the U-curve shifts to the left) as project complexity increases. As project complexity decreases, the U-curve flattens and tends to become monotonically decreasing, signifying that diseconomies from project managers' breadth of experience are less apparent in simpler projects. From a practical standpoint, these findings suggest that project managers' breadth of experience is a critical driver of project performance that should be a key consideration in the selection of managers to lead knowledge work, especially for complex projects.

KEYWORDS

complexity, experience, generalists, performance, project managers, specialists

1 | INTRODUCTION

Should managers be generalists or specialists? This age-old question continues to spur debate. While some practitioners argue strongly in favor of specialization (Kovac, 2016), others emphasize the importance of a diverse portfolio of experiences (Hansen & Von Oetinger, 2001; Lovegrove, 2016; Mansharamani, 2012). The latter opinion prevails among human resources practitioners, who often consider generalist skills a qualifying condition for managerial hiring and promotion (Custódio et al., 2013), especially in knowledge-intensive industries (Wallace & Creelman, 2015).

The view that a more general, rather than specialized, background is preferable for managerial roles is widespread among scholars as well. Drucker (1954) and Mintzberg (1971), in their seminal works, contended that managerial experience should be of a general rather than narrowly specialized nature. This view has received some empirical support. Studies have shown that chief executives with broader experience earn higher pay (Custódio et al., 2013) and that their firms are more highly valued (Betzer et al., 2020). They are more likely to take bolder (Geletkanycz & Black, 2001) and more innovative (Crossland et al., 2014) strategic action, are better at analogical reasoning (Gavetti et al., 2005), and can be more successful in leading turnarounds of poorly performing firms (Ryan & Wang, 2012).

However, not all research has been equally positive about the benefits of broad managerial experience. For example, when business diversification is sought through acquisitions, one might expect benefits from broad industry experience in the acquiring firm's top management. Instead, only specialized industry-specific experience has been found to predict acquisition success (Custódio & Metzger, 2010). Similarly, in entrepreneurship, an area where particularly strong benefits from broad experience have been proposed (Lazear, 2004), clear evidence has been lacking. Studies have found the relationship between founders' breadth of experience and different measures of entrepreneurial success to be negligible (Beckman & Burton, 2008), significantly negative (Åstebro & Thompson, 2011), or at best curvilinear so that only moderate breadth of experience is beneficial (Spanjer & van Witteloostuijn, 2017). Even when studies have linked managers' breadth of experience to intermediate benefits, such as invention novelty and qualitative assessments of commercial potential, the results have been negative with respect to invention acceptance and eventual economic success (Hwang et al., 2014).

In sum, while previous empirical research indicates that different facets of organizational performance can be affected by managers' breadth of experience, it does not provide clear insights into the direction of this effect. The existing literature also tends to focus on the highest levels of management (top management teams, boards of directors, and new venture founders), leaving open the question of whether specialized or generalist experience profiles should be favored at lower levels of management, such as among project managers who supervise teams of frontline workers. This represents a notable gap in the literature, since managerial roles at different organizational levels, in fact, have different experiential requirements (Bartlett & Ghoshal, 1997) and since it is those managers who are not at the top level who have the most immediate impact on worker productivity and operational performance (Sutton, 2010).

In this paper, we investigate the effects of the breadth of experience of project managers on the performance of the workers that they supervise. Following earlier research (e.g., Gavetti et al., 2005), we define a project manager's breadth of experience as encompassing the number of domains of activity in which they have led projects in the past. Building on worker-level empirical results suggesting that breadth of experience has a U-shaped effect on worker task execution time (Narayanan et al., 2009; Staats & Gino, 2012), we contend that project managers' breadth of experience may similarly have a U-shaped effect on the *project completion time* of the teams that they supervise. Furthermore, we argue that the nature of the supervised work influences project managers' ability to leverage their breadth of experience. Past research has suggested that complexity is one of the main factors affecting operational performance in knowledge work (Floricel et al., 2016; Nair et al., 2011). More complex work necessitates considering a greater number of cues and identifying a greater number of potential courses of action in planning as well as managing a greater number of factors, actions, and workers during the execution of plans (Pich et al., 2002; Vidal & Marle, 2008). Thus, complexity may significantly increase the mental costs of searching, retrieving, and applying relevant experience, possibly limiting or even offsetting the potential benefits of project managers' breadth of experience on the performance of the workers that they supervise.

The empirical setting for this paper is a business unit of a Fortune 500 global technology consultancy corporation that provides implementation and support services for the users of SAP, one of the world's leading enterprise resource planning (ERP) systems. Through the analysis of 9765 ERP system service projects, we find that project managers' breadth of experience does indeed have a U-shaped relationship with overall project completion time. We also provide novel insights into the moderating effect of project complexity on the relationship between the economies and diseconomies of breadth of experience and operational performance. Specifically, our results show that as project complexity increases, the performance-optimizing breadth of experience becomes narrower, suggesting that increasing complexity particularly augments the diseconomies associated with breadth of experience. At the same time, the convexity of the association between breadth of experience and performance increases with project complexity, further emphasizing the importance of having the "right" level of managerial breadth of experience for complex projects.

Considered together, these findings contribute to the literature on individual and organizational learning in project settings, which has so far investigated the effect of breadth of experience at the worker but not at the manager level (Avgerinos & Gokpinar, 2018; Boh et al., 2014; Huckman & Staats, 2011; Kc & Staats, 2012; Narayanan et al., 2009; Staats & Gino, 2012). It also contributes to past research investigating the effect of project managers' experience in leading project teams, which has mostly focused on the effects of role experience and depth of content experience on team performance (Choo, 2014; Easton & Rosenzweig, 2012; Madiedo et al., 2020). By investigating the moderating effect of project complexity on the relationship between project managers' breadth of experience and team performance, we also indirectly contribute to research on the performance effects of project complexity (Avgerinos & Gokpinar, 2017; Bendoly, 2011; Ramasesh & Browning, 2014). At a more general level, the results answer Mollick's (2012) call for research on the effect of middle-level managers' individual differences on firm performance. Finally, our findings have practical relevance for management development, project staffing, and project portfolio management.

2 | THEORY AND HYPOTHESES

Project managers play many critical roles in advancing project performance (Anand et al., 2010; Easton & Rosenzweig, 2015). Their responsibilities extend far beyond simply assigning tasks and liaising with different stakeholders. They also monitor progress, coordinate and supervise task execution, and occasionally step in to redirect efforts or mediate disputes among workers (McManus, 1997). Since these actions often involve complex problem solving, the potential economies and diseconomies of project managers' experience should be reflected in the performance of their supervised workers and, hence, in project performance. Past research has found that different facets of managers' experience can affect project performance, including the overall experience in leading projects (Choo, 2014; Easton & Rosenzweig, 2012), familiarity with project team members (Staats, 2012), and specialization in the content domain of the project (Easton & Rosenzweig, 2015). However, it remains unclear how project performance is affected by project managers' breadth of experience. Before developing hypotheses about these effects, we explain the empirical setting of this study and revisit past research findings on the performance effects of experience.

2.1 | Research setting

The organization that we studied services ERP systems from a major vendor (SAP) that are implemented in large client organizations. The operations of the service provider are organized into projects that serve a range of customer needs, from bug-fixing to the development and implementation of new software features. This type of setting has been used to investigate the performance effects of experience in several earlier studies (Boh et al., 2007; Clarke, 2012; Narayanan et al., 2014).

Project managers play a central role in the ERP software service delivery process. The process starts when a customer creates a new service request. In response to this event, a key account manager verifies that the request contains all necessary information (e.g., that the focal ERP system module of the request has been identified, a proper priority level has been derived from the customer's service level agreement, etc.) and relays it to a manager responsible for leading work in the focal ERP system module of the request. This module manager either becomes the project manager or, if already under a very high workload, delegates the project to another qualified project manager, considering the workloads of the qualified managers (such delegation occurred in approximately 10% of the projects in our sample). Whoever ends up managing the project assigns tasks to workers and is responsible for ensuring that the workers execute the project swiftly and in full compliance with customer requirements. Workers execute the assigned tasks by directly accessing clients' ERP applications in a test environment where they can check that the project specifications are met. They also document their work by updating the service provider's workflow system with the status of each service task (e.g., started, in process, in testing, and completed). After all project tasks are completed, the outcome is passed on to the client for approval.

A fundamental metric to evaluate project success is the project completion time, that is, the time elapsed between when project team members begin project activities to when they complete the last activity of the project. While labor costs are certainly considered important by managers, a swift turnaround is essential for ERP system services. A service that takes a long time to complete, in fact, may have severe implications for customers' own processes, disabling functionality in the case of bugs, or impeding the rollout of new feature implementations and software improvements. In any case, project completion time also indirectly captures labor costs because the required amount of analysis, parameterization, and programming activities is reflected in the project duration. Likewise, labor costs associated with fixing errors in any of these activities are reflected in project completion time as well.

Project managers support ERP system service teams in the successful execution of project activities through four main functions. First, project managers translate customer requirements into clear and loosely coupled task specifications for project team members. Second, project managers assemble project teams ensuring the right mix of expertise and other individual characteristics. Third, project managers lead the team by devising soft incentives (e.g., public recognition and work flexibility) to enhance worker commitment and by developing monitoring strategies that ensure control without getting in the way of workers' productivity (e.g., daily checks and unobtrusive monitoring through the workflow system). Finally, project managers help workers solve problems, directly proposing problem-solving strategies to the workers, referring workers to relevant experts, or pointing workers to appropriate reference materials (e.g., internal reference handbooks and solution libraries).

The studied organization considers managerial experience a fundamental driver of project management effectiveness, which is in line with past research in other project settings (Easton & Rosenzweig, 2015). As managers lead new projects under time pressure, they actively strive to capitalize on their past experience, reusing previously devised solutions and avoiding previous errors that were time-consuming to redress. Since the previous solutions and errors are often context specific, experience does not automatically translate into knowledge of what to do in the new project (Langer et al., 2014; Wagner & Sternberg, 1985). Both tacit and explicit processes are needed to translate experience into such knowledge that affects organizational performance (Orlikowski, 2002). Yet substantial evidence exists for an overall positive effect of experience on performance (Avgerinos & Gokpinar, 2018; Boh et al., 2014; Huckman & Staats, 2011; Kc & Staats, 2012; Kim et al., 2012; Narayanan et al., 2009; Staats & Gino, 2012) suggesting that, to some extent, practical knowledge is accrued through experience. This discrepancy is actually central to our study: while we adopt the premise of the studied organization that managerial experience is related to project management effectiveness, we expect that drawing from context-specific experience requires effort and is occasionally erroneous, making the relationship non-monotonic.

The context-specificity of experience is also a critical feature of our research setting, which informs our operationalization of this study's focal variable of interest: managerial breadth of experience. We conceptualize it as the number of different ERP system modules (e.g., Financial Accounting or Plant Maintenance) in which a manager has planned and supervised projects. Although the technical work contexts and practical knowledge requirements can vary greatly across different ERP system modules, project managers are not exclusively assigned projects pertaining to a single module. Instead, as they accumulate supervisory experience, they are usually assigned projects across a number of different ERP system modules. Therefore, measuring managers' breadth of experience as the number of different ERP system modules in which they have led projects is fitting to our empirical setting and appropriately captures the context-specificity of the accrued practical knowledge that has been discussed in earlier research (Langer et al., 2014). We also note that software module-based measures of breadth of experience have been used in other studies in similar contexts (Boh et al., 2007; Narayanan et al., 2009).

2.2 | Project managers' breadth of experience and project completion time

There are several reasons why project managers' breadth of experience can positively affect their ability to lead project teams and foster project performance. In general, when people are exposed to different types of experiences, they tend to consolidate the underlying knowledge gained from these experiences into broader schemes (Gavetti et al., 2005; Schilling et al., 2003), also known as mental models (Cyert & March, 1992; March & Simon, 1958) or information patterns (Bunderson & Sutcliffe, 2002). These schemes enable the transfer of applicable knowledge and skills from projects in other domains to the current project, according to the principle of analogical encoding (Loewenstein et al., 1999). Breadth of experience also fosters an understanding of how separate parts of a system depend on one another and reduces the risk of missing critical interdependencies in the planning of changes or interventions in the system (Denrell et al., 2004).

In the ERP system services setting, as project managers accumulate broad experience, they become exposed to projects that relate to a wider set of customer requirements. By mapping all these heterogeneous customer requirements into corresponding sets of project tasks, they develop better mental models of how customers' business processes and needs map into the specific functions and modules of the ERP system. Thanks to these enhanced models, project managers can better translate customer requirements into tasks for analysts and programmers, who can complete the project in less time. Likewise, managers with greater breadth of experience have interacted with a broader set of different ERP system module specialists. Their experience has exposed them to a fuller spectrum of worker competencies available within the organization, in contrast to specialized managers. With a stronger comprehension of "who knows what" within the organization, they are better equipped to capitalize on diversity in worker skills and attitudes. Workers' behavioral differences observed by managers with broad experience can also be leveraged to build mental models of how different people respond to different motivational tactics and monitoring approaches. Finally, with broader experience, managers gain greater insight into effective solutions from a wider collective of workers. These managers can more easily transfer solutions observed in one area of specialization to another.

However, there are also reasons to suspect that the benefits of greater breadth can be undermined when experience becomes overly broad. First, as a repertoire of different experiences accumulates, the process of identifying and retrieving relevant information becomes more onerous, possibly inducing information processing errors (Anderson, 2003; Anderson et al., 1994; Bendoly, 2011; Johnson & Hasher, 1987) and detracting from project performance. Second, overly broad experience is more likely to be integrated in highly stylized mental models and schemas, which may miss important aspects and can hence become misleading in the context of a specific project. This, in turn, can increase the likelihood of errors in the planning and supervision of project work. These adverse effects are further aggravated by the fact that the fast-paced nature of ERP system service projects constrains the time that project managers can devote to sifting through their experience (Oliva & Sterman, 2001). All this points to the possibility that as project managers' breadth of experience accumulates, their decisions may become increasingly prone to omissions and errors that result in poorer project performance.

In the context of ERP system services, especially in fast-paced projects such as those executed at our research site, the costs of excessive breadth of experience can become apparent. Project managers know that time spent in project planning detracts from the time available for the project team to execute tasks. Spending execution time on planning increases the risk that service level agreements are not met, incurring serious contractual and reputational consequences. As managers face time pressure in project planning, the time that they have to recall past experiences and evaluate their applicability to the focal project is limited, increasing the probability of making mistakes (Choo, 2014). Additionally, managers with overly broad experience may develop excessively stylized models of how customer requirements map into ERP system features and modules. Workers who we interviewed at the research site reported that it was quite common for projects led by generalist managers to begin with poorly specified tasks. This, in turn, would typically result in extra time spent engaging with the manager to understand what the customer wanted, and which programming and analysis activities had to be executed. We also observed that the workers deemed generalist managers less credible, given that they were perceived as having sacrificed depth of understanding of the nuances of the ERP software. For this reason, workers tended to cross check and even contest directives from generalist managers, thereby increasing project completion times. Notably, a similar legitimacy–breadth of experience trade-off has been observed in entrepreneurial activities (Kacperczyk & Younkin, 2017).

We expect that the abovementioned costs and benefits of managers' breadth of experience are not linear, generating an overall convex effect of managers' breadth of experience on project completion time. First, since project completion time cannot be negative, the benefits of breadth of experience must be marginally decreasing. Additionally, the marginally diminishing nature of the economies of project managers' breadth of experience relates to the finding of Schilling et al. (2003) that broad experience improves task performance only as long as it is related to the task at hand. In ERP system service projects, when a manager's experience expands across more modules of the system, the likelihood of relatedness and thus relevance of the additional experience decreases. For example, experience in the Materials Management module is very relevant for a project in Production Planning due to the many technical relationships between the two modules, the understanding of which facilitates task assignment and coordination, as discussed earlier. However, not all modules are equally interconnected. For example, Production Planning has less to do with, say, the Financial Accounting module, rendering any experience in that module less useful for a project in Production Planning. It is safe to assume that managerial experience expands first to the modules that are more related to the module of their core expertise, resulting in reduced relatedness and thus diminishing benefits as breadth of experience increases.

At the same time, we expect the disadvantages of project managers' breadth of experience to be marginally increasing. This is because every additional unit of breadth of experience adds quadratically to the total stock of connections that could be relevant. That is, two ERP system modules have one set of potentially relevant connections, three modules have three sets of potentially relevant connections, four modules have six, five modules ten, and so on. This type of nonlinear accumulation of potentially relevant connections between past experiences translates into a steeper-than-linear increase in both the time that it takes to process all potential connections and the chances of errors in the processing. The coexistence of marginally decreasing benefits and marginally increasing diseconomies suggests a U-shaped relationship between project managers' breadth of experience and ERP system project completion time. We therefore propose the following baseline hypothesis:

Hypothesis 1. *Project managers' breadth of experience has a U-shaped association with ERP system service project completion time.*

2.3 | Project managers' breadth of experience and project complexity

Complexity is a fundamental feature of any project. Apart from its intuitive direct detrimental effect on performance (Griffin, 1997), project complexity also has an indirect impact by moderating the effects of many other project characteristics. For instance, project complexity has been found to moderate the effect of team integration on the aggregate performance of new product development projects (Ahmad et al., 2013), of team cognitive prowess on the quality of the designed product (Açikgöz et al., 2014), of team knowledge and motivation on team creative thinking (Cheng & Yang, 2014), of science-based partnerships on project duration (Du et al., 2014), of project control on conformance and maintainability of project outputs (Liu, 2015), of team familiarity on team productivity (Avgerinos & Gokpinar, 2017), and of protection from information leakages on project design quality (Wu et al., 2020).

Of particular relevance for our research question is the finding that project complexity interacts with the effectiveness of project planning, potentially resulting in both positive and negative contingency effects on project completion time (Choo, 2014). Since the effectiveness of project planning likely relates to project managers' experience, we set out to explore the interaction of project complexity with the curvilinear effect postulated in our first hypothesis. To this end, we define project complexity following Campbell's (1988, p. 42) notion of "complexity as [an] objective task characteristic." Multiple studies using objective operationalizations of complexity have defined the construct as the number of distinct mutually dependent elements in an object. Examples include the number of alternatives in a decision (Payne, 1976), the number of functions in a product (Griffin, 1997), the number of components in a product (Salvador et al., 2014), the number of objectives in a process improvement project (Choo, 2014), and the number of patents produced in a research project (Du et al., 2014). The definition that best fits our context of ERP system service projects is the number of distinct tasks that comprise the project (Mihm et al., 2003).

While project complexity can intuitively have a bearing on the ideal level of managers' breadth of experience, the nature of this impact has been largely ignored in prior research. Since complexity implies that a greater number of factors must be considered in decision making (Wood, 1986) and since the number of potentially relevant experiences increases with breadth of experience, one could conclude that broader experience is beneficial in complex situations. However, the information processing effort of searching through a broad experience landscape increases with project complexity because more project-related factors need to be matched to a broad range of experiences (Belack et al., 2019). Such heightened information processing and search effort requires additional time, a scarce resource for project managers operating in service industries, where understaffing and time pressure are commonplace (Kc & Terwiesch, 2009; Moore, 2000). The combined effect of time pressure and project complexity is hence likely to drive errors (Bowrin & King, 2010) that ultimately impede swift project execution. Additionally, cognitive psychology has established that, regardless of time pressure, individuals struggle to retrieve past memories when approaching an upcoming task whose execution may require new knowledge—a phenomenon that is known as retroactive interference (Eysenck, 2001). Since retroactive interference is stronger for complex tasks (Campoy, 2011), project managers may thus struggle to capitalize on a broad experience when leading more complex projects.

Conversely, when complexity decreases, planning and supervision activities become more straightforward, limiting the potential performance implications of managerial work in general (Fransoo & Wiers, 2006) and thus also mitigating the potential impact that insufficient or overly broad managerial experience may have on project completion time. Additionally, any errors that managers may make, including those resulting from their insufficient or excessive breadth of experience, should be more easily detectable in simple projects. Furthermore, managers with narrower experience, while potentially restricted in their understanding of every single detail of complex projects, may nonetheless be able to at least "connect the dots" within a reasonable time frame without getting "locked in" by their mental models, as proposed but so far not empirically tested in the entrepreneurship literature (Baron, 2006).

In the specific context of ERP system services, project complexity can further exacerbate the previously discussed downsides of project managers' breadth of experience. The difficulties that project managers with overly broad experience encounter in translating customer requirements into project tasks may become more problematic for complex projects, especially under time pressure. Workers may need to come back to managers to fill in missing information, clarify ambiguities, or simply report the complexities that managers missed in defining project tasks. Workers may also perceive project managers with very broad experience as overly confident of their ability to deal with complexity, further deteriorating workers' trust in generalist managers. Similarly, since managers with very broad experience may have a shallower understanding of individual workers' strengths and weaknesses (because they have led a broader set of workers), they may be more prone to making errors in assigning workers to complex projects. The performance of teams with ineffective compositions would suffer from mismatches in competencies and human traits, ultimately inflating project completion time.

In summary, the costs of leveraging project managers' breadth of experience may become negligible in the case of simple projects, while they may increase significantly in complex projects. Figure 1 offers a visualization of our propositions. Curve A captures the U-shaped effect of project managers' breadth of experience on project completion time in a baseline situation where project complexity is at an intermediate level. Curve B visualizes the effect of increased costs of project managers' breadth of experience when project complexity increases. As these costs increase, the optimal point of the curve shifts to the left, and the curve becomes steeper. Conversely, Curve C reflects the situation where project complexity is low. In this case, the costs of project managers' breadth of experience decrease. Hence, the benefits of project managers' breadth of experience dominate its incremental costs. As the stationary point shifts to the right, the steepness or convexity of the curve is reduced. These proposed interactions between project complexity and project managers' breadth of experience on ERP system project completion time can hence be formally expressed in the following hypotheses:

Hypothesis 2. *Project complexity moderates the U-shaped relationship between project managers' breadth of experience and a project's completion time such that the level of the project manager's breadth of experience that minimizes completion time increases as project complexity decreases.*

Hypothesis 3. *Project complexity moderates the U-shaped relationship between project managers' breadth of experience and a project's completion time such that the convexity of the U-shape decreases as project complexity decreases.*

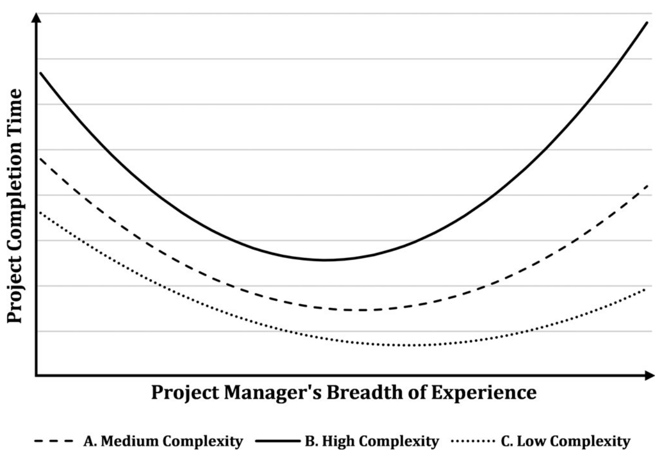

FIGURE 1 Expected effect of project complexity on the relationship between project manager's breadth of experience and project completion time

3 | DATA AND VARIABLES

We empirically investigate the proposed hypotheses using data about the ERP system maintenance projects stored in the archives of the workflow systems of the studied organization (see the "Research setting" section for an extended description). The studied organization offers an appropriate context for our investigation for various reasons. First, the organization systematically records and keeps detailed project data, including manager, worker and customer identities, project completion time, and associated covariates, which provide a nuanced view of the hypothesized relationships. Second, the duration of most projects is relatively short. Thus, a substantial number of observations per manager are available. This allows us to account in our modeling for unobserved manager-specific characteristics (by means of fixed effects) and disentangle the effects of those characteristics from those of breadth of experience, the focus of our study.

From the workflow system of the organization, we obtain detailed records of 9765 projects executed during a period of 43 months, which began soon after the business unit started its operations and continued between 2006 and 2009. The data include information on projects led by 226 different project managers for 54 different customers. Following the workflow of the organization, we collect detailed information about the client of each project, the project manager overseeing the execution of the project, the workers executing the project tasks, the module being serviced, the priority level of the request, the start and end dates of the project, and other project details. For each project, longitudinal information, such as the time spent on each of its tasks, is recorded in the workflow system. From these data, we derive a host of measures for our analyses.

3.1 | Dependent variable

Completion time ($cTime_{ij}$). We compute the completion time of project j led by manager i as the time elapsed (in hours) from the beginning of the first task to the completion of the last task assigned to project team members. Shorter completion times mean that customers receive faster service, which is an important dimension of operational performance. Completion time can be shorter than the sum of the execution time of project tasks if some tasks are performed in parallel by multiple workers, or it can be longer if tasks are executed intermittently. We apply a natural logarithm transformation in the analyses to correct for the positive skew of project completion times. Finally, we note that workers are paid a fixed salary with no performance-based variable element. Therefore, the observed differences in completion times are not driven by variable compensation.

3.2 | Independent variables

Project manager's breadth of experience ($mBreadth_{ij}$). Adopting the operationalization of Narayanan et al. (2009), we compute a project manager's breadth of experience as the number of different ERP system modules in which manager i has planned and supervised projects prior to focal project j. The variable ranges from 1 to 12 based on the main modules of the ERP system (e.g., Financial Accounting, Materials Management, Production Planning, etc.). Leading projects in different ERP system modules fosters an understanding of their interfaces and links to other modules, the underlying business processes, and the pool of workers with expertise in different components of the software.

Project complexity ($pComplex_j$). We measure the complexity of project j as the number of distinct tasks that the project comprises. Managers in the studied setting split more complex projects into a greater number of subproblems (tasks) that can be more easily managed and addressed by workers. This practice is consistent with the more general fact that problem partitioning is a key approach to dealing with complexity (Simon, 1962). Partitioning complex projects into multiple tasks provides managers with more timely and precise information about where workers may encounter difficulties and require help (Athayde et al., 2013). The operationalization of complexity as the number of tasks also has precedents in practice and in the research literature (Bonet & Salvador, 2017). This operationalization of project complexity should not be confused with the project team size (i.e., the number of workers involved in the project) because a worker could be responsible for multiple tasks for the same project.

3.3 | Control variables

Project manager's depth of experience ($mDepth_{ij}$). This variable is the natural logarithm of the number of projects that the manager has led in the module of the focal project prior to project j. We include this variable as a control because it has been found to improve project performance (Easton & Rosenzweig, 2015). Moreover, we use the logarithmic transformation because our intention is to capture the diminishing returns of experience, as previously established by the literature on learning curves (e.g., Anderson & Sullivan, 1993; Gujarati, 2003).

Herfindahl–Hirschman Experience Index ($mHHEI_{ij}$). Earlier studies have suggested that there are performance implications of the degree to which an individual's experience is concentrated in a few domains of activity versus uniformly distributed across all the domains of activity in which that individual has worked (Demirkan & Spohrer, 2018; Narayanan et al., 2009). To control for the effects of the concentration of experience, we include in the model a variable that Narayanan et al. (2009) labeled the *Herfindahl–Hirschman Experience Index*. It is calculated as $mHHEI_{ij} = \sum_m P_{ijm}^2$, where m represents the ERP system modules in which manager i has supervised projects prior to the focal project and P is the proportion of the manager's experience in that module relative to total experience in all modules. The $mHHEI_i$ variable can take values between $1/mBreadth_{ij}$ and 1, with the former indicating that the experience of the manager is uniformly distributed across all the modules in which she has led projects and the latter that her experience is fully concentrated in a single module.

Project manager's customer experience ($mCustDepth_{ij}$). The manager's familiarity with the customer's ERP system can facilitate her understanding of requests and allow her to effectively manage projects for that client. Thus, we control for such familiarity by including in the model a variable that captures the number of projects that the manager has led for the same customer.

Project team size ($workers_j$). We control for the number of workers in the team to account for the time required to coordinate work in larger teams.

Average experience of workers on the project team ($wDepth_j$, $wBreadth_j$, ${wBreadth_j}^2$). These variables capture project-level averages of depth and breadth of experience across all workers involved in the execution of project j. Prior to computing the average, individual worker-level measures were computed in the same manner as those of the manager, $mDepth_{ij}$ and $mBreadth_{ij}$. We include the square of $wBreadth_j$ to control for the possible curvilinear effect that has been found at the individual worker level (Narayanan et al., 2009; Staats & Gino, 2012).

Manager-team breadth of experience mismatch ($mismatchBreadth_{ij}$). Based on their experience, the team and the manager can complement each other and influence project completion time. Thus, we include in our model the variable $mismatchBreadth_{ij}$ to capture mismatch between the breadths of experience of the manager and the team. We measure it as the absolute value of the difference between a project manager's breadth of experience ($mBreadth_{ij}$) and the average breadth of experience of the workers in the project team ($wBreadth_j$).

Workload-related controls. Two workload controls were included given that past studies have shown that workload may affect processing time in service operations (Kc & Terwiesch, 2009). First, we include a measure of *manager workload* ($mLoad_{ij}$), which is computed as the number of other projects that manager i was working on in parallel with focal project j. Second, we also include a measure of the *average worker workload in the project team* ($wLoad_j$). This variable represents the average number of other projects that workers are assigned at the time that they started working on focal project j.

Customer engagement ($custEngagement_{ij}$). If a manager happens to supervise several projects for the same customer at the same time, the projects may benefit from scale economies in client communications, for instance. Thus, we include in the model a variable that takes the value of 1 if, at the time of being selected to lead project j, manager i was working on any other project for the same customer and zero otherwise.

Module managers ($moduleMgr_i$). In certain cases (e.g., when the demand for projects in the module of the focal project is very high), the module manager can assign the project to another project manager to level out workloads among project managers (this happened in 10.36% of the studied projects). The responsibilities of these project managers are not different from those of module managers when the latter assume the role of project manager. Nevertheless, we include in our model a dummy variable to capture any potential differences between the module manager and other project managers, given the former's official position. This variable takes the value of 1 when the project manager of the focal project is a module manager and 0 otherwise.

Project priority ($priority2_j$, $priority3_j$). Based on service level agreements, customer characteristics, and other situational factors, each project had a priority level (low, medium, or high priority). We take the highest priority as the baseline and create two dummy variables to capture situations where the project priority was low ($priority3_j = 1$) or medium ($priority2_j = 1$). We include these variables to account for the basic tenet of goal-setting theory that priorities influence worker productivity (Locke & Latham, 2002) and hence the dependent variable of this study.

Project classification ($pclass1_j$ to $pclass4_j$). Projects were classified based on their nature into five types: corrective, minor and major support, and minor and major modification. We therefore take corrective projects as the baseline case and compute four dummies to capture the other four cases. Minor projects required less work and less time to execute, while corrective, modification, and support projects entailed different types of activities, which possibly had different impacts on the dependent variable.

Programming of new features ($programming_j$). Some projects required programming work to develop entirely new features. We add a dummy control variable for such projects, as this type of work might have an impact on project completion time.

Module ($module_j$). This categorical variable accounts for circumstances that are unique to the module of focal project j, controlling for differences across the modules in the time required to execute work and deliver the service.

Year ($year2_j$ to $year4_j$). To account for potential time-variant organizational changes, we add a control for the year in which project j started.

Table 1 presents the correlations and descriptive statistics of the variables included in our analyses.

4 | ANALYSES AND RESULTS

We specify a regression model to analyze the impact of project managers' breadth of experience and project complexity on the project's completion time. Consistent with the hypothesized U-shaped relationship, we include in the model the first- and second-order terms of project managers' breadth of experience. We allow both terms to interact with project complexity to capture the moderation effects on both the stationary point and the convexity of the relationship. We control for manager fixed effects and estimate clustered robust error terms by manager. A fixed-effects model was chosen over a random-effects model based on the Hausman (1978) test ($\chi^2 = 41$, $p < .001$). Using vector β to denote the regression coefficients for the control variables, we estimate the regression equation:

$$
\begin{aligned}
LN\left(cTime_{ij}\right) = {} & \beta_0 + \beta_1 mBreadth_{ij} + \beta_2 mBreadth_{ij}^{\ 2} \\
& + \beta_3 complex_j + \beta_4 complex_j * mBreadth_{ij} \\
& + \beta_5 complex_j * mBreadth_{ij}^{\ 2} + \beta \cdot controls_{ij} \\
& + e_{ij}
\end{aligned}
$$

4.1 | Results

Table 2 presents our model estimation results. On the one hand, we find that most control variables (Model 1) as well as project complexity (Model 2) influence the dependent variable, and the direction of the significant effects is consistent with the findings of previous literature (Boh et al., 2007; Clark et al., 2013; Narayanan et al., 2009; Staats & Gino, 2012). On the other hand, Model 3 shows that project managers' breadth of experience does not have a significant linear effect on the project completion time.

TABLE 1 Descriptive statistics and correlations (n = 9765)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) $LN(cTime_{ij})$	1														
(2) $pComplex_j$	0.36*	1													
(3) $mBreadth_{ij}$	−0.33*	−0.08*	1												
(4) $wDepth_j$	−0.36*	−0.07*	0.35*	1											
(5) $wBreadth_j$	−0.23*	0.02	0.41*	0.48*	1										
(6) $wLoad_j$	0.25*	0.13*	0.04*	−0.10*	0.23*	1									
(7) $mLoad_{ij}$	0.03*	0.01	0.46*	0.08*	0.06*	0.29*	1								
(8) $mCustDepth_{ij}$	−0.28*	−0.05*	0.50*	0.53*	0.47*	0.00	0.21*	1							
(9) $mismatchBreadth_{ij}$	0.11*	0.04*	−0.41*	−0.04*	0.23*	0.07*	−0.28*	−0.14*	1						
(10) $custEngagement_{ij}$	−0.09*	0.02	0.26*	0.11*	0.05*	0.05*	0.29*	0.29*	−0.24*	1					
(11) $moduleMgr_i$	−0.16*	−0.14*	0.39*	0.09*	0.03*	0.00	0.31*	0.16*	−0.33*	0.24*	1				
(12) $mDepth_{ij}$	−0.26*	−0.16*	0.58*	0.37*	0.26*	0.01	0.40*	0.45*	−0.28*	0.27*	0.43*	1			
(13) $mHHEI_{ij}$	0.28*	0.00	−0.56*	−0.29*	−0.34*	−0.07*	−0.21*	−0.56*	0.31*	−0.28*	−0.18*	−0.09*	1		
(14) $workers_j$	0.49*	0.48*	−0.27*	−0.27*	−0.07*	0.15*	−0.09*	−0.17*	0.16*	−0.10*	−0.20*	−0.22*	0.22*	1	
(15) $programming_j$	0.39*	0.19*	−0.28*	−0.27*	−0.11*	0.13*	0.04*	−0.26*	0.14*	−0.07*	−0.15*	−0.19*	0.21*	0.30*	1
Mean	3.35	2.38	6.92	3.10	8.13	16.59	45.93	8.75	2.43	0.86	0.95	5.65	0.49	2.74	0.21
Standard deviation	2.77	2.31	2.78	4.10	2.85	11.08	29.52	12.02	2.23	0.35	0.22	1.82	0.27	1.40	0.41

*Denotes correlations that significant at the .05 level.

TABLE 2 Effect of managers' breadth of experience and project complexity on project completion time

	DV: LN (project completion time)									
	Base model (1)		Model with complexity (2)		First-order main effect model (3)		Second-order main effect model (4)		Model with interactions (5)	
Variables	Beta	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
$wDepth_j$	5.21E−03	7.40E−03	3.80E−04	7.21E−03	−1.26E−05	7.21E−03	−1.18E−03	7.22E−03	3.11E−03	7.11E−03
$wBreadth_j$	−1.27E−01*	4.51E−02	−9.56E−02*	4.42E−02	−9.45E−02*	4.41E−02	−9.05E−02*	4.41E−02	−5.45E−02	4.49E−02
$wBreadth_j^2$	4.04E−03	2.77E−03	1.85E−03	2.72E−03	1.92E−03	2.72E−03	1.75E−03	2.72E−03	−7.53E−04	2.77E−03
$wLoad_j$	2.72E−02**	2.67E−03	2.32E−02**	2.64E−03	2.31E−02**	2.64E−03	2.32E−02**	2.64E−03	2.13E−02**	2.63E−03
$mLoad_{ij}$	9.62E−03**	1.26E−03	9.16E−03**	1.21E−03	9.35E−03**	1.21E−03	9.41E−03**	1.21E−03	8.64E−03**	1.22E−03
$mCustDepth_{ij}$	1.13E−02**	4.03E−03	1.31E−02**	4.03E−03	1.18E−02**	4.23E−03	1.04E−02*	4.27E−03	9.96E−03*	4.17E−03
mismatch $breadth_{ij}$	−1.37E−02	1.58E−02	−1.73E−02	1.53E−02	−1.98E−02	1.55E−02	−2.39E−02	1.56E−02	−8.87E−03	1.57E−02
customer $engagement_{ij}$	6.10E−02	7.69E−02	7.76E−02	7.64E−02	8.00E−02	7.64E−02	8.55E−02	7.62E−02	5.31E−02	7.44E−02
$module\_mgr_i$	−2.79E+00*	1.24E+00	−1.86E+00$^+$	1.04E+00	−1.92E+00$^+$	1.04E+00	−2.05E+00$^+$	1.07E+00	−2.67E+00*	1.22E+00
$mDepth_{ij}$	−1.02E−01**	2.45E−02	−6.06E−02**	2.40E−02	−5.18E−02*	2.57E−02	−4.56E−02$^+$	2.59E−02	−4.44E−02$^+$	2.55E−02
$mHHEI_{ij}$	2.94E−01	3.99E−01	−5.48E−02	4.40E−01	−1.05E−01	4.41E−01	−2.77E−01	4.46E−01	−2.35E−01	3.98E−01
$workers_j$	4.69E−01**	3.62E−02	2.83E−01**	3.32E−02	2.82E−01**	3.32E−02	2.82E−01**	3.34E−02	2.95E−01**	3.50E−02
$programming_j$	5.62E−01**	7.78E−02	5.95E−01**	7.13E−02	5.97E−01**	7.14E−02	5.92E−01**	7.15E−02	5.35E−01**	7.10E−02
$pComplex_j$			2.89E−01**	3.19E−02	2.90E−01**	3.19E−02	2.89E−01**	3.20E−02	1.48E−01**	4.97E−02
$mBreadth_{ij}$					−2.56E−02	2.54E−02	−1.39E−01*	6.99E−02	−1.71E−01$^+$	9.60E−02
$mBreadth_{ij}^2$							8.90E−03$^+$	5.02E−03	−2.44E−03	7.72E−03
$pComplex_j\#mBreadth_{ij}$									−1.69E−02	2.58E−02
$pComplex_j\#mBreadth_{ij}^2$									7.40E−03**	2.53E−03
manager (fixed effects)	—Included—		—Included—		—Included—		—Included—		—Included—	
module (fixed effects)	—Included—		—Included—		—Included—		—Included—		—Included—	
year (fixed effects)	—Included—		—Included—		—Included—		—Included—		—Included—	
pclass (fixed effects)	—Included—		—Included—		—Included—		—Included—		—Included—	
priority (fixed effects)	—Included—		—Included—		—Included—		—Included—		—Included—	
constant	2.21E+00$^+$	1.40E+00	2.25E+00*	1.20E+00	2.28E+00*	1.20E+00	2.55E+00*	1.23E+00	2.82E+00*	1.37E+00
Observations	9765		9765		9765		9765		9765	
Adjusted R^2	0.47		0.50		0.50		0.50		0.52	
R^2	0.49		0.52		0.52		0.52		0.54	

Note: Models 1 to 5 were estimated using clustered robust errors by manager.
$^{**}p < .01$; $^{*}p < .05$; $^{+}p < .1$.

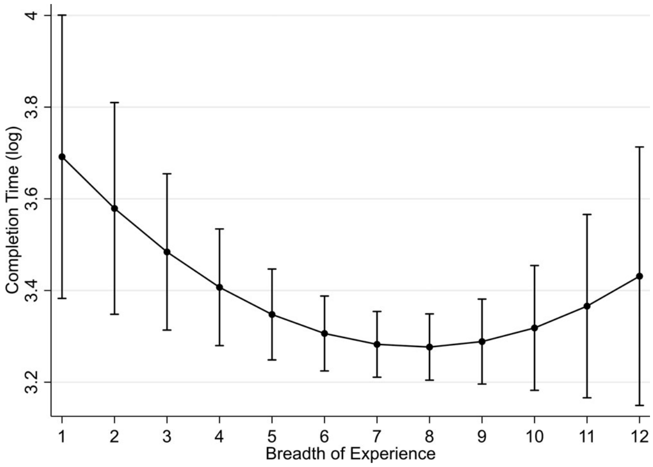

FIGURE 2 Overall relationship between project manager's breadth of experience and project completion time. The figure depicts the 90% CIs of the estimated value

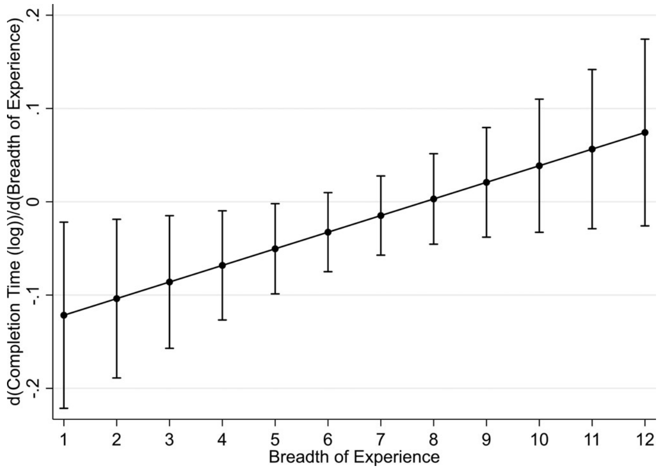

FIGURE 3 First derivatives of the overall relationship between project manager's breadth of experience and project completion time. The figure depicts the 90% CIs of the estimated value

Parameter estimates for Model 4 suggest the existence of a U-shaped relationship between project managers' breadth of experience and project completion time ($\beta_{mBreadth} = -1.5 \times 10^{-1}$, $p < .05$; $\beta_{mBreadth}{}^{2} = 9.16 \times 10^{-3}$, $p < .1$). Figure 2 depicts the resulting U-shaped relationship.

The parameter estimate of the second-order term of the project manager's breadth of experience, $\beta_{mBreadth}{}^{2}$, is to the expected direction but only marginally significant ($p = .06$), which suggests that support for the hypothesized relationship should be taken as tentative. Thus, we further investigate the U-shaped relationship between project managers' breadth of experience and project completion time following the recommendations of Lind and Mehlum (2010). First, we analyze the stationary point of the curve. It is located at $mBreadth_{ij}* = 8.18$, which is well within the empirically observed range of project managers' breadth of experience (i.e., 53rd percentile of $mBreadth_{ij}$). Second, we check the sign and significance of the first-order derivatives $\partial ln(cTime_{ij})/\partial mBreadth_{ij}$ (before and after the observed stationary point in $mBreadth_{ij}*$), obtained from the parameter estimates of Model 4 in Table 2. The results are shown in Figure 3. The derivatives are negative when $mBreadth_{ij}$ is less than $mBreadth_{ij}*$ and positive when $mBreadth_{ij}$ is larger than $mBreadth_{ij}*$. Taken together, these findings lend support for the nonmonotonicity postulated in Hypothesis 1.

Hypothesis 2 states that the optimal level of project managers' breadth of experience regarding project completion time (i.e., the level at which the project completion time is minimized) decreases when project complexity increases. Figure 4 shows the conditional effects of $mBreadth_{ij}$ on $ln(cTime_{ij})$ under low and high levels of complexity (i.e., the 20th and 80th percentiles of $pComplex_j$) with the corresponding 90% confidence intervals (CIs). As hypothesized, at high levels of project complexity, the stationary point of the curve shifts to the left toward lower values of project managers' breadth of experience. Since the location of the stationary point is a function of the ratio of linear to quadratic coefficients of the estimated regression equation, the results in Table 2 and Figure 4 do not directly allow us to draw conclusions about the significance of the change in such a ratio (Haans et al., 2016). Therefore, to test whether the shift of the stationary point is significant, we compute the estimate and the confidence intervals of the difference between the stationary points of the low- and high-complexity curves. The difference was found to be significantly different from zero (2.71, 95% CI: [*0.62*; *4.81*]), thus offering support for Hypothesis 2.

Finally, Hypothesis 3 states that the convexity of the parabolic effect of project managers' breadth of experience on project completion time increases when project complexity increases. Testing for changes in the convexity (i.e., flattening or steepening) of a U-shaped relationship due to a moderation effect is achieved by testing whether the parameter estimate of the interaction between the second-order term of the independent variable and the moderator is significant. Convexity decreases (i.e., flattening occurs) when the estimate is negative and significant. Conversely, convexity increases (i.e., steepening occurs) when the estimate is positive and significant (Haans et al., 2016). In our case, the parameter estimate of the interaction between the second-order term of project managers' breadth of experience and complexity is positive and significant ($\beta_{pComplex\ x\ mBreadth}{}^{2} = 7.29 \times 10^{-3}$, $p < .01$). This means that increasing project complexity is associated with

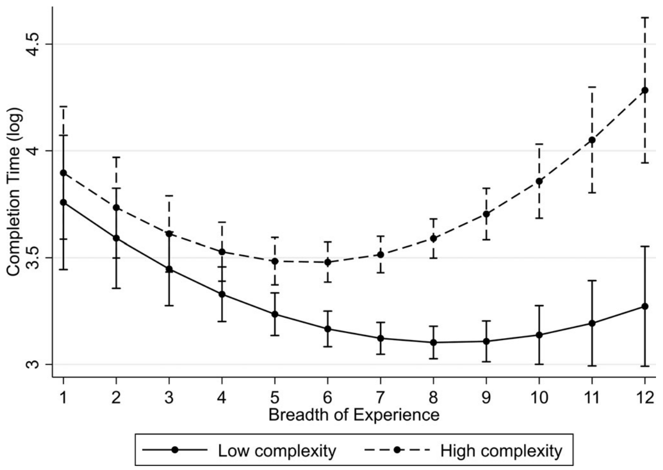

FIGURE 4 Relationship between project manager's breadth of experience and project completion time at high and low levels of project complexity. The figure depicts the 90% Confidence Intervals of the estimated value

increasing convexity of the relationship between project managers' breadth of experience and project completion time, lending support for Hypothesis 3. In other words, when moving away from the optimal level of project managers' breadth of experience, project completion time increases at a faster rate in projects with high levels of complexity than in those with low levels of complexity (see Figure 4).[1]

4.2 | Endogeneity checks

In our model, endogeneity concerns may stem from self-selection or unobserved factors that simultaneously affect our dependent and independent variables. Thus, we estimate models that aim to address those concerns. First, our sample could suffer from selection bias because managers may not be randomly selected to lead projects. We therefore estimate a model based on Dahl's (2002) multiple-choice two-stage selection approach that corrects for potential selection bias. In this approach, Stage 1 represents the selection decision (of the manager to whom the project is assigned). Stage 2 represents the performance model after adjusting for potential selection bias. This approach allows the modeling of complex choice sets in which more than two discrete alternatives exist for a selection decision (Wu et al., 2017). In our study, it allows us to model how managers' individual characteristics (e.g., their breadth and depth of experience or experience working with the project customer) may lead to the systematic selection of a specific manager for a project.

Assuming that manager i is selected to manage project j when her expected project completion time is the shortest among the expected completion times of any manager l who could have led that project, we specify a (Stage 1) selection model using conditional logistic regression to estimate the odds of that manager being selected for the project (Wu et al., 2017):

$$P\{l_j = i\} = \frac{\exp(Z_{ij}\theta)}{\sum_l \exp(Z_{ij}\theta)}$$

where i denotes the manager selected for project j and l any manager who could have been selected, while Z_{ij} is a set of variables that explains the utility of selecting manager i from a possible candidate set of managers ($l = 1, ..., n$).

Specifying a conditional logit model allows us to take into consideration that observations related to a specific project are not independent of each other. This accounts for the fact that once a manager has been selected for a project, no other manager will lead that project. Thus, in the conditional logit model, the dependent variable of the observations grouped under a project takes the value of 1 for the manager who was selected to lead the project and of zero for the rest of the managers in the choice set (i.e., the managers who could have led the project but were not selected to do so). The manager choice set, l ($l = 1, ..., n$), comprises all managers who were in charge of a project in the same module during the month leading to the execution of the focal project. The set also includes manager i, who was selected for the focal project.

To identify the system of equations, we also include in the selection model the additional variable *manager share of work* ($mShare_{lj}$). This is different from $mLoad_{ij}$ in Table 2 and serves to satisfy the exclusion restriction of the selection model. We compute the *mSharelj* as the ratio of the workload of manager l to the total number of open projects in all modules at the time when manager i is selected for project j. This variable captures the extent to which the manager is allocated work in comparison to other managers. We expect the manager's share of work to predict the selection of a manager for a project because social justice is considered when assigning projects. Specifically, to the extent possible, work is allocated so that managers carry similar workloads. For example, a manager with a workload of 10 projects at time t_0 may not be selected to lead the focal project if that workload translates to a share of work (the exclusion restriction) that is larger than that of other managers. She may, however, be selected at time t_1 when she has a workload of 20 projects if that workload at that point in time translates to a share of work that is lower than that of the other managers. That is, even though the manager has a larger absolute workload in t_1 than in t_0, she could still be allocated the

TABLE 3 Results of Dahl's selection (Stage 1) model

	Beta	SE
$mLoad_{jl}$	6.00E−03**	−1.00E−03
$mCustDepth_{jl}$	2.00E−02**	−1.00E−03
$custEngagement_{jl}$	6.13E−01**	−2.30E−02
$moduleMgr_{l}$	1.11E−01**	−4.10E−02
$mDepth_{jl}$	3.42E−01**	−7.00E−03
$mHHEI_{jl}$	−7.00E−02	−4.80E−02
$mBreadth_{jl}$	−5.00E−02**	−5.00E−03
$mShare_{jl}$	2.99E−01*	−1.23E−01
Observations	142,291	
Chi-squared (d.f.)	7918.01 (8)	

$^{**}p < .01$; $^{*}p < .05$.

focal project in t_1 if at that point in time she has a lower share of work than other managers. Hence, the manager's share of work variable meets the relevance condition.[2] To distinguish between the manager's share of work and her absolute workload, and to take into account that the latter may influence project completion times, we include the manager workload control variables ($mLoad_{lj}$ and $mLoad_{ij}$) in both the selection (Stage 1) model and the performance (Stage 2) model. By including these variables in the two models, we aim to avoid endogeneity from omitted variables. That is, once manager workload is included in the model, there is no reason to expect a significant correlation between manager share of work and the error term in either of the stage models. In other words, we expect this variable to meet the exclusion restriction.

In addition to manager share of work and manager workload, we include other variables in the Stage 1 model that may influence selection: managerial depth of experience ($mDepth_{lj}$), Herfindahl–Hirschman Experience Index ($mHHEI_{lj}$), managerial customer experience ($mCustDepth_{lj}$), customer engagement ($custEngagement_{lj}$), and module manager ($moduleMgr_{l}$).

For the Stage 2 model, we specify the selection correction function $\lambda(.)$, a second-order polynomial series expansion of P_{ij}. $[\lambda(P_{ij}) = \phi_1 \times P_{ij} + \phi_2 {*} P_{ij}{}^2]$ using the estimates from the Stage 1 model and include $\lambda(P_{ij})$ in the performance model to estimate selection-corrected parameters for the variables of interest (Dahl, 2002; Wu et al., 2017):

$$\begin{aligned} LN\left(cTime_{ij}\right) = {} & \beta_0 + \beta_1 mBreadth_{ij} + \beta_2 mBreadth_{ij}{}^2 \\ & + \beta_3 complex_j + \beta_4 complex_j * mBreadth_{ij} \\ & + \beta_5 complex_j * mBreadth_{ij}{}^2 + \boldsymbol{\beta} \cdot \boldsymbol{controls_{ij}} \\ & + \phi 1 * P_{ij} + \phi 2 * P_{ij}{}^2 + r_{ij} \end{aligned}$$

where r_{ij} represents a disturbance term assumed to be independent and identically distributed.

The procedure of introducing the first- and second-order terms of the estimated likelihood from Stage 1 offers unbiased and robust estimates. It is also efficient because it captures the multiple selection alternatives (i.e., managers to lead the project) with a limited loss in degrees of freedom (Wu et al., 2017). Tables 3 and 4 show the results for the selection (Stage 1) and performance (Stage 2) models, respectively. The results (Table 4, Model 1) are consistent with those obtained in the main regression model. Correcting for selection bias based on the probability of the best-choice selection (the manager who was chosen) assumes that only the probability of the utility-maximizing choice matters for the parameterization of the distribution function of the error term. Following Dahl (2002), we relax that assumption and use an extended model where in addition to the first- and second-order terms of the best choice probability, we enter the first- and second-order terms of the second-best (manager) choice probability, $\max_l(P_{lj})$ $l \neq i$, into the correction function. The results of this extended model are similar to those obtained with the initially specified correction function. Significant parameter estimates of the new correction function suggest that the extension of the model is appropriate (Table 4, Model 2). Nevertheless, the results remain consistent with those of our main model and indicate a U-shaped relationship between managers' breadth of experience and project completion time contingent on the level of project complexity.

Due to recent commentaries about the potential downsides of selection correction models (Wolfolds & Siegel, 2019), we further triangulate our results regarding the endogeneity concern by estimating an additional model based on the Gaussian copula approach proposed by Park and Gupta (2012). This model includes four generated regressors corresponding to the endogenous variables: the first- and second-order terms of the manager's breadth of experience and their interaction terms with complexity (Blauw & Franses, 2016). After we add the newly generated regressors to the model, the results remain consistent with those of the original model (see Appendix, Table A1), further reinforcing the empirical support for the three hypotheses.

4.3 | Robustness checks

To test the robustness of our results to alternative operationalizations of the independent and dependent variables, we start by following Staats and Gino (2012)

TABLE 4 Results of Dahl's performance (Stage 2) model

	Dependent variable: LN(project completion time)			
	(1)		(2)	
Variables	**Beta**	**SE**	**Beta**	**SE**
$wDepth_j$	3.40E−03	7.13E−03	4.28E−03	7.15E−03
$wBreadth_j$	−5.16E−02	4.49E−02	−3.79E−02	4.50E−02
$wBreadth_j^2$	−8.96E−04	2.77E−03	−1.76E−03	2.78E−03
$wLoad_j$	2.13E−02**	2.63E−03	2.16E−02**	2.64E−03
$mLoad_{ij}$	8.35E−03**	1.23E−03	8.42E−03**	1.24E−03
$mCustDepth_{ij}$	9.12E−03*	4.23E−03	7.75E−03$^+$	4.26E−03
mismatch breadth$_{ij}$	−8.28E−03	1.57E−02	−4.15E−03	1.58E−02
customer engagement$_{ij}$	3.41E−02	7.91E−02	6.71E−02	7.96E−02
$module\_mgr_j$	−2.64E+00*	1.22E+00	−2.72E+00*	1.21E+00
$mDepth_{ij}$	−5.29E−02$^+$	2.82E−02	−4.43E−02	2.85E−02
$mHHEI_{ij}$	−2.44E−01	3.99E−01	−2.89E−01	3.99E−01
$workers_j$	2.95E−01**	3.50E−02	2.97E−01**	3.49E−02
$programming_j$	5.34E−01**	7.11E−02	5.33E−01**	7.10E−02
$pComplex_j$	1.47E−01**	4.95E−02	1.48E−01**	5.13E−02
$mBreadth_{ij}$	−1.70E−01$^+$	9.59E−02	−1.49E−01	9.72E−02
$mBreadth_{ij}^2$	−2.56E−03	7.70E−03	−3.76E−03	7.79E−03
$pComplex_j{*}\ mBreadth_{ij}$	−1.70E−02	2.57E−02	−1.80E−02	2.61E−02
$pComplex_j{*}\ mBreadth_{ij}^2$	7.43E−03**	2.53E−03	7.55E−03**	2.55E−03
Pij	3.12E−01	6.13E−01	6.36E−01	6.27E−01
Pij^2	−5.02E−02	5.66E−01	−2.37E−01	6.18E−01
Pij second_best			−1.09E+00$^+$	6.62E−01
Pij second_best^2			2.22E+00**	7.94E−01
manager (*fixed effects*)	—Included—		—Included—	
module (*fixed effects*)	—Included—		—Included—	
year (*fixed effects*)	—Included—		—Included—	
pclass (*fixed effects*)	—Included—		—Included—	
priority (*fixed effects*)	—Included—		—Included—	
constant	2.72*	1.37E+00	2.56E+00*	1.38E+00
Observations	9765		9765	
Adjusted R^2	0.51		0.51	
R^2	0.54		0.54	

Note: Models 1 and 2 were estimated using clustered robust errors by manager.
$^{**}p < .01$; $^{*}p < .05$; $^{+}p < .1$.

and compute the manager's breadth of experience ($mBreadthAlt_{ij}$) as the number of projects that a manager has led in modules other than the module of the focal project before the beginning of the project. In this case, we again apply log-transformation to deal with the skewness of the variable. The results using this alternative measure are consistent with those in the main model (Table B1, Model 1).

We also repeat the analyses using a different operationalization of project complexity, given that the broader concept of complexity comprises not only the number of elements in a system but also their heterogeneity and interrelatedness (Choi & Krause, 2006; Jacobs & Swink, 2011). Our main measure of project complexity—the number of tasks in the project—captures the first dimension. Two of our control variables—the number of project team members and the presence of programming tasks—relate to the other two facets of the broader notion of project complexity. Project teams that comprise more people tend to be more heterogeneous, and the presence of programming tasks is linked to the heterogeneity of project tasks as well as to the need to coordinate analysts and programmers. To create a measure ($pComplexAlt_j$) that simultaneously captures all three facets of project complexity, we follow Staats and Gino (2012) and use principal component analysis to compute a complexity variable as a linear combination of the three variables. Each of the three variables loads with a positive value on the first component (0.73, 0.85, and 0.67, respectively). The first component's eigenvalue is 1.73, and it explains 58% of the variance. The results of the model using the composite variable (Table B1, Model 2) are consistent with the results reported in the main analysis.[3]

We further test our hypotheses against an alternative measure of project performance, namely, the project *execution time* ($eTime_j$). This is measured as the sum of the hours spent by the members of the project team in the execution of project tasks. We obtain this number based on the information workers submitted daily into the workflow system to indicate how they split their workday on the various assigned tasks. Execution time is a crucial operational performance measure in ERP system services because fewer labor hours translates to lower labor costs. Accordingly, managers of the studied unit used execution time in their own assessments of project performance, and it has been a common outcome variable in other empirical studies in this operating context (Boh et al., 2007; Bonet & Salvador, 2017; Narayanan et al., 2009). We note that shorter execution times cannot be achieved at the expense of functionality because projects are released into the client's ERP system only when they pass quality checks. Reworking and retesting of project tasks that fail the quality check are considered parts of the original project, and the time spent on these components is included in the execution time. For this reason, only a small fraction of projects (approximately 5% in our sample) were rejected directly by clients. As in the case of project completion time, to address the positive skew of project execution times, we apply a natural logarithm transformation in the analyses. Also in this case, the results provide support for the hypothesized relations (Table B1, Model 3).

In addition to alternative operationalizations, we investigate the robustness of the results to alternative model specifications. First, in the main analysis, we estimate clustered errors to allow for heteroscedasticity across managers and potential unknown residual correlations between managers. However, since clustering of errors has received some criticism (Freedman, 2006; King & Roberts, 2014), we repeat the regression model without clustering. This change does not have an impact on our results (Table C1, Model 1).

We also test whether the results are sensitive to unobserved events preceding the data collection. Even though our dataset begins shortly after the organization started its operations, we lack information to measure the experience of managers and workers before the beginning of their tenure in the organization. Following Avgerinos and Gokpinar (2018), we address this problem by dropping from the data all projects led by the 29 project managers who led projects before the beginning of the data collection. The results obtained from the new sample lead to the same statistical conclusions as those derived from the main model, and the coefficient estimates are similar. We hence conclude that the truncated breadth of experience measures that we have for some managers in our main analyses do not bias the results (Table C1, Model 2).

There is also a possibility that managers who acquire broader experience in leading projects previously accumulated broader experience in executing projects as workers, creating a risk of confounding effects. We therefore compute this variable ($mBreadthAsWorker_i$) and find that it correlates with the project manager's breadth of experience, $mBreadth_{ij}$, ($r = 0.35$, $p < .001$). Because of this correlation, managers' technical execution experience ($mBreadthAsWorker_i$) rather than their managerial experience ($mBreadth_{ij}$) might drive project completion time. To eliminate this possible bias, we add $mBreadthAsWorker_i$ as a control to the regression models. This variable is positive and significantly related to the project completion time, but the statistical conclusions, again, remain consistent with the results of the main model (Table C1, Model 3).

Finally, we note that our theoretical arguments suggested that the diseconomies of managers' breadth of experience can be partially explained by their lesser familiarity with the workers. Since the performance effect of familiarity can be studied on its own, too, we follow Staats (2012) and compute a variable that captures the average familiarity of the project manager with the workers of the project team ($mFamWorkers_{ij}$). We added this familiarity variable and its interaction with complexity ($pComplex_j$) to our model to check how sensitive the effect of $mBreadth_{ij}$ is to the inclusion of this control. Support for our hypotheses remains significant upon introducing these familiarity controls (Table C1, Model 4), thus suggesting that familiarity is only one of the possible explanations for the hypothesized effects.

5 | DISCUSSION

With this paper, we contribute to the burgeoning literature on the performance effects of operations managers' experience and the long-standing debate on whether managers should be generalists or specialists. Our findings suggest that project managers breadth of experience has an effect on project completion time, contingent on project complexity. At substantially low levels of project complexity the relationship tends to be monotonically decreasing. However, as project complexity increases, the relationship becomes U-shaped, which suggests that diseconomies from project managers' breadth of experience gain salience. That is, the optimal level of project managers' breadth of experience becomes lower, and the detrimental effect of deviating from that optimum becomes stronger. These results have implications for research and practice in operations and general management.

5.1 | Implications for research

By examining the effect of project managers' breadth of experience on team performance, this study contributes to the growing stream of research on the role of middle-level managers in driving employee and organizational performance. Past studies have focused on other dimensions of managers' experience, such as their experience in leading teams (Choo, 2014; Easton & Rosenzweig, 2012), familiarity with project team members (Staats, 2012), and specialization in the content domain of the project (Easton & Rosenzweig, 2015). However, when managers lead projects in different content domains, they also acquire a broader scope of experience that may affect their ability to plan and supervise projects. For example, Easton and Rosenzweig (2015) found that projects led by managers who interacted with a more connected network of employees performed better than those led by managers who interacted with a less connected network. With our study, we extend this line of research by conceptualizing project managers' previous experience in terms of the breadth of the different knowledge domains in which they have led projects. In broader terms, we extend past research on middle managers, which so far has focused on how they contribute to shaping strategy (Burgelman, 1994; Tarakci et al., 2018; Westley, 1990) and enacting it (Huy, 2002; Rouleau & Balogun, 2011) but—unlike research on top managers—has paid little attention to the performance effects of their experiential background.

Another contribution of this study relates to the nonmonotonic nature of the performance effect of breadth of experience. Past operations management research has established the U-shaped performance effect of breadth of experience at the worker level (Guo et al., 2017; Narayanan et al., 2009). We further elaborate on the dark side of broad experience by showing that project managers' breadth of experience has a curvilinear performance effect such that beyond a certain level, it adds to project completion time. In part, this finding helps reconcile past mixed findings in the long-running debate concerning the virtues and risks of broad experience versus specialization in the managerial profession. While much of the existing research in general management has produced mixed results in favor of either breadth or specialization (Spanjer & van Witteloostuijn, 2017), the results of this study promote the view that moderate breadth of experience is beneficial (Spanjer & van Witteloostuijn, 2017) and that the optimal level depends on the nature of the work that is being managed.

Our work also contributes to the understanding of the contingent nature of the performance effect of breadth of experience. Prior studies at the worker level have found that this effect is moderated by at least mid-course changes in project requirements (Huckman & Staats, 2011), individual-level depth of experience (Staats & Gino, 2012), and team-level diversity of experience (Narayanan et al., 2014). Our study contributes to this stream of research by pointing out how a salient project-level characteristic—project complexity—can moderate the performance effect of breadth of experience. Indeed, project complexity anticipates the level at which the diseconomies of project managers' breadth of experience start dominating its benefits (i.e., the turning point of the U-curve shifts to lower values of breadth of experience). At the same time, project complexity increases the salience of the benefits and diseconomies of project managers' breadth of experience (i.e., the convexity of the U-curve becomes more pronounced).

Finally, our study adds to past research on how project complexity interacts with other project characteristics to drive project performance (Nair et al., 2011). Previous studies have highlighted how project complexity strengthens the effects of team familiarity and team cognitive prowess (Açikgöz et al., 2014) as well as protection from information leakages (Wu et al., 2020) but weakens the positive effect of team knowledge (Cheng & Yang, 2014). Our study is among the first to examine the interaction between project complexity and the characteristics of project managers.

5.2 | Managerial implications

Our findings also offer insights for management practice. Notably, the results indicate that a manager's breadth of experience has a bearing beyond individual-level considerations. Such experience influences the performance of the supervised project teams in a U-shaped pattern that an organization can statistically identify, as we did in our field setting. Specifically, the detection of optimal levels of project managers' breadth of experience provides useful information about the appropriate experience profile that project managers should acquire to improve project completion times. Furthermore, the contingency effect of project complexity suggests that organizations should monitor and match the experience profiles of project managers with project complexity levels. Our findings suggest that under very low project complexity (a single task), project completion time decreases monotonically within the range of the breadth of experience of the managers in our sample. For example, when breadth of experience decreases from its optimal value (i.e., the maximum of the sample range) by one standard deviation (i.e., approximately two modules), completion time increases by approximately 15%, from 9.3 h to 10.9 h (see Table 5). On the other hand, when project complexity is high (7 tasks), the relationship between project managers' breadth of experience and project completion time is U-shaped. At the optimal value of breadth of experience (3 modules), the estimated project completion time is 75.9 h. This is 18% lower than the estimated project completion time (92.9 h) when breadth of experience is one standard deviation below its optimal value and 17% lower than the estimated project completion time (92.1 h) when the value of breadth of experience is one standard deviation above the optimal value.

The conclusions from this study point out that simply following specialization-based heuristics that ignore the interplay of managers' breadth of experience and project complexity can have a negative effect on project performance. In simple projects, the penalty of a mismatch may not be critical, but in complex projects, both insufficient and excessive breadth of experience of project managers hurt performance. By extension, and although not directly examined in our study, the findings suggest that when project portfolios change over time in their average complexity, as a result of strategic initiatives or market forces, it may become critical to recalibrate the experiential profiles of project managers.

5.3 | Limitations and future research

This study is subject to several limitations that are worth noting because they offer opportunities for either methodological improvements or theoretical extensions. First, the secondary data collected from the workflow system of the studied organization did not include information on project quality. As we noted earlier, quality checks were an integral part of the workflow such that nonconformities naturally translated into longer project completion times. In other words, our performance measure includes the additional time spent in rework, and hence, the observed improvements in the project completion time do not disregard the potential costs of "haste making waste." However, there may be subtler dimensions of software quality that we did not capture but that could be fruitfully investigated in future research. For instance, rushed workers may fail to provide proper documentation for the changes that they have made to the software, thereby complicating future projects in the modified parts of the software.

Another limitation lies in the measurement of project complexity. In the context of this study, we could not rely on the typical software engineering measures of complexity

TABLE 5 Level of project manager's breadth of experience that minimizes completion time at different levels of complexity

		Predicted project completion time in hours				
Complexity	Optimal breadth of experience	At optimal level of breadth of experience	At optimal level of breadth of experience − 1 SD (approx. 2 modules)	Time reduction of using optimal breadth of experience	At optimal level of breadth of experience + 1 SD (approx. 2 modules)	Time reduction of using optimal breadth of experience
1	12	9.3	11.0	15%	—	
2	9	22.0	22.6	3%	23.7	7%
3	6	32.7	34.9	6%	36.0	9%
4	5	42.8	45.5	6%	50.1	15%
5	4	52.7	59.2	11%	62.0	15%
6	3	64.0	80.3	20%	71.3	10%
7	3	76.0	92.9	18%	92.0	17%

based on the number of lines of code written (Boh et al., 2007; Staats & Gino, 2012) because most ERP system service projects (84% in our context) do not entail any programming. Therefore, consistent with the sequential nature of task dependency of the projects in the studied setting, we used a simple project complexity metric that has also been used in other studies in this same empirical context (Bonet & Salvador, 2017; Mihm et al., 2003). To mitigate concerns that the measure might oversimplify the concept of complexity, we also used a more articulated measure of project complexity and found support for the proposed hypotheses. However, since this measure had its own disadvantage of lacking a practically interpretable scale, we resorted to the simple measure in the main analyses. Future research might pursue the development of measures that are practically interpretable without compromising the richness of the complexity construct.

Third, our measure of project managers' breadth of experience is based on the scope of software module-specific knowledge accumulated from earlier projects, which is aligned with previous worker-level studies (Boh et al., 2007; Narayanan et al., 2009; Staats & Gino, 2012). However, other studies have conceptualized breadth of experience differently, for instance, as the number of different clients worked with in the past (Clark et al., 2013). Future research could therefore test the robustness of our results in contexts where aspects other than product-specific knowledge constitute the relevant content of managerial experience.

Finally, we must also acknowledge that the software services projects investigated in this study are arguably less complex than, for example, new product development projects, both within the information technology sector (e.g., new software development) and in other (e.g., aerospace, pharmaceutical) industries. It remains an open question whether managers would benefit more (or less) from broad experience under very high project complexity. Future research on the performance effects of project managers' breadth of experience in highly complex contexts could therefore either extend or qualify our results.

In sum, we believe that this paper provides a step toward understanding how generalist project managers can enhance or hinder project completion time and the role that project complexity plays in moderating this managerial breadth of experience–project performance relationship. Looking forward, we note that our investigation reveals several new avenues for future research into the effects of managerial experience and how it optimally aligns with task characteristics.

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ENDNOTES

[1] The R^2 of the model that includes the interaction effects is 54%. This represents statistically significant increases of 2 and 6 percentage points in the variance explained in the project completion time over the R^2 in the models that include the main effects and the control variables, respectively. The magnitude of these changes in the R^2 is in line with observations that interactions "often account for only a few percentage points of variance over and above first order effects" (Cohen et al., 2013, p. 297). Moreover, these increases of the R^2 are compatible with the ones reported in other studies on the operational performance effects of experience (Avgerinos & Gokpinar, 2018; Kc & Staats, 2012; Staats & Gino, 2012). Finally it is worth noting that the correlations among project complexity and control variables such as $programming_j$ (r = 0.19) and $workers_j$ (r = 0.51) may have depressed the increase in the R-squared associated with the introduction of $pComplex_j$ and of the interaction terms.

[2] A selection model with the *workload of the manager* and the *manager share of work* variables as the sole covariates shows that *manager share of work* has a negative and significant effect on the likelihood of the manager being selected to lead the focal project.

[3] The estimates of the first and second-order terms of the project manager's breadth of experience, in models that include interactions with complexity, represent the effect of the breadth of experience variable on project completion time, when the value of complexity is zero. We note that in the model that uses the alternative measure of complexity, the parameter estimate of the second-order term of the project manager's breadth of experience variable is significant. The significance level differs from the one reported in the main analysis (See Model 5 in Table 2) because a value of zero of the complexity variable in this model represents the mean level of complexity of the projects in our sample. Whereas, in the main analysis, it corresponds to a non-existing condition because it represents a project that comprises no tasks.

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APPENDIX: Gaussian Copula Approach—Effect of Managers' Breadth of Experience and Project Complexity on Project Completion Time

Unobserved factors could affect, simultaneously, project manager's breadth of experience and the completion time of the project. If this were the case, the breadth of experience variable and the errors of the model could be correlated, and the parameter estimates of our model could be biased. Thus, in order to ease potential endogeneity concerns we estimate a model following the Gaussian Copula Approach as proposed by Park and Gupta (2012). In doing so we consider the regression model equation:

$$LN\left(\text{Completion time}_{ij}\right) = \beta_0 + \beta_1 mBreadth_{ij} + \beta_n X_{ij} + \epsilon_{ij}$$

Where $mBreadth_{ij}$ denotes breadth of experience of project manager i, X_{ij} is a set of variables that explains the

TABLE A1 Estimation results using the Gaussian copula approach

Variables	Beta	SE
$wDepth_j$	−1.30E−03	7.00E−03
$wBreadth_j$	−4.39E−02	4.16E−02
$wBreadth_j^2$	−1.30E−03	2.58E−03
$wLoad_j$	1.71E−02**	2.46E−03
$mLoad_{ij}$	7.82E−03**	1.17E−03
$mCustDepth_{ij}$	1.11E−02**	4.10E−03
$mismatchBreadth_{ij}$	−1.12E−02	1.51E−02
$custEngagement_{ij}$	6.22E−02	7.18E−02
$moduleMgr_j$	−2.91E+00*	1.36E+00
$mDepth_{ij}$	−1.68E−02	2.39E−02
$mHHEI_{ij}$	−6.24E−01$^+$	3.78E−01
$workers_j$	2.78E−01**	3.21E−02
$programming_j$	4.36E−01**	6.74E−02
$pComplex_j$	−3.87E−01*	1.63E−01
$mBreadth_{ij}$	−6.57E−01**	9.76E−02
$mBreadth_{ij}^2$	3.81E−02**	8.12E−03
$pComplex_j$*$mBreadth_{ij}$	3.18E−01**	3.00E−02
$pComplex_j$*$mBreadth_{ij}^2$	−1.15E−02**	1.68E−03
Copula Terms		
_$mBreadth_{ij}$*	−1.10E+00$^+$	5.94E−01
_$mBreadth_{ij}^2$*	1.02E+00	6.13E−01
_$pComplex$*$mBreadth_{ij}$*	−1.17E−02	7.29E−02
_$pComplex$*$mBreadth_{ij}^2$*	−2.72E−01**	1.62E−02
manager (*fixed effects*)	—Included—	
module (*fixed effects*)	—Included—	
year (*fixed effects*)	—Included—	
pclass (*fixed effects*)	—Included—	
priority (*fixed effects*)	—Included—	
constant	3.02E+00$^+$	1.50E+00
Observations	9765	
Adjusted R^2	0.57	
R^2	0.58	

Note: The model was estimated using clustered robust errors by manager.
$^{**}p < .01$; $^{*}p < .05$; $^{+}p < .1$.

completion time of the project when manager i is in charge of the execution of focal project j, and ϵ_{ij} represents the structural error vector. Because unobserved factors could influence simultaneously project manager's breadth of experience and the completion time of the project, the error, ϵ_{ij}, may correlate with the former, that is $E(\epsilon_{ij} | mBreadth_{ij}) \neq 0$, leading to biased parameter estimates.

The copula method (Park & Gupta, 2012) allows estimating the joint distribution function of the structural error and the endogenous regressor. The joint distribution, in turn, is used to account for and correct for correlation-induced biases, easing endogeneity concerns. The method builds on Sklar's theorem (Sklar, 1973), which states that a joint distribution can be written as a copula function of its margins. Such function can be described as:

TABLE B1 Robustness tests—Alternative operationalization independent and dependent variables

	DV: LN (project completion time)				DV: LN (project execution time)	
	Alternative measure for Manager's breadth of experience (1)		Alternative measure for project complexity (2)		Alternative measure for project performance (3)	
Variables	Beta	SE	Beta	SE	Beta	SE
$wDepth_j$	5.04E−03	7.20E−03	1.39E−02$^+$	7.90E−03	−6.45E−03**	2.24E−03
$wBreadth_j$	−5.46E−02	4.48E−02	−7.37E−02$^+$	4.09E−02	−7.57E−02**	1.16E−02
$wBreadth_j^2$	−6.15E−04	2.75E−03	2.13E−04	2.52E−03	2.95E−03**	7.16E−04
$wLoad_j$	1.99E−02**	2.64E−03	2.50E−02***	2.34E−03	3.14E−03**	6.69E−04
$mLoad_{ij}$	9.64E−03**	1.25E−03	8.89E−03***	1.22E−03	1.14E−04	3.46E−04
$mCustDepth_{ij}$	6.99E−03	5.18E−03	9.63E−03**	4.12E−03	−1.46E−03	1.17E−03
$mismatchBreadth_{ij}$	−1.51E−02	1.54E−02	−9.96E−03	1.50E−02	−3.53E−04	4.23E−03
$custEngagement_{ij}$	6.65E−02	7.51E−02	6.65E−02	7.11E−02	8.58E−04	2.02E−02
$moduleMgr_i$	−2.50E+00*	1.13E+00	−2.66E+00	2.18E+00	−1.65E+00*	6.18E−01
$mDepth_{ij}$	−4.60E−02*	2.36E−02	−6.91E−02**	2.31E−02	6.48E−03	6.58E−03
$mHHEI_{ij}$	−4.90E−01	4.10E−01	−1.08E−01	3.81E−01	−2.24E−01*	1.08E−01
$workers_j$	2.96E−01**	3.62E−02			2.06E−01**	5.65E−03
$programming_j$	5.53E−01**	7.10E−02			4.35E−01**	1.95E−02
$pComplex_j$	1.94E−01**	4.83E−02			8.45E−02**	7.99E−03
$mBreadthAlt_{ij}$	−1.35E−01$^+$	1.16E−01				
$mBreadthAlt_{ij}^2$	−2.18E−02	1.55E−02				
$pComplex{*}mBreadthAlt_{ij}$	−5.97E−02$^+$	3.27E−02				
$pComplex{*}mBreadthAlt_{ij}^2$	1.91E−02**	5.25E−03				
$pComplexAlt_j$			6.91E−01***	7.33E−02		
$mBreadth_{ij}$			−1.90E−01***	6.56E−02	−5.71E−02**	2.05E−02
$mBreadth_{ij}^2$			1.30E−02***	4.76E−03	6.20E−04	1.55E−03
$pComplexAlt_j{*}mBreadth_{ij}$			1.92E−02	2.84E−02		
$pComplexAlt_j{*}mBreadth_{ij}^2$			6.22E−03**	2.57E−03		
$pComplex_j{*}mBreadth_{ij}$					1.79E−03	3.26E−03
$pComplex_j{*}mBreadth_{ij}^2$					1.00E−03**	3.14E−04
manager (*fixed effects*)	—Included—		—Included—		—Included—	
module (*fixed effects*)	—Included—		—Included—		—Included—	
year (*fixed effects*)	—Included—		—Included—		—Included—	
pclass (*fixed effects*)	—Included—		—Included—		—Included—	
priority (*fixed effects*)	—Included—		—Included—		—Included—	
constant	2.69E+00*	1.29E+00	3.49E+00**	1.15E+00	2.27E+00**	6.50E−01
Observations	9765		9765		9765	
Adjusted R^2	0.53		0.51		0.73	
R^2	0.54		0.52		0.74	

Note: Models 1 to 3 were estimated using clustered robust errors by manager.
**$p < .01$; *$p < .05$; $^+p < .1$.

TABLE C1 Robustness Tests—Alternative model specifications and sample

Variables	DV: LN (project completion time)							
	Unclustered errors (1)		Unobserved experience (2)		Manager's breadth of experience as a worker (3)		Manager's familiarity with the team as control (4)	
	Beta	SE	Beta	SE	Beta	*SE*	Beta	*SE*
$wDepth_j$	3.11E−03	7.78E−03	−7.62E−03	2.31E−02	3.37E−02*	1.58E−02	3.25E−02**	1.16E−02
$wBreadth_j$	−5.45E−02	4.04E−02	−7.76E−02	5.94E−02	−1.14E−01*	5.69E−02	−2.24E−02	4.38E−02
$wBreadth_j^2$	−7.53E−04	2.49E−03	3.35E−03	3.70E−03	−1.83E−03	3.32E−03	−3.11E−03	2.69E−03
$wLoad_j$	2.13E−02**	2.32E−03	2.00E−02**	4.12E−03	1.69E−02**	2.97E−03	1.78E−02**	2.62E−03
$mLoad_{ij}$	8.64E−03**	1.20E−03	6.37E−03**	2.21E−03	1.02E−02**	1.50E−03	9.23E−03**	1.21E−03
$mCustDepth_{ij}$	9.96E−03**	4.07E−03	4.89E−02	3.65E−02	−1.78E−03	5.40E−03	4.79E−03	4.10E−03
mismatch $breadth_{ij}$	−8.87E−03	1.47E−02	−1.14E−02	2.31E−02	−1.43E−02	1.85E−02	−1.39E−02	1.56E−02
customer $engagement_{ij}$	5.31E−02	7.02E−02	1.14E−01	9.85E−02	6.38E−02	8.50E−02	6.76E−02	7.39E−02
$module\_mgr_j$	−2.67E+00	2.15E+00	−2.49E+00*	1.25E+00	−2.30E+00	2.18E+00	−2.92E+00*	1.23E+00
$mDepth_{ij}$	−4.44E−02$^+$	2.29E−02	−7.19E−02*	3.27E−02	−3.04E−02	2.80E−02	−5.54E−02*	2.55E−02
$mHHEI_{ij}$	−2.35E−01	3.77E−01	4.56E−01	4.28E−01	−3.67E−02	4.28E−01	−3.07E−01	3.97E−01
$workers_j$	2.95E−01**	1.96E−02	1.97E−01**	2.83E−02	2.48E−01**	3.64E−02	3.04E−01**	3.21E−02
$programming_j$	5.35E−01**	6.77E−02	3.29E−01**	8.64E−02	5.33E−01**	7.64E−02	5.71E−01**	6.99E−02
$mBreadthAsWorker_j$					8.19E−02**	1.52E−02		
$pComplex_j$	1.48E−01**	2.78E−02	2.10E−01**	5.78E−02	1.38E−01**	5.16E−02	1.44E−01**	4.78E−02
$mBreadth_{ij}$	−1.71E−01**	7.12E−02	−2.48E−01**	1.12E−01	−2.34E−01*	1.03E−01	−1.69E−01$^+$	9.01E−02
$mBreadth_{ij}^2$	−2.44E−03	5.40E−03	7.42E−03*	8.61E−03	2.99E−03	8.07E−03	3.62E−03	7.03E−03
$pComplex_j*mBreadth_{ij}$	−1.69E−02	1.13E−02	−1.10E−02	2.55E−02	−1.13E−02	2.59E−02	−1.94E−02	2.24E−02
$pComplex_j*mBreadth_{ij}^2$	7.40E−03**	1.09E−03	5.23E−03*	2.53E−03	6.66E−03**	2.50E−03	4.71E−03**	2.12E−03
$mFamWorkers_{ij}$							−7.37E−03**	5.72E−04
$mFamWorkers_{ij}*pComplex_j$							3.46E−03**	2.73E−04
manager, module, year, pclass and priority (fixed effects)	—Included—		—Included—		—Included—		—Included—	
constant	2.82E+00*	1.14E+00	2.66E+00**	1.34E+00	2.09E+00	2.29E+00	2.99E+00*	1.37E+00
Observations	9765		4013		7400		9765	
Adjusted R^2	0.54		0.41		0.40		0.55	
R^2	0.52		0.42		0.42		0.54	

Note: Models 2 and 3 were estimated using clustered robust errors by manager.
$^{**}p < .01$; $^{*}p < .05$; $^{+}p < .1$.

$$F(x_r, \epsilon) = C(F_{xr}, F_\epsilon)$$

Where x_r represents the endogenous regressor and F_{xr} and $F_\in$ represent the marginal distribution functions of the endogenous regressor and of the error, respectively. Following Park and Gupta (2012), we use the Gaussian Copula in our analysis. The Gaussian Copula assumes that the variables (i.e., the endogenous regressor and the error) feature a joint normal distribution. Thus:

$$C(F_{xr}, F_\epsilon) = N\left(\Phi^{-1}(F_{xr}(x_r)), \Phi^{-1}(F_\epsilon(\epsilon))\right) = N(x_r{}^*, \epsilon^*)$$

Where Φ denotes the univariate standard normal distribution function and N is the bivariate standard normal distribution with correlation coefficient ρ. Or:

$$\begin{pmatrix} x_r{}^* \\ \epsilon^* \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ \rho & \sqrt{1-\rho^2} \end{pmatrix} \begin{pmatrix} \nu_1 \\ \nu_2 \end{pmatrix}$$

where ν_1 and ν_2 are normally distributed and independent random variables. Assuming that F_ϵ is a normal distribution with mean 0 and variance $\sigma_\in{}^2$, the error in the regression model equation equals:

$$\epsilon = F_\epsilon^{-1}(\Phi(\epsilon^*)) = \Phi_{\sigma_\epsilon^2}^{-1}(\Phi(\epsilon^*)) = \sigma_\epsilon \epsilon^*$$

The regression model equation, thus, becomes:

$$LN\left(\text{Completion time}_{ij}\right) = \beta_0 + \beta_1 mBreadth_{ij} + \beta_n X_{ij} + \sigma_{\epsilon_{ij}}\left(\rho mBreadth_{ij}{}^* + \sqrt{1-\rho^2}\,\nu_2\right)$$

In this regression equation, the error term is replaced by two terms. The first, $\sigma_{\epsilon_{ij}}\left(\rho mBreadth_{ij}{}^*\right)$, correlates with the project manager's breadth of experience. The second, $\sigma_{\epsilon_{ij}}\left(\sqrt{1-\rho^2}\,\nu_2\right)$, does not. Dividing the error in such way allows obtaining consistent and unbiased estimates of β_1 because the correlation causing the endogeneity concerns can be accounted for by including the generated regressor, $mBreadth_{ij}{}^*$, in the model. Because our model specification is meant to capture a non-linear relationship between project completion time and the manager's breadth of experience, we include in the model four additional generated regressors that correspond to the four potentially endogenous variables, namely, the first- and second-order terms of manager's breadth of experience and their interaction terms with complexity (Blauw & Franses, 2016). These generated regressors are computed using the expressions: $mBreadth_{ij}{}^* = \Phi^{-1}(F_x(mBreadth_{ij}))$ and $mBreadth_{ij}{}^{2*}$ $\Phi^{-1}(F_x[mBreadth_{ij}{}^2])$ where Φ denotes the standard normal cumulative distribution function (CDF) and F_x represents the empirical CDF of $mBreadth_{ij}$ and of $mBreadth_{ij}{}^2$.

We used the Epanechnikov adaptive kernel function (Van Kerm, 2012) for estimating the marginal density of the endogenous regressors and Stata's akdensity command for computing the corresponding CDF. The copula method is robust to misspecifications of the error, ϵ_{ij}. However, for model identification purposes, the endogenous regressors should be non-normally distributed. We check for normality of the distribution of the endogenous regressors using Stata's sktest, which implements the test suggested by D'Agostino et al. (1990) with the adjustment by Royston (1991). The results of the test suggest that the regressors are non-normally distributed (i.e., the skewness and kurtosis of each variable are significantly different from those of a Normal distribution). The copula method estimation results are consistent with the findings from the main regression model, as shown in the table A1.