EFFECTS OF MANAGERS’ DEPTH AND BREADTH OF EXPERIENCE ON PLANNING AND EXECUTION PERFORMANCE IN SOFTWARE MAINTENANCE PROJECTS

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ABSTRACT

Many studies have examined the benefits and the pitfalls of experience gained by workers, but little is known about the generalizability of these findings to managers supervising the workers. In this study, we investigate the performance effects of managers’ depth and breadth of experience in a project-based setting. We examine whether these two dimensions of experience influence performance of both the managers and those that they supervise. Our findings emphasize the importance of examining the effects of managers’ experience at multiple organizational levels and have practical implications for the work design of supervisory roles.

Key words: task variety; specialization; operations planning; service management; performance

INTRODUCTION

The breadth and the depth of experience are established antecedents of individual performance. In the literature, breadth of experience refers to the variety of tasks an individual has been exposed to, depth of experience to specialization in particular task, and performance to task completion time (e.g. Boehm 1981; Boh et al. 2007; Faraj and Sproull 2000; Narayanan et al. 2009; Reagans et al. 2005; Staats and Gino 2012) or the quality of the outcome (e.g. Austin 1996; Boehm 1981; Fitz-Gibbon 1990; Huckman et al. 2009; Jones 1986). To date, the effects of breadth and depth of experience on performance have been studied only among the workers, who execute the value adding activities of the organization, but not at the level of managers, who plan and supervise the execution of those activities. We argue that managers’ breadth and depth of experience are no less important and have a potentially much wider resonance. Managers’ past
experience does not only plausibly affect their own performance (i.e., speed and quality of decision-making), but also has a bearing on the performance of the supervised workers. What is unclear is the strength and the form of these effects. It is thus crucial to examine the mechanisms through which the experience of managers affects performance.

Past research has consistently shown that the depth of experience has a monotonically positive effect on individual performance (e.g. Boh et al. 2007; Dutton and Thomas 1984; Hatch and Mowery 1998; Narayanan et al. 2009; Reagans et al. 2005; Simon and Chase 1973; Schilling et al. 2003; Staats and Gino 2012), which is in line with the principle of the economies of specialization (Smith 1766) and the learning curve effect (Ebbinghaus 1885; Henderson 1972). In turn, breadth of experience tends to have a reverse u-shaped effect on workers' performance. The positive impact of breadth on worker productivity results from a combination of motivational effects (Fried and Ferris 1987), lower impact of boredom (Warr 2007) and perceived mindlessness of the work (Hackman and Oldham 1976; Herzberg 1968), as well as from synergistic learning arising from experiences in different yet related knowledge domains (Ichniowski and Shaw 1999; Reber 1989; Simon 1991; Tucker et al. 2007; Wiersma 2007; Wulf and Schmidt 1997)—a phenomenon dubbed as "learning-by-doing-something-else" (Schilling et al. 2003). However, as breadth of experience increases diseconomies of breadth take over and the positive effects are suppressed due to the difficulty of human mind to integrate information pertaining to heterogeneous experiences (Hintzman 1990; Johnson and Hasher 1987; Paas and Van Merriënboer 1994) and due to a sense of exhaustion associated with having been engaged in too many distinct activities (Maslach and Jackson 1984; Maslach et al. 2001).

The bulk of the extant research on these effects has been conducted at the workers’ level, and consequently the findings cannot be generalized to the managers' level without empirical support. While the same motivational and learning effects of experience accumulation observed for workers may also contribute to managers’ performance, their impact at managers' level are not necessarily identical to the one at workers’ level. Managers may, for example, benefit more from the breadth of experience because the individuals who take on managerial responsibilities are likely to be better motivated and able to handle a broader mix of activities, while also having richer opportunities to learn from experience due to their greater levels of autonomy, feedback, and skill variety (Hackman and Oldham 1976). On the other hand, learning from experience may be an elusive goal for managers because they need to execute tasks associated with disparate domains involving different clients, products, etc. In these conditions the synergistic learning could be difficult to achieve (Schilling et al. 2003) and the cost of frequently switching among many different tasks may detract from managers' productivity (Monsell 2003; Schultz et al. 2003; Yeung and Monsell 2003). A first goal of this paper is thus to examine how managers' experience impacts proficiency in tasks that they personally execute.

Furthermore, and unlike workers, managers’ experience can also influence performance of people they supervise (Easton and Rosenzweig 2012), thus indirectly affecting organizational performance (e.g. project execution). In this case, the performance effects of experience are even less obvious due to the heightened cognitive complexity associated with the supervisory tasks in
comparison to the non-supervisory tasks, such as project planning. Workers’ performance is not only influenced by managers’ technical experience but also by managers’ experience about skills, attitudes, and characteristics of supervised workers (Staats 2012). It is therefore possible that the additional cognitive requirements associated with memorizing, recalling, and applying workforce related knowledge may call for a different balancing of depth and breadth of experience compared to the managers’ own personal tasks (e.g., project planning). A second goal of this paper is thus to examine how managers’ experience impacts proficiency in tasks that their subordinates execute.

Consequently, we empirically investigate the effects of managers’ depth and breadth of experience in the context of a project-based organization, distinguishing between the effects at managers’ level, on their own performance, and at workers level, on subordinates' performance. To this end, we leverage data from 34,228 projects that have been executed in time span of seven years by software maintenance unit of a multinational consulting and IT company. Software maintenance tasks are highly intangible and cannot be fully codified ex-ante, creating an environment where experience accumulation and learning are very important (Boh et al. 2007). These tasks usually are problem-solving, non-repetitive activities, where the heterogeneity of customer requests can easily trigger diseconomies of breadth for both managers and workers, thus providing an ideal setting for our study. No less important is the fact that software maintenance accounts for the largest part of the life cycle cost of any information system (Banker and Slaughter 1997; Banker et al. 1998; Canfora et al. 2001), making it compelling to study the antecedents of productivity in this context.

Our theoretical arguments and empirical findings address recent calls for behavioral operations research (Bendoly et al. 2010; Boudreau et al. 2003; Gino and Pisano 2008; Loch and Wu 2005), providing novel insights and evidence relative to the economies and diseconomies of managers’ experience in the context of non-repetitive operations.

**THEORY AND HYPOTHESES**

Prior to examining the effects of managers’ depth and breadth of experience, we provide an overview of literature on these effects at workers' level. Breadth and depth of experience are the outcomes of two different work design principles: specialization and task variety. Specialization refers to restricting the responsibilities of an individual worker to few, or even a single, area, whereas task variety refers to assigning tasks across various areas to an individual worker.

The benefits of specialization were explored by Adam Smith's (1982[1766]) research on division of labor, Ebbinghaus's (1885) learning and Henderson's (1972) experience curve principles. There is a general consensus that higher specialization in a given task leads to higher productivity. With higher specialization, a worker becomes more efficient by learning from past experience, incrementally improving the methods applied and becoming more familiar with the processes and tools that are used (Argote 1999; Huckman and Pisano 2006). Aside from relevant
knowledge transfer directly from previous tasks there is also an improvement in the learning ability itself, an effect dubbed "learning to learn" (Ellis 1965). Empirically, the benefits of specialization have been established in the past across various settings, including chess playing (Simon and Chase 1973), industrial engineering (Dutton and Thomas 1984), semiconductor manufacturing (Hatch and Mowery 1998), and healthcare provision (Reagans et al. 2005). In the context of information systems (the context of this paper), it has been shown that more experience in software development is associated with faster development times (Banker and Slaughter 1997; Banker et al. 1998), and experience in a particular software module is associated with shorter resolution times for maintenance tasks in that module (Narayanan et al. 2009). Boh et al. (2007) in their study took an additional step by distinguishing between depth of experience at individual and group levels. Their results demonstrated that depth has a positive effect on productivity at both levels, but its greatest productivity impact is at the individual level.

While there is a general agreement over the positive effects of depth of experience, no similar agreement exists about the effects of breadth of experience on an individual's performance. A number of studies have found the effect to be negative For example, Johnson and Hasher (1987) considered variety of tasks assigned to workers and argued that poor performance follows due to the limitation of human short-term memory. This limitation can seriously hinder processing and storing of large amounts, or complex forms, of information. Paas and Van Merriënboer (1994) described how, in complex cognitive domains, increased variety can inhibit the learning process. Fisher and Ittner (1999) demonstrated how increased task variety at workstations of an automotive plant increases processing time and leads to additional operational complexity and challenges in assigning workers. From the behavioral perspective, increased tasks variety can lead to feelings of being overworked and when accumulated can lead to a "burnout" effect due to mental and emotional exhaustion (Maslach and Jackson 1984; Maslach et al. 2001).

Contrasting the findings about the negative effect, there is also evidence on the breadth of experience leading to improved performance through different mechanisms of implicit learning. Simon (1985) claimed that diverse knowledge might facilitate learning and problem solving skills. Even though an individual might not be aware of it, the similarities between tasks in different domains are being stored in memory—providing opportunities to apply solutions and best practices from one domain to another (Ichniowski and Shaw 1999; Schilling et al. 2003; Tucker et al. 2007; Wiersma 2007) and to transfer applicable skills (Herzberg 1968; Reber 1989; Wiersma 2007). Also the results of Boh et al. (2007) suggested that variety at workers’ individual and group levels can be beneficial to performance. Additional arguments in favor of variety come from behavioral scientists who have claimed that variety increases motivation, engagement and subsequently performance (Hackman and Oldham 1976; Herzberg 1968; Fried and Ferris 1987).

The apparent tension between the positive and negative effects of breadth of experience and workers performance has been recently addressed. The study of Narayanan et al. (2009) showed the benefits of achieving a balance between breadth and depth of experience on workers’ performance, stating that "too much variety" can impede learning. Results of a later study by
Staats and Gino (2012), in the context of repetitive knowledge work, also supported existence of an inverted U-shaped relationship between breadth of experience and workers' productivity.

Yet, despite these contemporary insights into the role of workers’ experience, and despite the suggestions to extend the analyses to managers’ influence on project performance (Edmondson et al. 2001; Huckman and Pisano 2006), the research on the performance effects of managers' experience remains at an embryonic stage. Two recent papers by Huckman et al. (2009) and Easton and Rosenzweig (2012) have partially addressed this call for research, suggesting that team managers' tenure is positively associated with performance. However, these studies conceptualize managers' experience in a very stylized way and do not examine its effects multi-level performance effects of managers' experience.

Therefore, our aim is to extend the current knowledge about the performance effects of experience in two ways. First, we capture in a richer way managers’ experience, by distinguishing between its depth and breadth dimensions. Second, we examine the effects of managers’ experience at two levels: at the level of tasks that are completed by the managers themselves and at the level of tasks that are executed under the supervision of each of those managers. In the empirical setting of this study, the former is represented by project planning performance (hereafter: planning performance) and the latter by project execution performance (hereafter: execution performance). Both of them are further considered two-dimensional, consisting of the processing time (e.g. Boehm 1981; Boh et al. 2007; Faraj and Sproull 2000; Narayanan et al. 2009; Reagans et al. 2005; Staats and Gino 2012) and the failure rate (e.g. Austin 1996; Boehm 1981; Fitz-Gibbon 1990; Huckman et al. 2009; Jones 1986). These
Performance metrics play a key role in the success of the organization, as time and the amount of failures drive cost (Gray et al. 2006; Krishnan et al. 2000) as well as clients’ satisfaction (Kekre et al. 1995; Krishnan et al. 2000; Lapré 2010). Figure 1 provides an overview of the variables and the effects that we examine in the remainder of this paper.

**Effects of Managers’ Experience on Planning Performance**

In the context of software maintenance projects, a fundamental individual responsibility of managers is operational planning: namely, to evaluate whether client's requirements can be fulfilled\(^1\), how they can be fulfilled, and how quickly. The time managers take to complete these tasks, or *project planning time* (hereafter, *planning time*), is an important performance metric because managers need to address a stream of heterogeneous requests from clients while complying with pre-established service level agreements. Prolonged planning time means a decreased responsiveness to clients and may lead to delays in other planning and supervision activities of the managers. An equally important measure is *project planning failure* (hereafter, *planning failure*), which we define as an error in estimating the duration of the project and therefore the delivery time promised to the client. Delays in fulfilling a maintenance request do not only reduce clients' satisfaction and thus damage the reputation of the service provider (Walsh et al. 2009) but they can also create contractual liabilities (Williams 2003) and increased costs (Gray et al. 2006). We therefore consider both the planning time and the planning failure as the measures of *planning performance*.

Conceptually, the mechanisms underlying economies of specialization at workers level plausibly apply to managers as well. Repetition in planning of a specific type of activity—maintenance of specific software module, in our case—implies that much like workers, managers become familiar with typical failure modes, design logic, and nuances of that module (Banker et al. 1998; Banker and Slaughter 1997; Boh et al. 2007). With every repetition, managers’ understanding of how a certain type of activity should be planned is compared with the specific instance of the task at hand. Each comparison promotes an incremental refinement in the managers' understanding of that activity (Jaikumar and Bohn 1992), driving reduction in planning time and decreasing probability of incorrectly estimating project's length. This learning effect is particularly important in the context of non-repetitive work, such as software maintenance and development (Wastell 1999), because slight variations in task characteristics imply that understanding how a certain task type is to be addressed requires the accumulation of a deep experience with relevant software module. We therefore formulate the following hypothesis:

**Hypothesis 1a:** Managers' depth of experience with specific module reduces the time spent in planning how to address clients' maintenance requests within that module

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\(^1\) In the broader context of IT projects, five different surveys have found that project failure rates are typically between 48% to 61% (ITCortex 2002), while other studies have reported that only 16% of all IT projects in the U.S. are completed on time and on budget (Collyer 2000; Ives 2005; Peled 2000).
Hypothesis 1b: Managers' depth of experience with specific module reduces the probability of failure in estimating project delivery date within that module

There are also reasons to expect that managers' breadth of experience has non-monotonic relationship with planning performance, similar to those observed in workers’ level studies (e.g. Narayanan et al. 2009; Staats and Gino 2012). However, in the case of the managers, we suggest that the economies of breadth emerge more from the "learning-by-doing-something-else" effect (Schilling et al. 2003) than from reduced boredom (Warr 2007), mindlessness (Hackman and Oldham 1976; Herzberg 1968) or from increased motivation (Fried and Ferris 1987). This is because of the intrinsically more versatile (Mintzberg 1971) and unstandardized (Whitley 1989) nature of managerial work that makes boredom and alienation less likely than for workers. Additionally, breadth of experience may benefit managers’ planning performance by providing a wider view of how the module that is being maintained is linked to other modules in client’s system. Individual software modules rarely work in isolation from others, and therefore the knowledge of other modules can help in anticipating execution problems tied to inter-module interfaces (Anquetil et al. 2007).

However, while a modest level of breadth of experience can be positively related with planning performance, individuals with excessively broad experience may face a greater challenge in their attempts to navigate, identify, and connect the right dots across their past experiences (Bendoly 2011; 2013). In other words, excessive breadth of experience may hamper learning due to the limitations of the human memory (Hintzman 1990; Johnson and Hasher 1987). We therefore hypothesize a curvilinear relationship between the breadth of managers' experience and the planning performance:

Hypothesis 2a: Managers’ breadth of experience has a nonlinear, U-shaped relationship with the time spent in planning how to address clients’ maintenance requests

Hypothesis 2b: Managers’ breadth of experience has a nonlinear, U-shaped relationship with the probability of failure in estimating project delivery date

Effects of Managers' Experience on Execution Performance

Project managers have more responsibilities than simply planning the work. They are also coordinators and supervisors, as they must oversee project's progress and completion. On occasion, they need to step in and intervene in the execution of the work, to redirect or to serve as mediators for conflicts among workers involved in related tasks within a given project (McManus 1997; Meredith and Mantel 2011). As a result, it is natural to expect that the potential costs and benefits of the depth and breadth of managers’ experience be also reflected in the performance of the people that they supervise. We conceptualize execution performance as
comprised of two components: *execution time*, which we define as the total time spent by workers in executing all project-related tasks, and *execution failure*, which we define as the occurrence of non-conformity in the project output that is serious enough for the client to require re-processing of the project.

Depth of experience provides managers with the knowledge about “technical” requirements for addressing a specific type of project. In addition, it provides them with the "workforce" knowledge required to supervise the projects executed by teams of workers. The workforce knowledge may indicate, for example, where more supervision is needed or where the interests of workers performing interrelated tasks might clash (Chinowsky et al. 2008; Doloj 2009; Schmidt et al. 2009). It can also provide managers with a deeper knowledge of workers who have dealt with the same modules before, and which tasks they have executed most competently for each module. Such knowledge about where the expertise resides is important for both planning the projects (Liang et al. 1995; Faraj and Sproull 2000) and the supervision of their execution (Schmidt et al. 2001). We therefore expect that *execution performance* benefits from depth of managers' experience due to the simultaneous accumulation of both technical and workforce knowledge.

**Hypothesis 3a:** Managers' depth of experience with specific module reduces the time workers spend on the execution of the project's tasks within that module

**Hypothesis 3b:** Managers' depth of experience with specific module reduces the probability of execution failure

The amount of information associated with the workforce knowledge can be sizeable, adding to the complexity of the mental models that managers create to supervise the execution of a specific project type (Johnson-Laird 1983). Incremental refinement of these models, which usually follows the repetition process (Markovits and Barrouillet 2002), becomes increasingly difficult with the additional complexity, reducing the marginal productivity gains normally associated to learning-by-doing (Gary and Wood 2011). It is therefore likely that the performance impact of managerial depth of experience will be weaker at the execution level than it is at the planning level. We propose the following:

**Hypothesis 3c:** Managers' depth of experience has weaker impact on the execution time than on the planning time

**Hypothesis 3d:** Managers' depth of experience has weaker impact on the execution failure than on the planning failure

Similarly to the depth of experience, the breadth of experience provides managers not only with technical but also with workforce knowledge covering different project types. Wider breadth of experience means familiarity with a broader set of workers, their skills, and social dynamics among them. This additional information becomes relevant and potentially critical when it comes
to supervising workers in projects' execution. For example, let us consider a project on software module “A” that indirectly affects module “B”—a typical situation given the common interdependencies across different enterprise software modules (El Amrani et al. 2006; Santamaría-Sánchez et al. 2010). Managers with broader experience should be better able to design a project team that incorporates a mix of workers with knowledge of both modules, team that will be more capable of effectively executing the work. Furthermore, should a conflict occur between workers specialized in these two modules, the managers’ knowledge of both the workers and the nuances of the interactions between modules “A” and “B” may help in resolving the conflict.

We expect that as managers' breadth of experience increases, complexity associated with integration of information across multiple modules becomes increasingly challenging. In line with previous workers’ level studies, we expect to see a threshold beyond which further increases in the breadth of experience yield negative marginal effects on managers' ability to supervise project teams. That is, beyond this threshold, execution performance will be negatively affected by further increases in managers' breadth. We therefore formulate the following hypotheses:

Hypothesis 4a: Managers' breadth of experience has a nonlinear, U-shaped relationship with the time workers spend on tasks at the execution phase

Hypothesis 4b: Managers' breadth of experience has a nonlinear, U-shaped relationship with the probability of execution failure

Although execution performance may benefit from managers’ breadth of experience, integrating knowledge that spans both technical and workforce domains across different modules may be a challenging task. A level of breadth that is beneficial for planning performance could thus be excessive for execution performance, because of the difficulty for the manager to process not only technical but also workforce-related knowledge. Because of these difficulties, errors in recalling previous experiences (Sweller 1989; Jelsma et al. 1990; Paas and Van Merriënboer 1994), excessive economizing on decision-making (Campbell and Gingrich 1986), and learning diseconomies (Argyris and Schon 1978; Edmondson 2002) are more likely to arise, with adverse consequences on managers' ability to supervise project execution. Consequently, we expect the diseconomies of breadth to be more prominent for execution performance than for planning performance, and hypothesize as follows:

Hypothesis 4c: The level of managers' breadth of experience that minimizes project execution time is smaller than the level of breadth of experience that minimizes project planning time

Hypothesis 4d: The level of managers' breadth of experience that minimizes the probability of execution failure is smaller than the level of breadth of experience that minimizes the probability planning failure
In sum, hypotheses 3c, 3d and 4c, 4d suggest that there is an additional cognitive load on managers at the execution stage, which results in: (1) a reduced impact of depth of experience on the execution performance and (2) a shift of the U-shaped relationship between breadth of experience and the execution performance to the left. Figure 2 visualizes the hypothesized effects.

**DATA**

We test our hypotheses using data from a software maintenance unit that belongs to a global IT and consulting corporation. The unit is responsible for servicing the Enterprise Resource Planning (ERP) systems of very large clients. This setting is ideal for examining the effects of experience on performance for two reasons. On the one hand, the inherent uniqueness of software maintenance projects hinders the possibility to tightly codify workers’ tasks making tacit knowledge accumulated through experience essential. On the other hand, this industry is characterized by a fierce competition in terms of price and service levels, making productivity and low failure rates vital goals for organizational viability.

The data we use to test our hypotheses consist of detailed records of software maintenance projects generated over a period of seven years by a proprietary state-of-the-art workflow system, which has been licensed to other subsidiaries of the multinational due to its advanced
features. Over this period of time, the unit has employed over 87 managers and attended to 82 different clients. This accounts for a total of 34,228 projects with complete data from the beginning to the end. We also conducted 30 semi-structured field interviews during a period of two years to ensure correct interpretation the data downloaded from the workflow system.

The general workflow in the studied business unit begins with a client entering a request for service directly into the unit’s workflow system or passing it to a key account manager. Upon receiving a service request from a client, the key account manager evaluates the request and relays it to a relevant project manager. The project manager is responsible for analyzing client's request, planning the execution of the actual software maintenance activities, supervising workers’ activities to ensure that time and functionality goals are met and resolving any emerging problems. Workers execute software maintenance tasks by directly accessing clients’ ERP applications in a test environment. They also document each activity by updating the workflow system with the status of each maintenance task (e.g., received, in process, in testing, etc.) After completion of all tasks, the outcome is passed on to the client for approval or rejection.

Corresponding to the workflow of the business unit, the data collected include detailed project information regarding all service requests, client id numbers, software modules being maintained, levels of priority of the maintenance requests, project managers and workers involved in the projects, project start dates, and the estimated and the actual project end dates. For each project, longitudinal information, such as detailed time spent on each task within the project, was recorded in the workflow system. The measures that were created from this information are detailed in the next section.

**MEASURES**

**Dependent variables**

*Planning time (pTime*<sub>hij</sub>*)*: Time spent by a manager “i” to analyze client's requirements and to plan execution of project “j” in module “h”. Given that the distribution of planning times are positively skewed, we applied customary logarithmic transformation (Cohen et al. 2002).

*Execution time (gTime*<sub>hij</sub>*)*: Time spent by all workers on execution of tasks in project “j”, module “h” under supervision of manager “i”. This variable is calculated from each worker’s daily report of which part of the workday was spent on which task. Although workers self-report this data, this information is considered accurate since inflating the time spent on a task implies deflating the time spent on some other task. This type of work time measurement is common in non-repetitive work settings where expert workers address client-specific requirements (Schmenner 1998). Logarithmic transformation was applied also to this variable.
Planning failure \( (pFails_{hij}) \): This dichotomous variable captures inaccurate estimation of project completion time, thus being a measure of error at the managers' level. \( pFails_{hij} \) equals 1 if project "j", module "h", supervised by manager "i" ended beyond estimated delivery date, and 0 otherwise. The variable is not affected by situations wherein the client asks for such mid-course adjustments that have an impact on the delivery date, because in these cases, the delivery date is renegotiated with the client and adjusted in the data records.

Execution failure \( (eFails_{hij}) \): This dichotomous variable captures situations where the client detects unconformities in the project outcome that require corrective action (external quality failure) from the project team, indicating failure at the execution level. \( eFails_{hij} \) equals 1 if the outcome of project "j", module "h" supervised by manager "i" was rejected by the client, and 0 otherwise.

Independent variables

Managers' depth of experience \( (mDepth_{hij}) \): Number of times that manager "i" has planned execution of projects in module “h” prior to project “j”. This measure of specialization is used in prior studies undertaken in similar settings (e.g. Boh et al. 2007; Narayanan et al. 2009; Staats and Gino 2012). Due to the skewness of the data, a logarithmic transformation was applied. Like all the other experiential variables, \( mDepth_{hij} \) is recalculated prior to each new project, thus reflecting the evolving nature of managers’ experience.

Managers' breadth of experience \( (mBreadth_{ij}) \): Number of distinct types of projects that have been planned by manager “i” prior to the current project “j”. Distinct project types are determined according to project's affiliation to particular software module. Following our goal to test a U-shaped relationship, we also computed a quadratic term of \( mBreadth_{ij} \).

Control variables

Based on the insights of the interviewed managers and previous studies, we included a number of different control variables into the analyses of each level of activity to help account for variance specific to the nuanced nature of projects and tasks. These variables are described in the following paragraphs.

Managers' Herfindahl-Hirschman Experience Index \( (mHHEI_{ij}) \): Measure of experience concentration across various modules. For a given level of \( mBreadth_{ij} \) and \( mDepth_{hij} \) relative to project "j" in module "h", the HHEI control variable captures weather managers’ experience is more concentrated on a few modules or more evenly shaped across modules. In other words, it's a measure of balance between individual's depth and breadth. Even though we did not formally include this managers-level variable within our hypotheses, we include it in the analyses.
following Narayanan et al. (2009), who found it to be a significant predictor of execution time in software maintenance tasks. Specifically, the index is calculated as follows: if \( C_{hij} \) represents the total number of projects planned by manager “i” within module “h” until and not including the project “j”, and \( D_{ij} \) represents the total number of projects handled by manager “i” across all the modules until but not including project “j” then \( P_{hij} = C_{hij}/D_{ij} \) equals to the proportion of projects planned by manager “i” within module “h” across all handled projects, not including “j”. From that, the Herfindahl-Hirschman Experience Index of manager “i” prior to planning of project “j” is calculated as \( m\text{HHEI}_{ij} = \sum_{h} P_{hij}^2 \). An HHEI of 1 indicates that the manager had specialized within just one module. In contrast, when HHEI is at its minimum possible value of \( 1/N \), the managers’ experience is equally distributed across all previously encountered modules. In line with our goal to test the U-shaped effects, we also included a quadratic term of HHEI in our models.

Workers’ Team Depth, Breadth, and Herfindahl-Hirschman Experience Index (\( g\text{Depth}_j, g\text{Breadth}_j, g\text{HHEI}_j \)) capture the project-level averages of depth, breadth and HHEI across the workers involved in the execution of project “j”, similar to Boh et al. (2007). These variables were first calculated for each worker involved in project “j” prior to the start of the project, following the same criteria as for managers’ depth, breadth and HHEI, and then their average was taken. The inclusion of these controls allows us to partial out confounding effects of workers’ experience on execution performance.

**Project priority (priority\(_j\)):** Reflects the amount of time available to complete the project, based on clients’ requirements and pre-negotiated service level agreements categories. The variable assumes integer values from 0 to 9, where lower numbers correspond to lower project priority. Project priority is meant to affect project performance because it motivates both project managers and workers to meet service level agreements and it affects the allocation of organizational resources.

**Managers’ workload (pLoad\(_{ij}\)):** Number of other projects for which manager “i” executed planning activities while planning project “j”. This control is included because past studies have shown that workload may affect both the processing time and the error rate in service operations (e.g. Kc and Terwiesch 2009).

**Total projects completed prior to date (tPriorProjects\(_i\)):** Total number of projects that manager "i" has completed prior to date. This variable reflects overall experience accumulation of a manager.

**Project Type (pType\(_j\)):** This categorical variable reflects the nature of the project "j". The nature of the project in some cases directly affects its planning and execution time. For example, major modification projects that involve developing new features take more time to complete, as compared to corrective maintenance projects. In total, twelve project types were identified and
the categorical variable \( pType_j \) was used to generate 11 dummies to capture the fixed effects of different projects types.

*Client-specific effects control (pClient)_j*: This categorical variable accounts for circumstances unique to specific customers (Huckman et al. 2009), which can affect the measures of dependent variables (e.g. to increase planning and/or execution time).

Table 1 provides correlations and descriptive statistics of all variables included in the final models, with the exception of the categorical variables.

**TABLE 1**

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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4) ( pLoad )</td>
<td>0.2676</td>
<td>0.0501</td>
<td>0.2654</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5) ( \text{PriorProjects} )</td>
<td>-0.0476</td>
<td>-0.0597</td>
<td>-0.0557</td>
<td>-0.0364</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(6) ( \ln_Depth )</td>
<td>-0.1811</td>
<td>-0.1496</td>
<td>-0.0899</td>
<td>-0.3054</td>
<td>0.2069</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(7) ( gBreadth )</td>
<td>0.0793</td>
<td>-0.0692</td>
<td>-0.0129</td>
<td>0.0584</td>
<td>0.0724</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(8) ( gHHEI )</td>
<td>-0.1667</td>
<td>-0.0950</td>
<td>-0.0973</td>
<td>-0.2216</td>
<td>0.0818</td>
<td>0.3590</td>
<td>-0.6172</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(9) ( mHHEI )</td>
<td>-0.0496</td>
<td>-0.0467</td>
<td>-0.0345</td>
<td>-0.1273</td>
<td>-0.0198</td>
<td>0.2640</td>
<td>-0.2458</td>
<td>0.3807</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(10) ( \ln_mDepth )</td>
<td>-0.1723</td>
<td>-0.0799</td>
<td>-0.0738</td>
<td>-0.1696</td>
<td>-0.4767</td>
<td>0.5914</td>
<td>-0.0867</td>
<td>0.3064</td>
<td>0.1832</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(11) ( mBreadth )</td>
<td>-0.0808</td>
<td>-0.0410</td>
<td>-0.0381</td>
<td>0.4893</td>
<td>0.0321</td>
<td>0.1484</td>
<td>-0.0303</td>
<td>-0.5365</td>
<td>0.2097</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(12) ( gTasks )</td>
<td>0.0676</td>
<td>0.5794</td>
<td>0.1003</td>
<td>-0.0425</td>
<td>-0.0275</td>
<td>-0.027</td>
<td>-0.0480</td>
<td>0.0246</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**MODELS AND ESTIMATION APPROACH**

We test our hypotheses using the models outlined in the following equations:

**Planning Performance**

\[
\ln_mTime_{hij} = \beta_0 + \beta_1 \ln_mDepth_{hij} + \beta_2 mBreadth_{ij} + \beta_3 mBreadth_{ij}^2 + \beta_4 mHHEI_{ij} + \beta_5 mHHEI_{ij}^2 + \sum(\beta_i*[control\ variables]) + u_j + e_{hij}
\]  

(1.1)

**Planning Performance**

\[
pFail_{hij} = \beta_0 + \beta_1 \ln_mDepth_{hij} + \beta_2 mBreadth_{ij} + \beta_3 mBreadth_{ij}^2 + \beta_4 mHHEI_{ij} + \beta_5 mHHEI_{ij}^2 + \sum(\beta_i*[control\ variables]) + u_j + e_{hij}
\]  

(1.2)
We applied Hierarchical Multilevel Modeling (HLM) to test our hypotheses, with projects nested within project managers. Running multilevel analysis of repeated measures data, organized by project manager, accounts for those unobserved characteristics of managers, which are project invariant (e.g., managers' background). To verify that HLM is statistically appropriate method, we calculated intraclass correlation coefficient for the base models that had no predictors (Hox 2010). The intraclass correlations (0.2239 and 0.2194 for planning and execution performance, respectively) indicate that about 22% of total variability lies between individual managers, thus justifying the use of the HLM method (Heck et al. 2010).

We employed the `xtmixed` procedure of Stata 11.2 to test the effects on planning and execution time and the `xtmelogit` procedure to test the effects on the probability of the failures, due to their dichotomous nature. We used the maximum likelihood estimator (MLE), which allows comparison of the fit of nested models with fixed effects parameters (Heck et al. 2010). To account for the correlation across time periods, we used first-order autoregressive (AR(1)) specification. In fact, the analysis confirmed that a small amount of autocorrelation existed in the data (~0.25, p < 0.001).

Furthermore, although having a large sample alleviates the effects of multicollinearity (Kennedy 2008), we checked for its presence by running an ordinary least squares (OLS) regression for the full models with all variables included and examined the variance inflation factors (VIFs) and the models’ condition indices (CIs). The VIFs had generally low values with the highest being 2.19. Similar to the study of Narayanan et al. (2009), the only exceptions were, as expected, breadth of experience and HHEI variables with corresponding quadratic terms. However, all relevant estimates were significant with t-statistics higher than two (Kennedy 2008; Maddala and Lahiri 2009) and the CIs below the suggested threshold of 30, indicating that the models were stable (Cohen et al. 2002).
RESULTS

Our findings are summarized in four tables, presenting respectively the results associated to the proposed four models. The tables are organized as follows: the first column contains the base model, the second column includes all control variables, and in the following columns, the variables of theoretical interest are added in separate steps. The last two rows of the tables show the gradual improvement in each successive model—a Chi-square test of change in log likelihood statistics indicates significant improvements in the model and a decrease in residual variance indicated that a model explain a larger portion of variance compared to the previous one.

Planning Performance

<table>
<thead>
<tr>
<th>Table 2a. Planning Time (log) as dependent variable</th>
<th>Table 2b. Planning Failure as dependent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model 1</strong></td>
<td><strong>Model 1</strong></td>
</tr>
<tr>
<td>Intercept</td>
<td>1.3225***</td>
</tr>
<tr>
<td>priority</td>
<td>0.0638***</td>
</tr>
<tr>
<td>pLoad</td>
<td>0.0509***</td>
</tr>
<tr>
<td>tPriorProjects</td>
<td>-0.0003***</td>
</tr>
<tr>
<td>pClient</td>
<td>---</td>
</tr>
<tr>
<td>pType</td>
<td>---</td>
</tr>
<tr>
<td>mHHEI</td>
<td>-2.4987***</td>
</tr>
<tr>
<td>mHHEI²</td>
<td>1.9953***</td>
</tr>
<tr>
<td>ln_mDepth</td>
<td>-0.0799***</td>
</tr>
<tr>
<td>mBreadth</td>
<td>-0.0851***</td>
</tr>
<tr>
<td>mBreadth²</td>
<td>0.0054***</td>
</tr>
</tbody>
</table>

-2 log Likelihood: 96857.512 92136.528 91528.516 90910.692
sd (Residuals): 1.7091 1.5825 1.5147 1.4034

Notes: Number of planners equals 87. N = 34228 observations. ML estimation

The fourth columns of Tables 2a and 2b are the final models for project planning time and planning failure, respectively. The coefficients show that the effects of managers’ depth and breadth of experience are similar to the effects found in the past studies at workers’ level (e.g. Boh et al. 2007; Narayanan et al. 2009; Staats and Gino 2012). As hypothesized, depth of experience decreases the time spent on planning ($\beta_{mDepth} = -0.0750$, $p < 0.01$) and reduces the probability of estimation errors ($\beta_{mDepth} = -0.0608$, $p < 0.01$). Hypotheses $H1a$ and $H1b$ are
therefore supported. Breadth of experience has a U-shaped relationship with the planning time ($\beta_{mBreadth} = -0.0851, p < 0.01; \beta_{mBreadth}^2 = 0.0054, p < 0.01$) and the probability of planning failure ($\beta_{mBreadth} = -0.0538, p < 0.01; \beta_{mBreadth}^2 = 0.0044, p < 0.01$). The minima of U-shape curves for planning time and planning failure correspond to breadth of experience of 7.88 and 6.11 modules, respectively. Since both values fall within the range of the observed values [1-25] for the breadth measure, we conclude that $H2a$ and $H2b$ are supported.

In addition, and as mentioned previously, past research has found that workers’ performance benefits from a balancing of specialization and breadth (Narayanan et al. 2009). As can be seen from the final models results, the linear coefficient of $mHHEI$ is negative and its squared coefficient is positive, both for the planning time ($\beta_{mHHEI} = -2.5355, p < 0.01; \beta_{mHHEI}^2 = 1.7820, p < 0.01$) and for the probability of planning failure ($\beta_{mHHEI} = -1.6242, p < 0.01; \beta_{mHHEI}^2 = 1.0928, p < 0.01$). Since the minima for $mHHEI$ (0.7114 and 0.7431, respectively) fall within the range of observed values, we conclude that managers should also benefit from a balancing of depth and breadth in planning tasks.

**Execution performance**

Prior to testing $H3$ and $H4$, we verified that, consistently with the previous literature (Boh et al. 2007), group-level controls for workers experience are significantly associated with *execution performance*. Specifically, $gDepth$ has a negative impact on execution time and execution failure, while $gBreadth$, and $gHHEI$ have a U-shaped relation with both dependent variables, as in the studies of Narayanan et al. (2009) and Staats and Gino (2012).

The fourth columns in Tables 3a and 3b show the effects of managers’ depth and breadth of experience on the execution time and on the probability of execution failure. In both models, managers’ depth of experience is beneficial for execution performance: $\beta_{mDepth} = -0.0139, p < 0.05$ for the execution time and $\beta_{mDepth} = -0.0347, p < 0.01$ for the probability of execution failure. Thus, hypotheses $H3a$ and $H3b$ are supported.

In order to test $H3c$ and $H3d$, the slope of $mDepth$ in Table 2 (effects on *planning performance*) needs to be compared to the slope of $mDepth$ in Table 3 (effects on *execution performance*). Focusing on Model 4 in Tables 2a and 3a, the absolute value of $mDepth$ coefficient is higher in Table 2a ($\beta_{mDepth} = -0.0750, p < 0.01$) compared to Table 3a ($\beta_{mDepth} = -0.0115, p < 0.05$), suggesting tentative support for hypothesis $H3c$. Statistical comparison of the difference in coefficients yielded $Z= 6.80$ leading to conclusion that the effect of depth of experience on execution time is indeed weaker. When it comes to $H3d$, the comparison of the point estimates again provides tentative support, as the absolute value of the $mDepth$ coefficient on *planning performance* in Model 4 of Table 2b ($\beta_{mDepth} = -0.0608, p < 0.01$) is higher compared to that of the *execution performance* in Table 3b ($\beta_{mDepth} = -0.0196, p < 0.05$). However, statistical comparison of these coefficients resulted in $Z= 1.84$ leading to rejection of $H3d$. Figure 3 reports
the conditional effect plots for the effects of \textit{mDepth} on \textit{pTime} (top left quadrant) and \textit{eTime} (bottom left quadrant).

\textbf{FIGURE 3}

Unlike planning performance, the effect of managers' breadth of experience does not have a curvilinear association with execution performance, as quadratic terms are non-significant. Instead, greater breadth of experience is associated with decreased performance (Figure 3, bottom right quadrant) in terms of longer execution time ($\beta_{m\text{Breadth}} = 0.0553, p < 0.01$) and higher probability of execution failure ($\beta_{m\text{Breadth}} = 0.1568, p < 0.01$). Therefore, hypotheses \textit{H4a} and \textit{H4b} are not supported.

\textbf{Post-hoc Analysis}

A possible explanation for the lack of support for \textit{H4a} and \textit{H4b} is that, in the studied context, managers’ supervisory task is so much more complex than planning task that the minimum of the U-shaped curve moves effectively to the minimum of the scale (i.e., one software module). Such shift, although unexpectedly radical, would be conceptually aligned with the theory behind \textit{H4c} and \textit{H4d}. Therefore, we decided to probe whether such shift could be actually taking place in the data. To do so, we divided the sample into projects of low and high complexity based on the median of the number of separate execution tasks included in them. Since the key argument behind \textit{H4c} and \textit{H4d} is that the increased cognitive complexity of the supervisory task drives the
shift of the minimum to the left, one could expect that the shift would be less radical in projects that have lower overall complexity (i.e., less execution tasks). Consequently, the U-shaped effect on the execution performance and its shift to the left should be visible in the subsample of the less complex projects.

**TABLE 3**

<table>
<thead>
<tr>
<th>Table 3a. Execution Time (log) as dependent variable</th>
<th>Table 3b. Execution Failure as dependent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intercept</strong></td>
<td><strong>Intercept</strong></td>
</tr>
<tr>
<td>1.8558***</td>
<td>4.2327</td>
</tr>
<tr>
<td>(0.0555)</td>
<td>(0.5144)</td>
</tr>
<tr>
<td><strong>priority</strong></td>
<td><strong>priority</strong></td>
</tr>
<tr>
<td>-0.0820***</td>
<td>-0.0328**</td>
</tr>
<tr>
<td>(0.0095)</td>
<td>(0.0149)</td>
</tr>
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<td><strong>tPriorProjects</strong></td>
<td><strong>tPriorProjects</strong></td>
</tr>
<tr>
<td>-0.0002***</td>
<td>-0.0005***</td>
</tr>
<tr>
<td>(0.0029)</td>
<td>(0.0002)</td>
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<tr>
<td><strong>pClient</strong></td>
<td><strong>pClient</strong></td>
</tr>
<tr>
<td>-- significant</td>
<td>-- significant</td>
</tr>
<tr>
<td><strong>pType</strong></td>
<td><strong>pType</strong></td>
</tr>
<tr>
<td>-- significant</td>
<td>-- significant</td>
</tr>
<tr>
<td><strong>glnDepth</strong></td>
<td><strong>glnDepth</strong></td>
</tr>
<tr>
<td>-0.0789***</td>
<td>-0.1039***</td>
</tr>
<tr>
<td>(0.0051)</td>
<td>(0.0375)</td>
</tr>
<tr>
<td><strong>gBreadth</strong></td>
<td><strong>gBreadth</strong></td>
</tr>
<tr>
<td>-0.0094***</td>
<td>-0.0174**</td>
</tr>
<tr>
<td>(0.0016)</td>
<td>(0.0086)</td>
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<td><strong>gHHEI</strong></td>
<td><strong>gHHEI</strong></td>
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<td>-0.4275***</td>
<td>-0.6225**</td>
</tr>
<tr>
<td>(0.0433)</td>
<td>(0.2541)</td>
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<tr>
<td><strong>mHHEI</strong></td>
<td><strong>mHHEI</strong></td>
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<tr>
<td>-0.8178***</td>
<td>-1.8288*</td>
</tr>
<tr>
<td>(0.2597)</td>
<td>(0.9135)</td>
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<tr>
<td><strong>mHHEI</strong></td>
<td><strong>mHHEI</strong></td>
</tr>
<tr>
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<td>1.6540**</td>
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<td>(0.2096)</td>
<td>(0.8264)</td>
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<td><strong>ln_mDepth</strong></td>
<td><strong>ln_mDepth</strong></td>
</tr>
<tr>
<td>-0.0119***</td>
<td>-0.0658**</td>
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<tr>
<td>(0.0054)</td>
<td>(0.0309)</td>
</tr>
<tr>
<td><strong>mBreadth</strong></td>
<td><strong>mBreadth</strong></td>
</tr>
<tr>
<td>0.0553***</td>
<td>0.1568***</td>
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<tr>
<td>(0.0071)</td>
<td>(0.0373)</td>
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<tr>
<td><strong>mBreadth²</strong></td>
<td><strong>mBreadth²</strong></td>
</tr>
<tr>
<td>0.0003</td>
<td>0.0106</td>
</tr>
<tr>
<td>(0.0003)</td>
<td>(0.0095)</td>
</tr>
</tbody>
</table>

Notes: N = 34228 observations. ML estimation.

The results of the post-hoc tests support our conjecture that the underlying cross-level relationship is U-shaped and the shift to the left occurs as stated in Hypothesis H4c. In the low project complexity sample, when execution time was used as the dependent variable, the mBreadth coefficients ($\beta_{mBreadth} = -0.0037, p < 0.10$; $\beta_{mBreadth}^2 = 0.004, p < 0.01$) yielded a U-shape minimum at 4.63, which is smaller than the minimum of 13.85 ($\beta_{mBreadth} = -0.0666, p < 0.01$; $\beta_{mBreadth}^2 = 0.0024, p < 0.01$) at the planning level that was calculated using same subsample (Figure 4). With regard to the effect on execution failure, $\beta_{mBreadth}$ had negative sign but $\beta_{mBreadth}^2$ remained insignificant, thus Hypothesis H4d was not supported. In conclusion, it appears that managers’ breadth of experience benefits also execution performance, measured as execution time, but only if the overall project complexity is limited. Otherwise, the additional

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As expected, in the high project complexity sample the effect of mBreadth on eTime remained positive ($\beta_{mBreadth} = 0.0779, p < 0.01$ and $\beta_{mBreadth}^2$ insignificant).
cognitive complexity of the supervisory task becomes overwhelming and moves the optimum breadth of managerial experience to the minimum of its scale. As we can see the complexity also has its bearing at managers’ level (the minima of 13.85 in low complexity subsample versus 7.88 in the full sample), though not so drastic that it would eliminate the beneficial part of the curve.

**FIGURE 4**

Robustness Checks

In order to test the robustness of our results, we conducted a number of additional tests. First, we confirmed that the results of the previous studies can be replicated with our data at the level of individual workers. To do so, we replicated the analysis of Narayanan et al. (2009) using the data from the execution stage of projects. The outcomes led to the same statistical conclusions as in that study, further supporting the legitimacy of our data and context.

Second, the tests were repeated for two alternative operationalizations of the depth of experience. For the first alternative operationalization, we used the actual hours spent on tasks in different modules instead of the number of times that the tasks were completed. This way, the measure took into account the intensity of involvement. To illustrate this, let us consider two cases of work performed in particular module. In the first case, an individual spends eight hours and in the second only one hour. *The count measure* treats these two cases the same, resulting in the
specialization score of two. Meanwhile, the *hourly measure* takes into account the time, resulting in the depth score of nine. In another alternative operationalization, we assigned weights to the hours spent on the tasks according to the time that had passed since their completion (i.e. weight equals to time lag). The idea is that eight hours spent on a task in particular module yesterday will have a larger contribution towards the depth of experience, in comparison to the eight hours spent on a task in the same module a month ago. This accounts for the limitations of human memory and the fact that the experience acquired may decay with time (Huckman and Staats 2011). As an alternative operationalization of the breadth of experience, we used the total number of tasks in other modules than the current one. This approach was also used by Staats and Gino (2012) as an alternative operationalization. The use of these alternative measures for breadth and depth resulted in only minor differences in the coefficients and did not affect the statistical conclusions.

Third, we repeated the analyses with additional control variables that could potentially affect the findings. For example, we added variables that controlled for date, temporal distance between two tasks within the same module (the further apart those tasks the lesser is the effect of depth), various group level averages, and whether or not the manager was promoted within the company (and therefore knows its environment well) or hired from outside. Including the additional control variables did not affect the statistical conclusions. Given these results, we opted to report the main results with a limited set of control variables, following the recommendations of (Spector and Brannick 2011).

Finally, as the effects of the breadth and depth of experience may vary across managers with different individual characteristics (Haas 2006; Huckman et al. 2009; Lapré 2010), we allowed for random effects parameters to covary freely, which did not lead to an improvement in the model's fit.

**DISCUSSION**

Our results extend past research, which has found a positive relationship between workers’ depth of experience and performance, and an inverted U-shaped relationship between workers’ breadth of experience and performance. In a study of a project-based software maintenance organization, we show that the results of past research at workers’ level can be generalized to managers as far as project planning performance is concerned. Furthermore, we demonstrate that managers’ depth and breadth of experience have different effects on *planning performance* and *execution performance*, and that these effects are influenced by the project complexity. The practical relevance of these results for work design accrues from our focus on low-level managers directly supervising workers. A clear understanding of economies and diseconomies of breadth of experience for low-level managers can have momentous effects on firm performance, since such understanding can be incorporated in the specification of requisite characteristics and formal responsibilities for low-level managers—one key aspect in designing the core value-adding processes of any company.
Theoretical and Practical Implications

Our findings support the direct generalization of the results of past workers-level research to managers as far as planning performance is concerned. We find that managers’ depth of experience reduces both the planning time and the probability of planning failure, and that managers’ breadth of experience has a U-shaped association with these measures of planning performance. The contribution of this finding is twofold. First, this generalization could not be taken for granted, because the different skill requirements for managers and workers may affect the magnitude and perhaps even the existence of the relationship between experience and performance (Huckman et al. 2009). Second, we provide evidence in support of the "learning-by-doing-something-else" effect at managers’ level. Past empirical workers-level research has, in fact, left open the question of whether the positive effects of the breadth of experience on productivity are due to the "learning-by-doing-something-else" or the reduced boredom and mindlessness. Our analysis partially addresses this issue because managers are less likely to experience boredom and mindlessness than workers, due to the inherently greater levels of autonomy, skill variety, and feedback (Hackman and Oldham 1976). The presence of the economies of breadth at managers’ level thus provides novel evidence in favor of the "learning-by-doing-something-else" phenomenon.

The practical implications for planning performance can be assessed by looking into the effects sizes of managers’ depth and breadth of experience. We found that managers who had accumulated an experience of approximately forty projects in the same software module enjoyed a 26.76% reduction in the average time spent on planning a new project, corresponding to 1.21 hours. As for the effects of breadth of experience, moving from the optimum level of breadth (7.88 modules) to the 100th percentile (25 modules) increases the average planning time by about by 33.30% (corresponding to 1.58 hours). This is a non-trivial performance penalty if we compare this number to the average planning time (1.56 hrs).

Another contribution of our study is demonstrating that managers’ depth and breadth of experience have effects on the performance of the workers that are under their supervision, and that these effects are different from the ones found on planning performance. On the one hand, we find that the managers’ depth of experience has a positive effect on execution performance, but this effect is weaker compared to planning performance. On the other hand, managers' breadth of experience has a negative effect on execution performance, at least for comparatively more complex projects. For the projects of lower complexity, the relationship is curvilinear but, in line with the theory behind our hypotheses, the level of breadth of experience that optimizes execution performance is smaller compared to one that optimizes planning performance. These findings are important for at least two reasons. First, we extend previous research which has found support for the positive association between the number of projects that managers have supervised in the past and current project success (Easton and Rosenzweig 2012; Huckman et al. 2009). By decomposing managers’ experience into its breadth and depth components, we found that the former is not always beneficial for execution performance. Second, our results show that the "learning-by-doing-something-else" effect is not universal, as the effects of managers’
breadth of experience on project execution time can be monotonically negative, at least in the case of very complex projects. Post-hoc analysis reveals that complexity has a contingency effect on the presence of economies of breadth, as far as cross-level effects are concerned. These results are important because workers-level experimental (Schilling et al. 2003) and empirical studies (Narayanan et al. 2009; Staats and Gino 2012) has so far not found any boundary conditions to the "learning-by-doing-something-else" effect.

From a pragmatic standpoint, managers’ depth and breadth of experience have a nontrivial impact on execution performance. In our sample, accumulation by of approximately 40 repetitions of the same project type reduces execution time of similar projects by 17.47% (corresponding to 1.04 hours). Similarly, as managers’ experience expands to cover one more module execution time increases by 18.64% (corresponding to 1.11 hours).

**FIGURE 5**

![Scatter plots](image)

a. Managers experience **not included** in the model

b. Managers experience **included** in the model

One of the things that define whether the theoretical model is practically relevant is its predictive ability. Having extensive dataset allowed us to test how well our model fares in comparison to the models developed in past workers’ level studies. We excluded from our data 1000 random projects and used the rest to calculate "workers" only model and "workers and managers" model, where we take into account the effects from the managers’ level. We then applied these models for execution time prediction in the excluded projects. Figure 5 shows the scatter plots for both models, demonstrating that both models have some predicting power ($R^2 = 0.3798$ and 0.5048, respectively), with the model including the managers’ experience providing more precise predictions. These plots support the importance of inclusion of managers' level variables into models that software maintenance units may develop to address the need to estimate capacity requirements associated to customers’ requests.
LIMITATIONS AND VENUES FOR FUTURE RESEARCH

A limitation of our study is related to the measures of planning and execution failure, which were measured through dichotomous variables that do not quantify the extent of a failure. This metric limitation potentially explains the weaker empirical support for \( H_{3d} \) and \( H_{4d} \) compared to \( H_{3c} \) and \( H_{4c} \), which were examined using continuous measures as dependent variables. Second, our analysis used hierarchical linear modeling with longitudinal clustering of data by manager in order to identify general patterns across managers. Although this specification is meant to account for individual demographic differences it would be desirable for future research to look into specific demographic factors that more richly capture other contributing factors to managers’ performance, such as education level, skills, etc. The inclusion of such variables could increase the accuracy of the model’s predictions. Third and last, we used data from a single organization. This research design choice enabled us to examine in depth the links between the variables of interest in our hypotheses, but it also limits the generalizability of our findings. In particular, it would be interesting to examine whether our findings extend to managers operating in other contexts characterized by higher (e.g., back-office bank operations) or lower (e.g., strategic consulting) levels of repetitiveness.

CONCLUSIONS

Our study suggests that viewing the role of managers as detached from work once it is in the hands of workers would not reflect what happens in practice. We find that effects of managers’ experience, and especially of its breadth, are different depending on the level where performance is examined (i.e. planning versus execution performance). Had we examined the effects of managers’ experience only at one level, our results and the consequent prescriptions would certainly be misleading. Our findings suggest that future research should explicitly consider multilevel implications of different aspects of managers’ influence on organizational performance, or run the risk of reaching misleading conclusions. It also suggests that project complexity is an important contingency variable that affects the presence of economies versus diseconomies of breadth. Pragmatically, job design efforts should evaluate carefully the balancing of depth and breadth not only of workers but also of supervisory roles.

References


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