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Working Paper

09-035

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Addressing the Knowledge Acquisition-Application Problem

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September 8, 2008

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Acknowledgments

We thank Alexis Samuel, Vidya Sridhar, Sambuddha Deb, and many others at Wipro for their substantial dedication of time and effort to this endeavor. This paper benefited from the thoughts and comments of Amy Edmondson, Lee Fleming, Andy King, Gary Pisano, and David Upton. We are grateful to the Division of Research of Harvard Business School for generous funding. All errors remain our own.

Abstract

Prior work in organizational learning has failed to find a consistent effect of variation in experience on performance. While some studies find a positive relationship between these two variables, others find no effect or even a negative relationship. In this paper, we suggest that the differences in prior findings may be due to the failure to separate the processes of knowledge acquisition and knowledge application. While variation in experience may permit the *acquisition* of valuable knowledge, additional mechanisms may be necessary to enable the subsequent *application* of that knowledge in a team setting. We hypothesize that *team familiarity* – prior experience working with team members – may be such a mechanism. We use detailed project- and individual-level data from an Indian software services firm to examine the effects of team familiarity and variation in market experience on multiple measures of performance for over 1,100 software development projects Consistent with prior work, we find mixed results for the effect of variation in experience on performance. We do, however, see evidence of a moderating effect of team familiarity on the relationship between these two variables. Our paper identifies one mechanism for uniting knowledge acquisition and knowledge application and provides insight into how the management of experience accumulation affects the development of organizational capabilities.

Key Words: Experience, Knowledge, Software, Team Familiarity, Variation

Introduction

Prior work attempting to link variation in experience and performance has found effects running the gamut from positive (Schilling et al. 2003; Wiersma 2007) to neutral (Darr et al. 1995; Cummings 2004) to negative (MacDuffie et al. 1996; Fisher and Ittner 1999). We seek to explain these differential results by examining the underpinnings of the relationship between variation in experience and performance in a team setting. In particular, by drawing on related work from both learning and knowledge management (Argote 1999; Argote et al. 2003) and social networking (Hansen 1999; Reagans and Zuckerman 2001), we suggest that, in many cases, the differences in prior findings reflect a failure to separate the processes of knowledge acquisition[1] and knowledge application. Through diverse experiences, individuals may acquire valuable knowledge and an awareness of the potential application of the knowledge to a new setting (Burt 1992; Hargadon and Sutton 1997; Reagans and Zuckerman 2001). This knowledge, however, may not be applied successfully in the new setting. For example, if a leader with valuable, diverse experience joins a new team, the team initially may be unable or unwilling to use a new approach recommended by that leader (Katz and Allen 1982; Kane et al. 2005). In other words, conditions that assist in the acquisition of useful knowledge, such as variation in experience, will not guarantee—and may even deter–the eventual application of that knowledge. We label this *the knowledge acquisition-application problem*.

In this study, we seek to identify a theoretical mechanism that has the potential to address the knowledge acquisition-application problem. We hypothesize that team familiarity – prior experience working with other team members – is one such mechanism. Team familiarity helps team members successfully locate knowledge within a group, share the knowledge they possess, and respond to the knowledge of others (Edmondson 1999; Gruenfeld et al. 2000; Edmondson et al. 2001; Lewis et al. 2005). This last point suggests that, while team familiarity may help all teams to better coordinate their

[1] An epistemologist would say that knowledge is not acquired, but rather created, since it is only when an individual interprets information that knowledge comes into being (C.f. Nonaka 1994). For the purposes of this paper the important point is that, regardless of the process, an individual eventually has the new knowledge.

actions, (Reagans et al. 2005; Huckman et al. 2008), it may play a particularly important role for teams with individuals looking to apply knowledge from their varied experience. This possibility leads to the question that serves as the foundation for this paper: does team familiarity moderate the relationship between variation in experience and performance?

As a significant amount of organizational knowledge resides at the level of the individuals within an organization (Nelson and Winter 1982; Walsh and Ungson 1991), we examine variation in experience at this micro level (Argote and Ingram 2000). The empirical setting for this paper is Wipro Technologies, one of the leading firms in the Indian software services industry. In software services, work is completed by project teams, so by exploring individual experience and team performance, we examine the core activity of the organization. This context is not only representative of a knowledge-based organization, but due to the significant coordination demands of software, experience plays an important role in driving performance (Krishnan 1998; Faraj and Sproull 2000). One of the challenges in studying the linkage between variation in experience and performance in the field has been identifying settings that offer the combination of detailed information on experience, objective measures of team performance, and the requisite controls. This setting offers all three. We evaluate performance of roughly 1,100 software development projects completed over three years. We couple this information with detailed human capital data (for over 13,000 individuals) that allows us to track the experience accumulation of individuals over a longer period of time.

We focus on the variation in market experience of project managers (PMs). PMs have full operational control of projects. We are able to examine the individual experience of leaders, as well as their experience working with other team members. Thus, while controlling for other types of experience, we examine both the main effect of variation in project managers' experience and whether team familiarity moderates its relationship to different performance measures.

We find that a project manager's team familiarity is positively related to both delivery and quality performance. Consistent with prior work, we also find that the relationship between variation in experience and the different measures of performance is sometimes positive, sometimes negative, and often statistically indistinguishable from zero. When we examine the interaction of project manager team familiarity and variation in experience, we see a moderating effect of team familiarity on the relationship between variation in experience and performance. This final result suggests that team familiarity may be one mechanism for increasing the likelihood that acquired knowledge is ultimately applied by teams.

Variation in Experience, Performance, and Team Familiarity

The learning curve – the positive relationship between increasing cumulative production experience and performance – has served as the foundation for the study of learning in organizations since Wright's (1936) initial work (Yelle 1979; Argote 1999). The basic relationship between experience and performance has been shown to hold for organizations, teams, and individuals (e.g. Newell and Rosenbloom 1981; Argote et al. 1990; Cohen and Bailey 1997; Delaney et al. 1998).

The strength of this relationship may vary across actors (Dutton and Thomas 1984; Pisano et al. 2001), and prior work has identified three classes of explanations for these differences: (1) structure; (2) resources; and (3) knowledge. Structural choices such as work design or team size may serve as ex-ante enabling conditions for more effective performance (Hackman 2002). Alternatively, organizations may devote differing amounts of resources to improvement (Sinclair et al. 2000). Finally, the underlying relationship between experience and performance may be driven by the knowledge that the focal actor acquires through experience and subsequently applies (Argote et al. 1990; Argote 1999; Huckman and Pisano 2006). This knowledge can take many forms and may be related to understanding: (1) other production *team* members (Reagans et al. 2005); (2) the *customer* (von Hippel 1994); (3) the production *technology* being used (Hirsch 1952); and (4) the *role* one holds in the production unit (Huckman et al. 2008).

While the linkage between knowledge and performance is well established, the question of how relevant knowledge is acquired remains open. There is significant scholarly debate over whether knowledge and subsequent performance is maximized through the repeated completion of the same task or by the execution of different, albeit related, tasks. Empirical work offers important clues, but has not resolved the debate, as various results show positive, negative, and non-existent relationships between variation in experience and performance (Darr et al. 1995; Fisher and Ittner 1999; Schilling et al. 2003)

Whether stated explicitly or implicitly, the commonly held view of organizational learning has been that performance is improved with repeated execution of the same task. Even from the early work of Smith (1776) and Taylor (1911), the standardization mindset has been pervasive. As noted by Schilling et al. (2003), the traditional formulation of the learning curve as $y = ax^{-b}$, where x is the number of times that a specific task has been repeated, suggests that repeated focus on the same task leads to the best performance and is the appropriate objective.[2]

The above view has likely become so widely accepted due to its overwhelming empirical support. Numerous studies across varied industries have noted the advantages of focus (Skinner 1974) in building knowledge around a specific task (see Yelle 1979; Argote 1999 for reviews). Additionally, a long line of work in psychology has shown that individuals improve both their productivity and quality with repeated execution of the same task (e.g. Thurstone 1919; Harlow 1949; Newell and Rosenbloom 1981). By focusing on the same task, a problem solver is able to gain an understanding of the relevant causal linkages (Bohn and Jaikumar 1992). Focus also aides process improvement as unnecessary steps are eliminated and sub-processes are optimized (March and Simon 1993). Work in problem solving suggests that individuals need very deep knowledge to become *experts* (Lenat and Feigenbaum 1987). For example, building on Simon's earlier work (Chase and Simon 1973), Gobet and Simon (2000) propose that a grand master in chess has acquired about 300,000 units of knowledge which are used to successfully play the game.

Variation in Experience Revisited

Traditionally, the question of whether one should complete diverse tasks has either not been considered, or has been answered in the negative, as diverse activities may be distracting and take the problem solver's focus away from critical issues (Skinner 1974). Schilling et al. (2003) reinvigorate this

[2] This formulation does, however, assume decreasing marginal returns, suggesting that over time, some sort of new thinking may be required to maintain an absolute amount of improvement.

debate, arguing theoretically and showing empirically that variation in activities may be good for performance. Their results from a laboratory experiment show that subjects' performance on the game, *Go*, is maximized through experience playing a related game. Several theoretical arguments support the positive linkage between variation in experience and performance suggested by these results.

First, the completion of related tasks may help a problem solver develop schema (Schmidt 1975; Gick and Holyoak 1980) or high-level organizing principles. If schema can be transferred from the related setting to the focal one, they may offer a new and perhaps improved approach to the problem at hand. For example, analogical problem solving uses this principle to map knowledge from one area to a potentially related one (Gick and Holyoak 1983; Gavetti et al. 2005). These findings are quite similar to work in innovation and product development. Clark (1985) suggests that product development involves moving up and down a design hierarchy. High-level processes are established enabling problem solvers to improve lower level components (i.e., move down the hierarchy). However, addressing roadblocks at lower levels may involve revisiting previous decisions at higher levels (i.e., climbing back up the design hierarchy). Since higher levels tend to involve more complex problems that rely on diverse knowledge bases (Simon 1962; Nickerson and Zenger 2004; Boudreau et al. 2008), a schema developed from multiple areas may provide the opportunity to reach a synthesized solution or simply borrow a solution from one area for application to another (Hargadon and Sutton 1997). This pattern is consistent with the observation that novel breakthroughs often involve the application of ideas from an area previously thought to be unrelated (Kuhn 1962; Fleming 2001).

Variation in experience may also be helpful in learning about the process of learning itself (C.f. Ellis 1965; Argyris and Schön 1978). While performance improvement from increasing cumulative experience may be due to learning it may simply be a result of increased scale (e.g. fixed costs being spread over a larger number of units). Inertia is a pernicious foe and many individuals and organizations may fail to attempt to improve even when the opportunity exists (Tushman and Romanelli 1985). March (1991) identifies a related key tension within organizations as that between exploration, or doing new things, and exploitation, continuing the status quo. Over time, the repetition of the same tasks (or processes) may lead to competency traps or core rigidities (Levitt and March 1988; Leonard-Barton 1992). As an organization loses its adaptability, its long-term survival may be compromised (Abernathy 1978), suggesting that organizations need dynamic processes for fostering learning and exploration (Teece et al. 1997; Brunner et al. 2008). As such, even if the knowledge acquired through diverse experience is not directly related to the focal task, the gains from learning how to learn, as well as the trigger that different tasks provide may be beneficial (C.f. Zollo and Winter 2002).[3]

Despite a strong theoretical argument for a positive relationship between varied (albeit related) experience and performance, empirical support for this relationship remains limited. The lab study of Schilling et al. (2003) offers a potentially intriguing clue. In their setting, teams are kept together while playing the different games, suggesting that an increase in team familiarity may enable teams to work better together (Reagans et al. 2005). Increases in team familiarity, however, may not just improve performance directly (Littlepage et al. 1997), but may also moderate the impact of variation in experience on performance. This premise is also consistent with the study of Darr, Argote and Epple (1995). While they do not find a relationship between variation in experience and performance, their setting, pizza stores, had annual employee turnover of around 300% (i.e., the stores were characterized by low team familiarity). This insight suggests what is potentially a more general problem: conditions that assist in the acquisition of useful knowledge (e.g. variation in experience) may not aide, and may even deter, its subsequent application. We now explicate and examine this issue – *the knowledge acquisition-application problem*.

The Knowledge Acquisition-Application Problem

The unclear relationship between variation in experience and performance is reminiscent of the long standing debate about the relationship between demographic diversity and performance. The empirical results regarding this issue are decidedly mixed with the occasional positive and negative finding, surrounded by many inconclusive results (Williams and O'Reilly 1998; Pelled et al. 1999). Using social

[3] Along with employee motivation, this reason is part of why some manufacturing firms use job rotation programs (Walker and Guest 1952; MacDuffie 1995).

network theory, Reagans and Zuckerman (2001) change this discussion. Their central insight is that demographic diversity leads to a differential impact on network density and network heterogeneity, each of which may independently have a positive impact on performance. With increasing demographic diversity, network density decreases (with negative performance implications [Coleman 1988]) while heterogeneity increases (with positive performance implications [Burt 1992]), thus making the relationship to performance unclear. While network density and heterogeneity *may* move in opposite directions, they need not do so, due to the different characteristics of global (i.e., outside of the team) and local (i.e., inside of the team) structural holes.[4] While bridging global structural holes may bring in innovative thinking and new ideas, closing local structural holes can build team familiarity and both of these effects may improve performance.

This framework may assist with our own puzzle. In practice, when individuals acquire varied experience they are not only gaining the potential benefits already discussed but are also building a more diverse network. When confronted with new problems, they thus may be able to leverage their broader network to acquire relevant knowledge from a previously unrelated area (Hargadon and Sutton 1997). However, even with a greater ability to *acquire* new knowledge, individuals may struggle in its subsequent *application* in a team production setting if the level of team familiarity is low.[5]

Prior work has shown that team familiarity has a positive relationship with performance (Liang et al. 1995; Littlepage et al. 1997; Moreland et al. 1998; Huckman et al. 2008). Team familiarity helps members locate knowledge within the group, share knowledge and coordinate their actions (Katz 1982; Edmondson et al. 2001; Reagans et al. 2005). Beyond its main effect on performance, team familiarity may play an important moderating role as well. When an individual is new to a group, the group may suffer not only from coordination difficulties due to low team familiarity, but also from a lack of trust impacting collective action (Coleman 1988; Kane et al. 2005). For example, Gruenfeld et al. (2000), find

[4] Burt (1992) argues that when two networks are not connected by ties there is a structural hole and that individuals can create value for themselves by filling the hole and brokering information between the two groups.
[5] We note that in most organizations, individuals are not rotated through diverse experiences together.

that when a new member joins an established group, the existing group is less likely to apply the new member's valuable knowledge than existing members' knowledge.

These findings suggest that even if an individual gains valuable knowledge from his or her diverse experience and uses this knowledge to identify a novel solution to a problem, he or she may struggle to apply the knowledge. Thus we are left with the *knowledge acquisition-application problem*. This problem describes a general phenomenon, parts of which have been examined in recent studies. For example, Hansen (1999) identifies the search-transfer problem – while weak ties help in the location of new knowledge, when the knowledge is complex, strong ties are required for its successful transfer. Sorenson (2003) notes that even when organizations identify valuable new knowledge, the interdependence between the new knowledge and existing knowledge within the firm (e.g. as resident in routines) may limit the ability of the organization to act upon the new knowledge. Obstfeld (2005) identifies the idea-action problem. He suggests that trading off of the valuable knowledge of others is not the only way that individuals can use their favored place within a network. Rather they can play a coordinating role that increases their likelihood of participating in innovation. Fleming et al. (2007) note that "collaborative brokerage can aid in the generation of an idea but then hamper its diffusion and use by others (p. 443)." Finally, in his study of alliances, Tiwana (2008) finds that the combination of bridging ties with strong ties improves knowledge integration. We suggest and empirically test the proposition that team familiarity may help address the knowledge acquisition-application problem by moderating the relationship between variation in experience and performance.

Setting, Data, and Empirical Strategy

Setting

The setting for our analysis is Wipro Technologies, a leading Indian firm in the outsourced software services industry. Wipro offers its customers a wide array of services including software development, research and development, business process outsourcing, and IT consulting. Though headquartered in India, the company executes projects for its clients around the world both at customer locations and in their own delivery centers (primarily located in India). In 2006, the company had annual revenues in excess of $3 billion and over 66,000 employees located throughout the world.

Our empirical analysis focuses on software development projects. Development projects involve complex and uncertain activities (Boh et al. 2007). The typical progression of activities within a software development project is to design a solution, write code, and then test and implement the final solution. An analysis of software development projects in 2004 found that only 35% were considered successful in meeting cost and schedule estimates while delivering to the customer's needs (Hartmann 2006). Our analyses leverage not only the variation that exists in project performance but also a number of controls in the data that permit us to compare performance across projects.

Wipro is divided into multiple business units targeting different classes of industries. These business units are broken down further into verticals targeting particular industries. Wipro markets its services through its verticals, so both sales and project staffing take place at this level. Figure 1 offers a stylized representation of the organization.

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Insert Figure 1 about here
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Projects at Wipro typically have three hierarchical levels. At the top is the project manager (PM), who has full operational control of the project. The PM is responsible for not only managing the day-to-day operations of the project team but also is the primary interface with the customer. Large projects may have more than one project manager. Middle managers, most often known as module leaders, manage a sub-unit of the project and report to the PM. A middle manager will usually have three to five reports and will both supervise the sub-unit and take part in writing code. Finally, project engineers make up the bottom level of the project hierarchy and are responsible for writing code. Individuals at all levels typically work on one project at any given time.

Sales personnel are responsible for estimating the schedule and effort requirements for a project. Once this estimation has taken place, project personnel, including the project manager, are staffed on the project. Project managers do not select their own project teams. The median project in our sample lasted for six months and included twelve team members. Project teams are not constituted to stay together for multiple projects and long periods of time, but rather are fluid in that they come together to execute a particular project before breaking up and moving on to other engagements (Cohen and Bailey 1997).

Data

The sample for our analysis starts with all 1,157 software development projects completed at Wipro between January 2004 and December 2006. We supplement this project-level data with detailed human capital information on the more than 13,000 individuals who took part in these projects. Though project controls and performance data only cover development projects back to 2004, data on individual team members goes back to 2000. Though we cannot use this individual data to evaluate earlier project performance, we are able to track the experience accumulation of individuals over time. This includes the customers for whom they have worked, their roles on specific teams, and the individuals with whom they have worked. To build our sample, we remove projects that are missing data as well as those with fewer than four team members.[6] A comparison of projects missing data with those not missing data does not expose any meaningful differences in the variables of interest.

As part of its process improvement efforts, Wipro was the first company in the world to achieve Level Five status (the highest level) for the Capability Maturity Model Integrated, version 1.1 (CMMI) (SEI 2001; Wipro 2008). This not only signifies a high level of process control but also that Wipro records its operational performance in fine detail. The company has developed an internal system for tracking project and employee information. Project managers use this system to input their monthly, quarterly, and end-of-project reports. All employees use the system to record the project on which they are working each week. All of the reports go through thorough quality assurance and are subject to random audits by the company's Software Engineering Process Group. Employee demographic information, such as birth date and start date at Wipro, is extracted from the firm's multiple HR systems.

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[6] Of the projects excluded from the sample, 463 lack a value for kilolines of code (KLOC). This occurs because not all development projects use KLOC as their unit of measurement (e.g. some use a customer specific measure) and some development projects do not include coding and therefore do not have a KLOC value.

Dependent Variables

Despite the well-known difficulty in finding objective measures of IT project performance (Banker and Kemerer 1989), our data allows us to examine two separate, customer-facing performance measures: (1) delivery performance and (2) quality performance. We use these measures, as they are the dimensions along which Wipro personnel are evaluated both internally and externally (i.e., by their customers[7]), and they are results over which the team has significant control.

Delivery Performance. A common measure of project efficiency, or delivery performance, is whether the project team adheres to its effort and schedule estimates (Boehm 1981; Faraj and Sproull 2000). Before a project starts, sales personnel at Wipro create estimates for the project's effort and schedule. These estimates are formally agreed to by the customer – often they serve as the basis for winning the project for Wipro in the first place – and are input into Wipro's project management system. Wipro faces significant competition in the marketplace from both Indian firms (e.g. TCS and Infosys) and global providers (e.g. IBM and Accenture). Given this competition, the company cannot add excessive slack to its estimates, as it may lose the opportunity to execute a given project.

As a project progresses, either of the two estimates are subject to alteration. This usually occurs as a result of changes in project scope by the customer. Given the importance of the estimates to contract fulfillment and internal evaluation, the revision process is managed quite closely. The first step in the process is for the project manager to have the customer formally sign off on the change. Then business finance and quality managers at Wipro review the change request to make sure that the PM is not attempting to subvert the system. All of these protections are in place to prevent PMs from changing estimates when a project falls behind. In our analysis, we use the revised estimates as these most accurately reflect a project's definitive goals.

To quantify a project's delivery performance we construct three dichotomous variables – *effort adherence*, *schedule adherence*, and *adherence* – which are set to one if a project meets or surpasses its

[7] For example, Wipro's customer satisfaction survey evaluates the operational performance of a project through separate questions about the project's quality and delivery performance.

effort estimate, schedule estimate, or *both* estimates, respectively, and is zero otherwise. We believe that a dichotomous variable most accurately reflects how customers, as well as project managers and more senior managers at Wipro, evaluate performance. Holding all other factors constant, delivering sooner or with less effort is preferable, but primary emphasis is placed on whether a project is delivered as promised. A project manager noted, "The deadline is what we're really looking at. My job is to make sure that there isn't slippage [in schedule] or overrun [in effort]."

Quality Performance. To evaluate the quality performance of development projects, we examine the number of defects found in customer acceptance testing (CAT). CAT occurs at the end of most, but not all development projects, and during this process the final code is tested against the project's pre-specified output measures. As the name suggests, either a customer or their assignee complete the testing, making it an outside, objective measure. In fact, if a project manager reports zero defects in the project tracking system, an individual from the Software Engineering Process Group follows up with the project team to make sure that customer acceptance testing took place. Defects found in CAT, known as post-delivery defects, measure the conformance quality of a project (Garvin 1987) and are a commonly used measure in software engineering (Boehm 1981; Jones 1986).

Wipro tells its customers that projects will have a post-delivery defect rate (defects from CAT / kilolines of code) that is less than or equal to a specific value, *X*.[8] Customers and project teams do not typically focus on the raw value that is derived (e.g., how much better is a project with a value of 0.2 as opposed to 0.3), but rather whether a project meets its defined standard. As with delivery performance, we thus dichotomize the outcome with a variable, *quality*, set to one if a project has a post-delivery defect rate less than or equal to *X*, and zero otherwise.

Independent Variables

Our study has three classes of independent variables: project manager team familiarity (PMTF), measures of variation in a project manager's market experience, and the interaction between the two. To help with the interpretation of the interaction terms in the non-linear models, all continuous variables, including

[8] For competitive reasons we cannot disclose the value of *X*.

PMTF and the measures of PM market experience, are standardized by subtracting the mean from each and dividing by the standard deviation.

Project Manager Team Familiarity (PMTF). To calculate PMTF, we first count the number of times that a project manager has worked with each team member on a prior project over the prior three years. We then divide this number by the total number of team members minus one (Reagans et al. 2005). If there is more than one project manager, we average the value across PMs. We use a three-year time period for two reasons. First, it accounts for the fact that, similar to the concept of organizational forgetting (Argote et al. 1990; Benkard 2000; Thompson 2007), familiarity may decay over time. Second, the three-year period incorporates the realities of the data, as the average employee has two years of experience and the median project in our sample lasts six months. This cutoff thus includes both multiple projects per person and most employees' total Wipro experience. Finally, it avoids problems of censored data since the historical employee data goes back to 2000.[9]

Variation in Market Experience. To evaluate the impact of variation in experience, we focus on one area – market experience. Market experience is important in software services, as it can provide information about different industries and customer's processes while helping manage market uncertainty (C.f. MacCormack and Verganti 2003). While our analyses control for the number of projects a PM has previously executed for the focal customer, we use three related measures to capture variation in a project manager's market experience.

As shown in Figure 1, Wipro's project personnel are organized into business units, each of which is further divided into verticals.[10] Within a given vertical, (e.g., retail), there are multiple customers. The first variable, *PM Number of Companies in Same Vertical*, is a count of the number of companies, for which a PM has worked over the prior three years that are located in the same vertical as the focal customer. Within a given business unit, such as enterprise solutions, there are multiple verticals (e.g. retail, manufacturing, utilities, etc.) Our second measure, *PM Number of Related Verticals*, is a count of

[9] As a robustness check, we conduct analyses with two- and four-year cutoffs and obtain the same pattern of results.
[10] At any moment in time an individual is located within a particular vertical. Individuals can move across verticals and business units over time at either the individual's or the company's discretion.

the number of verticals within the focal project's business unit, in which a project manager has worked over the previous three years. Finally, the company has multiple business units (e.g. enterprise solutions, banking, financial securities and insurance, etc.) Our final measure, *PM Number of Unrelated Verticals*, is a count of the number of verticals in which a PM has worked over the prior three years that are outside of the focal project's business unit. These measures capture market experience and its relatedness to the focal project. In projects where there is more than one PM, we average the values for each variable across PMs. Given our interest in examining the moderating effect of team familiarity, we construct the interaction of PMTF and each measure of variation in market experience.

Control Variables

In addition to the variables previously discussed, the project data offers numerous controls. Table 1 offers a summary of these variables, and Table 2 provides summary statistics.

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Insert Tables 1 and 2 about here
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We evaluate the delivery and quality performance of project teams using a logistic regression model, as our dependent variables are dichotomous. In particular, we use a conditional logistic model to control for any time-invariant characteristics of customers that may impact performance (Greene 2003).[11] Since the models condition on the customer, our final sample excludes customers with only one project and customers for which the dependent variable does not differ across projects. This leaves us with a final sample of 412, 388, 445, and 299 projects for schedule adherence, effort adherence, adherence, and quality performance, respectively.[12]

[11] Given the challenges in interpreting interaction terms in logistic regression models (Ai and Norton 2003; Hoetker 2007) we also repeat the analyses using a linear probability model and generate the same pattern of results.

[12] An alternative empirical approach would involve using hierarchical linear modeling (HLM). HLM is often a suitable technique to employ when data is nested within levels – such as individuals within teams or students within schools (Singer and Willett 2002). As noted by Reagans et al. (2005), HLM does not appear to be appropriate in our setting as project teams have "overlapping membership" and our dependent variables are solely at the team level.

Results and Discussion

Results

Column 1 of Table 3 presents the results from the conditional logistic regression model of effort adherence on variation in experience and PMTF. As expected the coefficient on PMTF is positive and significant. Looking at the different measures of market experience, we see that only the coefficient for PM Number of Related Verticals is significant (at the 10% level), with an increase of one standard deviation in the related verticals measure increasing the odds of adherence by 32%.

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Insert Table 3 about here
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In Column 2 we examine the moderating effect of team familiarity on variation in market experience. The interaction of PMTF with the PM Number of Related Verticals and the interaction of PMTF with the PM Number of Unrelated Verticals are positive and significant (the latter at the 10% level). While this provides potential support for the moderating effect of team familiarity, it is not conclusive. When interpreting output from nonlinear models, it is necessary to do more than just evaluate the sign and significance of the interaction coefficient (Ai and Norton 2003; Hoetker 2007). In particular, it is possible that the direction of the interaction effect may change over the support of the distribution. To address this concern, Figure 2 plots the effect of variation in experience on the probability of successful project delivery or quality performance for high and low levels of PMTF (one standard deviation above the mean and zero prior experience, respectively) (Haas and Hansen 2005; Hoetker 2007). Figures 2a and 2b present the impact of PM experience in related verticals and PM experience in unrelated verticals, respectively, on effort adherence for high and low values of PMTF. Together with the coefficients from Table 3, the figures provide support for the contention that team familiarity moderates the relationship of variation in experience and performance.

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Insert Figure 2 about here
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Columns 3 and 4 of Table 3 examine the relationship between our independent variables and schedule adherence. In Column 3 the coefficient on PMTF is positive, but not significant, while the coefficient on PM Number of Related Verticals is positive and significant, at the 10% level. An increase of one standard deviation in the related verticals measure yields a fitted odds ratio of 1.42. In Column 4, the interaction of PMTF and PM Number of Unrelated Verticals is positive and significant. Figure 2c again supports the moderation contention.

Columns 5 and 6 of Table 3 present the results of PMTF and variation in experience on overall adherence. In the model without interaction terms, the coefficient on PMTF is significant as is the coefficient on PM Number of Related Verticals. An increase of one standard deviation in the related verticals measure yields a fitted odds ratio of 1.50. Examining the interactions terms we see that two are now positive and significant: PMTF X PM Number of Related Verticals and PMTF X PM Number of Unrelated Verticals. Evidence of moderation is seen for both variables in Figures 2d and 2e, respectively.

Finally, Column 7 of Table 3 provides results from the conditional logistic regression of quality performance on variation in experience and project manager team familiarity (PMTF). Again, the coefficient on PMTF is positive and significant. With respect to quality performance, however, all three coefficients for market experience are negative, though only PM Number of Unrelated Verticals is significant (at the 10% level). An increase of one standard deviation in this last measure decreases the odds of adherence by 18%. Adding the interaction terms in Column 8, we see that the coefficient of the interaction of PMTF and the number of unrelated verticals is positive and significant (at the 10% level) while the coefficients on the other two interaction terms are positive, but not significant at conventional levels. Figure 2f provides support for the moderating role of PMTF.

Discussion

Consistent with prior work, we find that PM team familiarity is positively and significantly related to three of the four performance variables (Reagans et al. 2005; Huckman et al. 2008), In our interviews at Wipro, one PM commented that, “It is always better [with respect to performance] to work in different companies within the same domain [vertical].” Our results do not support this contention as the different measures of variation in experience are both positively and negatively related to the various performance metrics. When we examine the interaction of familiarity and the variation measures, however, we find support for a moderating relationship in several cases and for the framing of the broader knowledge acquisition-application problem.

Thus, some variation in experience may have a direct positive effect, while in other cases a project manager may only benefit from variation if she possesses familiarity with team members. At first blush, the two halves of this statement may seem contradictory. Does gaining diverse experience preclude working with the same team? Not necessarily. In some settings it may be possible for entire teams to move between different types of work. For example, in investment banking, the same team could lead an initial public offering, execute a merger, and then issue convertible debentures, all for different clients. While companies could choose to create teams that will together gain diverse sets of experience over time, that is not the norm, and it is not the case in this setting.

Project managers may not take part in their diverse experiences with other team members, but that does not mean that the focal team cannot benefit from that diversity. The team may not realize the benefit of this variation, however, until its members have worked together for some time. For example, if a PM has a new idea for structuring the team's work that is derived from another industry – but has no experience with other team members –team members may initially reject the idea (C.f. Katz and Allen 1982). As familiarity increases, however, team members may be more willing to use the brokered idea. This explanation is just one possible mechanism for the moderating effect of PM team familiarity on the relationship between variation in experience and performance, and the opportunity exists to detail these mechanisms further.

We note that in the models with only main effects in Table 3, we generally see opposite signs on the coefficients for the measures of variation in market experience for delivery performance as compared to quality performance. In the case of delivery performance, seven of the nine coefficients are positive, while in the case of quality performance the coefficients on all three have negative signs (although only one is significant, at the 10% level). This suggests a potentially important area for future research. While work on the learning curve was initially focused on cost and productivity, the findings have been broadly extended to other measures such as quality and customer satisfaction (Yelle 1979; Lapré et al. 2000; Lapré and Tsikriktsis 2006). While performance measures have changed, the unequivocal finding has been that increasing cumulative experience leads to improved performance.

As previously noted, compared to repetition, the relationship between variation in experience and performance may be more nuanced. Prior work has explored this nuance by examining how related a task is to the focal activity (Schilling et al. 2003). Our results highlight the possibility that it may matter how much the attributes of the task relate to the characteristics of the performance measures.

Alternative Explanations

Given the focal role that team familiarity plays in our analysis, the threat of selection bias is a meaningful concern. As mentioned earlier, project managers do not directly select their teams. The estimates, which are created by sales personnel, are used for project staffing. However, the PM does have the ability to reject individuals who are sent by the human resources group. In practice, the organization's culture frowns upon using this power and, as such, managers report that rejection seldom occurs. Nevertheless, if rejection was systematically used to remove "bad" team members; then it would prove problematic. To examine this hypothesis we use a Cox proportional hazards model (Cleves et al. 2004).

We examine two different groupings of team members: (1) all dyads of individuals from project teams and (2) each PM – team member dyad. While the first measure captures the possibility of selection in all team member relationships, the second focuses in particular on the PM – team member interactions. We define failure as the pair not working together on the following project. In the models we are focused on whether poor performance on the dependent variables predicts failure. The results in Table 4 show that none of the performance variables are significant predictors of failure.[13] These findings increase our confidence that selection is not driving our results.

****
Insert Table 4 about here
****

[13] We also run these analyses as logistic regression models and generate the same pattern of results.

One might also question how we operationalize variation in a PM's market experience. We count the number of companies in the same vertical and then number of verticals in related and unrelated business units to measure this construct. Our measure is based on the belief that the largest contribution of varied experience will come from initial exposure, so counting companies and verticals allows us to capture this. Alternatively, it is possible that cumulative volume in each of these other categories may be a more accurate representation. To examine this possibility, we construct the similar three measures of a PM's market experience using a project count for each (i.e., number of projects in the same vertical, number of projects in related verticals, and the number of projects in unrelated verticals). We drop the total count of a PM's projects, PM Total Experience, to avoid collinearity issues. The results in Table 5 illustrate that while the main effects of variation are generally no longer significant, we see support for the primary contention of this paper – that PMTF moderates the relationship of variation in experience and performance.

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Insert Table 5 about here
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Limitations

As with all studies, ours has its limitations, and one must be judicious in applying its results. First, any non-random assignment of individuals to teams might introduce bias in our results. The hazard analysis provides suggestive evidence that such selection is not taking place. Interviews with managers at Wipro highlight that processes are designed to prevent the "cherry picking" of personnel, and project managers concur that they are unable to choose particular individuals for their teams. Second, any non-random assignment of individuals to diverse industries could also bias our results. For example, there would be cause for concern if Wipro had an industry rotation program for "star" engineers. The firm, however, does not have such programs. Additionally, this bias would primarily impact the base term in our regressions (i.e., the measures of variation in experience), rather than the interaction terms, which are the key effects we seek to evaluate.

Also, while we lay out the theoretical argument in support of our story, we cannot conclusively say that the positive interactions of PMTF and the respective variation measures are solely a result of knowledge application. Nevertheless, even if additional knowledge is being acquired due to this combination, it is still necessary that it eventually be applied for there to be any performance gain. Finally, our study considers one firm in one industry, so there is the question of whether its findings will generalize to other settings. We believe that this limitation is offset by the detailed quantitative data and in depth fieldwork that allows us to unite deep knowledge of the setting with large-scale empirical testing of the research question.

Conclusion

Our study aims to understand the mixed results linking variation in experience and performance (Darr et al. 1995; MacDuffie et al. 1996; Fisher and Ittner 1999; Schilling et al. 2003; Cummings 2004; Wiersma 2007). We propose that these diverse findings may be at least in part a consequence of a knowledge acquisition-application problem. While variation in experience may provide valuable knowledge, it does not imply that the acquiree will subsequently able to apply the knowledge successfully. We suggest that diverse knowledge may be applied more successfully when team familiarity is present. In our setting, we are able to track multiple measures of individuals' experience over several years and link this with project performance. This linkage permits us to explore the relationship of variation in market experience and performance in a field setting.

As predicted, our results show a generally positive relationship between the main effect of project manager team familiarity and delivery and quality performance (Reagans et al. 2005; Huckman et al. 2008). We see both positive and negative relationships between our measures of variation in market experience and performance, in addition to many relationships that are statistically indistinguishable from zero. When we examine the interactions of PMTF and variation in market experience, we see a moderating effect of project manager team familiarity on the relationship of variation in experience and performance, in some, but not all cases.

Our paper has important implications for the study of teams, learning, and knowledge management. First, our work injects the concept of team familiarity into the study of how variation in experience affects team performance. We not only separate the two measures, but also relax the assumption that variation in experience and team familiarity move in lock-step together (e.g., the same team never executes multiple tasks in a single area) or apart (e.g., executing tasks in different areas means always working with different team members). Second, our results provide a potential response to the knowledge acquisition-application problem. Future work should not only identify conditions that enable the application of knowledge in different settings, but also look to understand in more detail when the knowledge acquisition-application problem is the constraint.

Third, our results suggest that diversity of experience may have different relationships to various performance measures in the same setting. There is need not only to understand the characteristics of diverse experience (such as related and unrelated) but also to identify the attributes of performance for which diverse experience may prove useful. For example, for innovative performance outcomes, the diversity of knowledge and the resulting opportunities for brokerage may lead to a positive linkage between diversity of experience and performance – though mechanisms to enable its application may still be necessary (Fleming et al. 2007). On the other hand, for more routine outcomes, it is possible that an increase in variation as a result of different types of experience may simply harm efficiency and decrease performance (C.f. March and Simon 1993).[14] This distinction may provide another path to, but also a way out of the problem whereby organizations that focus on short-term efficiency may compromise their long-term innovativeness and adaptability (Abernathy 1978; March 1991). If workers gain repeated experience with the same activity, they may improve their efficiency but lose their capabilities for innovation. One potential way out of this dilemma then may be for workers to gain more diverse sets of experience.[15]

[14] Our data do not permit direct examination of this question, as we do not have a measure for innovative performance. If anything, our data suggests that the actual story may be quite complex, as we find a positive relationship between some measures of variation in experience and adherence – a measure of efficiency.

[15] This is related to March's (1991) solution of bringing in new workers as a way to balance the need for exploration and exploitation. Workers from outside the organization are unaware of the organizational code and so may help the

Though the innovation-efficiency distinction is likely important, future work should seek to identify more fine-grained characteristics (e.g. observability, manageability, etc.) of various types of work.

Finally, our results contribute not only to the literature on learning and knowledge management, but also offer important insights for work in strategy and entrepreneurship. By explicitly studying the individual-level interactions that lead to organizational knowledge (C.f. Argote and Ingram 2000), we gain insight into the foundations of capabilities (Ethiraj et al. 2005; Gavetti 2005).

This work also offers useful implications for practicing managers and suggests that they must embrace a more nuanced view of experience. Not only does our work highlight the value of diverse experience, at least in some cases, but it suggests that managers may benefit from more detailed understanding of the types of experience that are relevant in their setting (e.g., market, technology, role). Having done this, managers can think about how to build both diverse sets of experience and team familiarity. If the most valuable assets of many companies are their employees, then organizations may need to shift from thinking about their project portfolio to their employee-experience portfolio. This process will require both the tracking of detailed data as well as new ways for optimizing experience sets (not only computationally, but also by balancing individuals' career development needs with company objectives). Doing so may offer managers an important new lever for improving organizational performance.

organization to stay innovative. In our case, workers might be able to acquire diverse experiences as a way to disrupt the status quo.

Figure 1. Stylized Version of Wipro's organizational structure.

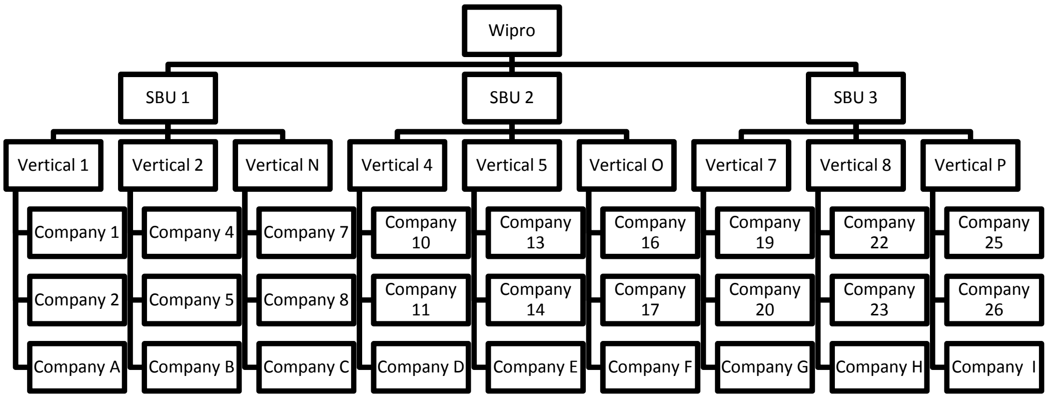
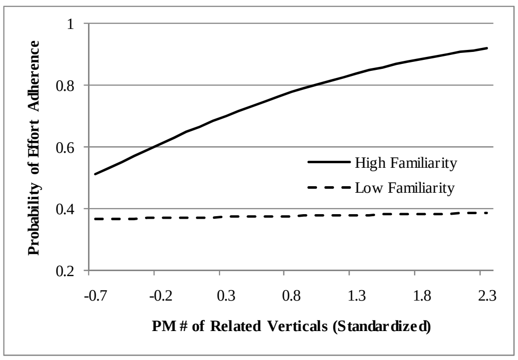
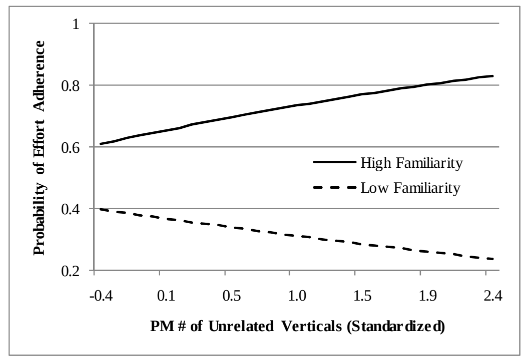


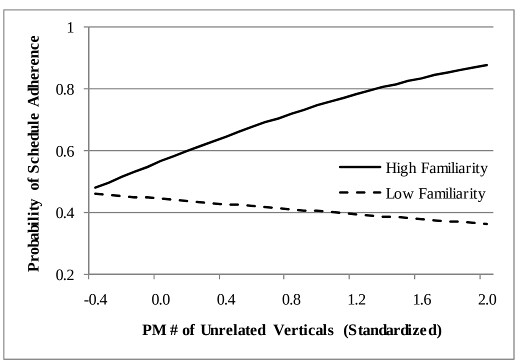
Figure 2. Plots of the net effect of variation in PM experience (from the 0th to 95th Percentiles) on the probability of successful performance for high and low PM team familiarity.



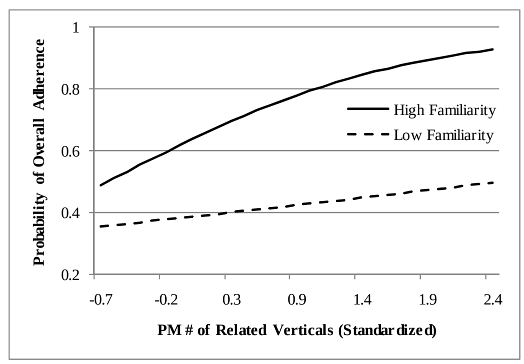
a. PMTF and variation in related vertical experience on effort adherence.



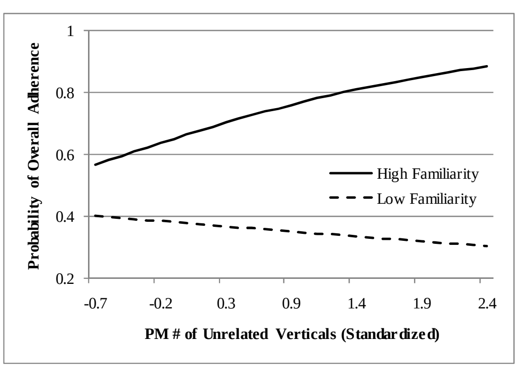
b. PMTF and variation in unrelated vertical experience on effort adherence.



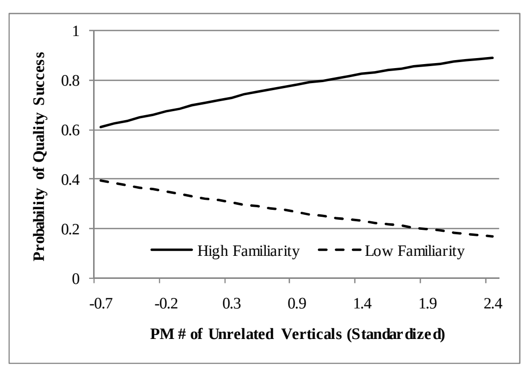
b. PMTF and variation in unrelated vertical experience on schedule adherence.



d. PMTF and variation in related vertical experience on overall adherence.



e. PMTF and variation in unrelated vertical experience on overall adherence.



f. PMTF and variation in unrelated vertical experience on quality performance.

Table 1. Control variables included in the regression models.

Control Variable	**Explanation**
PM Total Experience[1]	A count of the number of projects that a PM has executed over the previous three years at Wipro.
PM Customer Experience[1]	A count of the number of projects that a PM has executed over the previous three years for the focal customer.
PM Role Experience[1]	A count of the number of projects that a PM has executed over the previous three years in the role of project manager.
Rest of Team Experience[1]	Average of the count of the number of projects that all non-PM team members have executed over the previous three years at Wipro.
Fixed Price Contract	An indicator variable, which equals one if a contract is fixed price (set price and Wipro bears the risk of overage) or zero if the contract is time and materials (i.e. cost plus) (Banerjee and Duflo 2000).
Offshore Percentage	Percentage of the project's total hours which are completed offshore (at Wipro's locations in India).
Project Complexity[2]	Log of the kilolines of new source code (KLOC) written (Boehm 1981; Scacchi 1995).
Software Language	Indicator variables for six classes of software languages.
Number of Software Languages	Indicator variable equal to one if a project uses more than one software language and zero otherwise.
Technology	Indicator variable equal to one if a project uses more than one technology and zero otherwise.
Log (Estimated Effort)[2]	Log of the estimated total person-hours for the project. We use the estimate to avoid the problem of endogeneity since all other things being equal if a project misses its estimate it will have higher effort.
Log (Team Size)[2]	Log of the total number of individuals who were part of the project.
Log (Estimated Duration)[2]	Log of the estimated project length (in days).
Architect	An indicator set to one if a project has a technical architect on the team (16% of projects). Since projects with architects are slightly larger than those without an architect, the indicator variable accounts for any unobserved differences in projects.
Start Year	Indicators for the year in which the project started.

(1) Substituting years instead of project count for these variables and dropping the three year window, does not change the results for the dependent variables.

(2) To account for scale effects in software (Banker and Kemerer 1989) as well as outliers we log each of these variables. The results for the dependent variables do not change with unlogged variables.

Table 2.

Summary Statistics and Correlation Table of Dependent, Independent, and Control Variables of Interest –
N=445, except for effort adherence (N=412), schedule adherence (N=388), and quality performance (N=299).

	Variable	**Mean**	**σ**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1.	Effort Adherence	0.74	0.44																	
2.	Schedule Adherence	0.83	0.38	**0.35**																
3.	Overall Adherence	0.71	0.46	**0.86**	**0.63**															
4.	Quality Performance	0.70	0.46	0.08	0.04	0.05														
5.	Project Manager Team Familiarity[a]	0.59	0.70	0.07	0.09	**0.10**	**0.18**													
6.	PM Number of Companies in Same Vertical[a]	0.49	0.91	-0.05	**-0.11**	-0.05	-0.06	-0.06												
7.	PM Number of Related Verticals[a]	0.44	0.64	-0.09	-0.03	-0.08	-0.02	-0.02	-0.02											
8.	PM Number of Unrelated Verticals[a]	0.16	0.40	0.04	0.00	0.04	-0.05	-0.07	0.02	**-0.12**										
9.	PM Total Experience[a]	5.01	3.38	-0.03	0.03	0.00	0.09	**0.48**	**0.29**	**0.12**	**0.12**									
10.	PM Customer Experience[a]	3.10	3.14	0.04	**0.13**	0.07	**0.17**	**0.62**	**-0.15**	**-0.12**	-0.06	**0.75**								
11.	PM Role Experience[a]	1.82	2.66	-0.06	0.01	-0.02	0.10	**0.43**	**0.24**	0.00	-0.01	**0.71**	**0.58**							
12.	Rest of Team Experience[a]	2.60	1.47	0.10	0.05	**0.12**	0.09	**0.45**	0.02	-0.09	-0.01	**0.33**	**0.36**	**0.22**						
13.	Fixed Price Contract[a]	0.69	0.46	0.06	-0.02	0.04	0.02	**0.14**	0.05	**-0.16**	0.06	**0.14**	**0.14**	0.02	**0.20**					
14.	Offshore Percentage[a]	0.85	0.16	-0.10	-0.07	**-0.12**	0.06	0.06	-0.03	0.06	-0.09	0.00	0.02	0.06	**-0.10**	**-0.11**				
15.	Log (Kilolines of Code)[a]	3.41	1.23	-0.05	-0.04	-0.06	-0.09	**-0.14**	-0.02	-0.01	0.02	-0.06	-0.08	-0.07	**-0.13**	-0.03	**-0.10**			
16.	Log (Estimated Effort)[a]	8.69	1.10	0.06	-0.04	0.03	-0.11	**-0.18**	**-0.10**	0.03	0.01	**-0.14**	-0.09	**-0.20**	**-0.11**	**-0.15**	**-0.14**	**0.70**		
17.	Log (Team Size)[a]	2.59	0.75	-0.01	-0.04	-0.04	-0.09	**-0.17**	**-0.10**	0.03	0.02	**-0.10**	-0.08	**-0.17**	-0.06	**-0.10**	**-0.14**	**0.63**	**0.86**	
18.	Log (Estimated Duration)[a]	5.29	0.65	0.01	0.00	0.00	-0.09	**-0.13**	**-0.11**	0.05	-0.05	**-0.10**	-0.03	**-0.16**	**-0.11**	**-0.15**	-0.08	**0.49**	**0.75**	**0.57**

Table 3. Results of the Conditional Logistic Regression of Effort Adherence, Schedule Adherence, Adherence, and Quality Performance on Variation in Experience and PM Team Familiarity (n=412, 388, 445 and 299, respectively).

	Dep Var: Effort Adherence		Dep Var: Sched Adherence		Dep Var: Adherence		Dep Var: Quality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Project Manager Team	0.593***	0.611**	0.227	0.268	0.491**	0.550**	0.698**	0.696**
Familiarity (PMTF)[a]	(0.195)	(0.252)	(0.268)	(0.268)	(0.195)	(0.231)	(0.290)	(0.304)
PM Number of Companies in Same	0.100	0.102	-0.034	-0.083	0.140	0.115	-0.295	-0.367*
Vertical[a]	(0.176)	(0.222)	(0.225)	(0.214)	(0.178)	(0.179)	(0.211)	(0.191)
PM Number of Related	0.277*	0.381**	0.354*	0.385*	0.408***	0.491***	-0.306	-0.286
Verticals[a]	(0.152)	(0.170)	(0.198)	(0.198)	(0.153)	(0.169)	(0.189)	(0.195)
PM Number of Unrelated	-0.078	0.042	0.185	0.299	0.087	0.233	-0.211*	0.046
Verticals[a]	(0.129)	(0.156)	(0.186)	(0.187)	(0.135)	(0.148)	(0.127)	(0.224)
PMTF X PM Number of Companies		0.047		-0.072		0.002		0.170
in Same Vertical		(0.256)		(0.132)		(0.170)		(0.148)
PMTF X PM Number of		0.421***		0.186		0.351**		0.154
Related Verticals		(0.163)		(0.199)		(0.142)		(0.228)
PMTF X PM Number of		0.362*		0.552***		0.476**		0.540*
Unrelated Verticals		(0.199)		(0.211)		(0.198)		(0.321)
PM Total Experience[a]	-0.438*	-0.329	-0.242	-0.137	-0.526**	-0.411	0.312	0.435
	(0.241)	(0.240)	(0.284)	(0.309)	(0.249)	(0.255)	(0.508)	(0.502)
PM Customer Experience[a]	0.336	0.250	0.268	0.199	0.291	0.208	-0.219	-0.253
	(0.241)	(0.257)	(0.332)	(0.343)	(0.254)	(0.270)	(0.490)	(0.475)
PM Role Experience[a]	-0.055	-0.113	0.029	-0.002	0.176	0.130	0.007	0.017
	(0.163)	(0.162)	(0.208)	(0.224)	(0.154)	(0.154)	(0.289)	(0.313)
Rest of Team Experience[a]	0.026	0.022	-0.076	-0.038	0.068	0.064	0.165	0.183
	(0.163)	(0.168)	(0.185)	(0.185)	(0.129)	(0.128)	(0.195)	(0.201)
Fixed Price Contract	0.217	0.094	-0.530	-0.685	0.018	-0.118	-0.809	-0.915
	(0.478)	(0.478)	(0.417)	(0.441)	(0.430)	(0.447)	(0.647)	(0.683)
Offshore Percentage[a]	-0.076	-0.110	-0.478**	-0.540***	-0.211	-0.265	0.146	0.126
	(0.251)	(0.242)	(0.204)	(0.197)	(0.214)	(0.218)	(0.164)	(0.173)
Log (Kilolines of Code)[a]	-0.611***	-0.605***	0.046	0.109	-0.396*	-0.372*	-0.110	-0.066
	(0.204)	(0.198)	(0.230)	(0.239)	(0.218)	(0.224)	(0.258)	(0.259)
Log (Estimated Project Effort)[a]	1.465***	1.434***	-0.403	-0.482	0.924**	0.888**	0.236	0.165
	(0.489)	(0.502)	(0.370)	(0.381)	(0.379)	(0.385)	(0.423)	(0.433)
Log (Max Team Size)[a]	-0.761**	-0.767**	-0.192	-0.241	-0.684***	-0.713***	0.400	0.294
	(0.360)	(0.370)	(0.344)	(0.378)	(0.253)	(0.262)	(0.372)	(0.403)
Log (Estimated Duration)[a]	-0.400	-0.379	0.358	0.389	-0.131	-0.109	-0.450*	-0.382
	(0.296)	(0.306)	(0.279)	(0.266)	(0.246)	(0.245)	(0.241)	(0.262)
Observations	412	412	388	388	445	445	299	299
McFadden's Pseudo R^2	0.1467	0.1637	0.1653	0.1804	0.1195	0.1366	0.1849	0.2013
Log Pseudolikelihood	-127.3	-124.7	-89.62	-88.00	-152.1	-149.1	-100.8	-98.72
Wald chi-squared	150.1***	177.1***	110.8***	188.1***	117.8***	180.7***	157.3***	241.0***

Notes: *, ** and *** denote signficance at the 10%, 5% and 1% levels, respectively. All models condition on the customer (i.e. include customer fixed effects). Standard errors are heteroskedasticity robust. Models include, but results are not shown for the following variables: architect, number of languages, start year, software language, and number of technologies.

[a] Variable is standardized by subtracting the mean and dividing by the standard deviation.

Table 4. Summary results of Cox hazard models to examine the potential selection effects due to project performance.

	All Dyads	PM - Team Member Dyads
	(1)	(2)
Effort Adherence	-0.0007	-0.0167
	(0.0256)	(0.0216)
Schedule Adherence	-0.0312	-0.0192
	(0.0217)	(0.0195)
Post Delivery Defects	-0.00002	0.00005
	(0.00004)	(0.00004)
Fixed Price Contract	0.0240	0.0256
	(0.0252)	(0.0249)
Offshore	-0.0015	-0.0250
	(0.0895)	(0.0825)
Complexity	0.0027	-0.0114
	(0.0118)	(0.0119)
Log (Estimated Project Effort)	0.0007	0.0173
	(0.0213)	(0.0202)
Log (Max Group Size)	0.0104	-0.0231
	(0.0215)	(0.0183)
Log (Estimated Duration)	0.0495	0.0519
	(0.0192)	(0.0240)
Observations	97,438	11,452
Log Likelihood	-1,017,407	-98,579

Notes. *, ** and *** denote signficance at the 10%, 5% and 1% levels, respectively. The following variables are included in the regressions but are not shown in the table: project start year, software language, # of languages, # of technologies, and customer fixed effects. Standard errors are clustered by project.

Table 5. Results of the Conditional Logistic Regression of Effort Adherence, Schedule Adherence, Adherence, and Quality Performance on Project-based Measures of Variation in Experience and PM Team Familiarity (n=412, 388, 445 and 299, respectively).

	Dep Var: Effort Adherence		Dep Var: Sched Adherence		Dep Var: Adherence		Dep Var: Quality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Project Manager Team	0.634***	0.639***	0.259	0.309	0.523***	0.576**	0.679**	0.799***
Familiarity (PMTF)[a]	(0.201)	(0.235)	(0.269)	(0.269)	(0.194)	(0.235)	(0.284)	(0.301)
PM Number of Projects in Same	-0.292**	-0.256*	-0.107	-0.062	-0.188	-0.165	-0.259	-0.200
Vertical[a]	(0.134)	(0.140)	(0.140)	(0.125)	(0.127)	(0.128)	(0.255)	(0.262)
PM Number of Projects in Related	-0.136	-0.037	0.052	0.201	-0.073	0.093	-0.169	0.194
Verticals[a]	(0.128)	(0.146)	(0.180)	(0.182)	(0.120)	(0.152)	(0.125)	(0.274)
PM Number of Projects in	0.051	0.215	0.103	0.204	0.122	0.282**	0.087	0.232
Unrelated Verticals[a]	(0.143)	(0.158)	(0.183)	(0.172)	(0.137)	(0.138)	(0.181)	(0.229)
PMTF X PM Number of Projects in		0.007		0.048		-0.002		0.066
Same Vertical		(0.141)		(0.144)		(0.143)		(0.113)
PMTF X PM Number of Projects in		0.316		0.587***		0.448**		0.790**
Related Verticals		(0.193)		(0.221)		(0.208)		(0.370)
PMTF X PM Number of Projects in		0.418***		0.307*		0.421***		0.270
Unrelated Verticals		(0.157)		(0.175)		(0.128)		(0.262)
Observations	412	412	388	388	445	445	299	299
McFadden's Pseudo R^2	0.1464	0.1608	0.1554	0.1782	0.1112	0.1311	0.1815	0.2034
Log Pseudolikelihood	-127.3	-125.2	-90.69	-88.25	-153.5	-150.1	-101.2	-98.46
Wald chi-squared	177.6***	228.1***	74.87***	163.8***	147.8***	186.6***	190.0***	322.5***

Notes: *, ** and *** denote signficance at the 10%, 5% and 1% levels, respectively. All models condition on the customer (i.e. include customer fixed effects). Standard errors are heteroskedasticity robust. Models include, but results are not shown for the following variables: PM customer experience, PM role experience, rest of team experience, contract type, offshore %, KLOC, effort, team size, duration, architect, number of languages, start year, software language, and number of technologies.

[a] Variable is standardized by subtracting the mean and dividing by the standard deviation.

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