

Team Familiarity, Role Experience, and Performance: Evidence from Indian Software Services

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Much of the literature on team learning views experience as a unidimensional concept captured by the cumulative production volume of, or the number of projects completed by, a team. Implicit in this approach is the assumption that teams are stable in their membership and internal organization. In practice, however, such stability is rare, because the composition and structure of teams often change over time (e.g., between projects). In this paper, we use detailed data from an Indian software services firm to examine how such changes may affect the accumulation of experience within, and the performance of, teams. We find that the level of team familiarity (i.e., the average number of times that each member has worked with every other member of the team) has a significant positive effect on performance, but we observe that conventional measures of the experience of individual team members (e.g., years at the firm) are not consistently related to performance. We do find, however, that the role experience of individuals in a team (i.e., years in a given role within a team) is associated with better team performance. Our results offer an approach for capturing the experience held by fluid teams and highlight the need to study context-specific measures of experience, including role experience. In addition, our findings provide insight into how the interactions of team members may contribute to the development of broader firm capabilities.

Key words: experience; learning; teams; performance

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1. Introduction

In many contexts, ranging from product development to service delivery, a significant amount of an organization's work is conducted by *fluid teams* that aim to create innovative output (Edmondson and Nembhard 2008). Fluid teams exist only for the duration of a single project and are composed of members who may join or leave a team during the course of that project. In settings characterized by such fluidity, simple measures of cumulative output may not accurately capture team experience, particularly when changes in team composition are substantial over time.

In this study, we consider an approach for capturing the experience held by fluid teams. In doing so, we extend the concept of team fluidity to allow not only for changes in overall composition but also for changes in a team's internal structure over time as junior members assume more-senior roles. This broader approach for capturing team fluidity allows for greater granularity in the measurement of team experience and a finer understanding of the determinants of team performance.

Scholars studying organizational learning have focused on understanding differences in rates of learning across firms and teams for some time (Dutton and

Thomas 1984, Argote et al. 1990, Pisano et al. 2001). Explanations for this phenomenon include variation in resources devoted to improvement (Sinclair et al. 2000), team structure, team beliefs (Edmondson 1999), and task experience (Schilling et al. 2003). Furthermore, teams and firms may differ on aspects such as the degree to which members observe others in the use environment and the extent to which the experience of individuals is specific to the context of a given team or firm (Huckman and Pisano 2006).

Though the concept of team fluidity is recognized in some work on learning (e.g., Arrow and McGrath 1995, Cohen and Bailey 1997, Hackman 2002, Edmondson and Nembhard 2008) there have been relatively few field-based empirical studies of the phenomena (Arrow and McGrath 1995). We focus on two factors that impact the accumulation of team experience: (1) the familiarity of team members with one another and (2) changes in the roles played by individual team members. Each of these factors gains increasing theoretical interest once one assumes that teams are not stable over time. Whereas the latter factor is not widely considered in existing literature, there is a longer stream of work on familiarity within teams as discussed in detail in the next section. Katz (1982) uses cross-sectional analysis to identify the

relationship of team familiarity with communication patterns. Edmondson et al. (2001) use detailed case studies to provide theoretical support for the importance of familiarity in teams, and Reagans et al. (2005) go further still, using longitudinal data to provide empirical support for familiarity in teams of surgeons.

Building upon this prior work, we aim to shed light on the degree to which changes in team composition may affect performance. First, we are able to combine project data from one firm with information about each member of each team in order to observe longitudinally how individuals move across teams over time. As highlighted by others, it is useful to examine team leadership when attempting to explain team performance, but it is even more beneficial to include all members of the team (Edmondson et al. 2001, Huckman and Pisano 2006). We examine a measure of team familiarity that accounts for the degree to which each member of a team has worked with every other member of that team on previous projects. This measure allows us to consider the fluid nature of teams explicitly. Second, we examine the impact of what we term *role experience*—the experience that individuals have operating in their current roles of either team member or team manager—on team performance. We thus do not need to make the restrictive assumption that each team member gains the same experience from a given project and are able to explore the degree to which the buildup of experience may be affected by changes in a team's internal structure.

The setting for our empirical analysis is Wipro Technologies, a large firm in the Indian software services industry. The attention devoted to this industry has increased in recent years because of its rapid growth and central role in globalization. Beyond its current relevance, the Indian software services industry is an appropriate setting for our analysis for several reasons. First, the business is based around the completion of projects, which allows multiple observations of the dimensions of team experience that are central to our study. Second, the technological sophistication of Wipro—and other firms in this industry—yields a wealth of internal data not only about the composition and performance of teams but also about the characteristics of individual team members and the specific roles (i.e., management versus team member) they play on a given project. Similar to previous studies, we use project-level data. However, we are also able to link project data to data for individual team members, thereby allowing us to analyze teams, team members, and outcomes for which the teams are responsible. With this clear linkage between a team's composition and its performance, we are able to shed light on the relationship between different measures of team experience and operational outcomes.

We find that team familiarity (i.e., the average number of times that each team member has worked with every other member of the team) is positively related with team performance, but we do not find that various measures of individual experience—measured by the average years of either total experience or firm experience across team members—have a consistent effect on performance after controlling for team familiarity. When we substitute role experience for individual experience, we find evidence of positive, though somewhat different, effects for both managers and team members.

In the following section, we examine the impact of experience on performance and build our hypotheses. Next we describe the setting for our study and our data. We then discuss our empirical approach and results and, finally, offer concluding remarks.

2. Impact of Experience on Performance

In his seminal paper extolling the performance benefits of a focused factory, Skinner (1974, p. 115) argues that, "Repetition breed[s] competence." The idea of repetition plays a major role in both organizational learning and in the creation of routines and capabilities in general (Nelson and Winter 1982). Although the strategy of "copy exactly" has worked well for Intel's fabrication facilities (McDonald 1998), repetition in most settings is a more nuanced phenomenon, which we explore further below.

The learning curve, or the finding that cumulative production experience is associated with an increase in performance, plays a central role in the study of organizational learning (Wright 1936, Dutton and Thomas 1984, Adler 1990, Argote et al. 1990). Although most studies focus on the organization or team level, the learning curve is also seen at an individual level (Newell and Rosenbloom 1981, Delaney et al. 1998). Further work finds that organizations may learn at different rates (Dutton and Thomas 1984, Pisano et al. 2001) and that they may forget (Argote et al. 1990, Benkard 2000, Thompson 2007).

The finding of the majority of these works is that the key driver of improved performance is increasing cumulative experience. Organizations, teams, and individuals each develop routines for solving problems. Learning then consists of the process of exploring, selecting, and replicating new routines for performance improvement (Nelson and Winter 1982, Zollo and Winter 2002). Thus, with increasing experience one may get better at executing existing routines and developing new ones.

Other work within organizational learning suggests a more qualified and, in some cases, pessimistic view of the impact of experience on performance (Sinclair

et al. 2000). Building on the underlying state of the knowledge being used and the user's understanding of cause-and-effect relationships, Pisano explores the idea of learning by doing versus learning before doing (Pisano 1994, 1996). He proposes that if a user understands a problem's cause-and-effect relationship then it is possible to reach a solution without going to the actual use environment. This suggests that the link between experience and performance might be weak in environments where learning before doing is possible. In a similar vein, Upton and Kim (1998) identify the risk of lock-in with different learning modes, and Edmondson et al. (2003) link the state of knowledge to differential learning performance.

The value of experience is also called into question by the idea of competency traps or core rigidities (Levitt and March 1988, Leonard-Barton 1992). These suggest that groups may become fixed in their way of doing things and that, as conditions change, the group will not respond. This implies that experience may have a decreasing, or even negative, return when change enters a model. Staw (1980) also highlights the potential negative impact of experience as he suggests that skill increases with tenure, but effort and drive decrease over time, generating an inverted U-shaped relationship to performance.

2.1. Team Familiarity

Beyond the cumulative experience of a team or its members, we are interested in the impact of team familiarity—the degree to which team members have worked with one another in the past—on performance. In settings where teams are stable over time in terms of composition or structure, a team's level of familiarity can simply be measured by its cumulative experience. This is often referred to as team tenure (Cohen and Bailey 1997, Hackman 2002). When teams are not stable, as in our study, familiarity and cumulative experience of a team are, in general, distinct concepts. In particular, certain team members may have worked with one another on past projects that did not involve *all* members of the current team.

As a starting point, it is important to consider why team familiarity might yield superior performance. The explanations can be broken down into two classes: (1) coordination and (2) willingness to engage in a relationship (Reagans et al. 2005). With respect to the former, if a team is involved in a task that requires joint activity and the knowledge to be shared is tacit (Polanyi 1967), familiarity may improve the ability of the group to act in a coordinated manner (Moreland et al. 1998). For example, the literature on technology transfer suggests that the transmission of technical knowledge between two parties is often a social and costly process (Arrow 1969, Teece 1981). Repeated experience with each other may provide a

means to “unstick” some of this vital but difficult-to-transfer information as the dialogue around potential solutions becomes more structured (von Hippel 1994, Monteverde 1995).

Because of shared experiences, individuals may develop team human capital (Chillemi and Gui 1997) or network-specific human capital (Mailath and Postlewaite 1990), which aids performance. For example, to explain the nearly flawless operation of an aircraft carrier's flight deck, Weick and Roberts (1993) claim that familiarity leads to “heedful interrelating,” which provides the team with a common platform for learning and action.

A similar argument with respect to coordination can be found in the literature on transactive memory systems. In particular, a transactive memory system—the combination of knowledge and an accurate representation of who knows what—can have a positive impact on performance (Wegner 1987). This idea of knowing where key expertise resides may prove important if positions in a team are not predefined and judgment is used to assign individuals to tasks (Liang et al. 1995, Faraj and Sproull 2000).

The second class of explanations for a positive relationship between team familiarity and performance revolves around the willingness of individuals to engage in a relationship. For example, team beliefs—in particular, team “psychological safety”—can impact both learning and performance, especially if team members do not feel comfortable taking risks. Edmondson (1999) shows that team familiarity (among other things) can contribute to psychological safety. Additional work has shown that shared experience can lead to trust, thereby increasing the amount and quality of information shared by individuals (Granovetter 1985, Uzzi 1997, McEvily et al. 2003).

As with individual and organizational experience, some question whether the benefits of team familiarity are always positive. Katz (1982) examines team longevity and finds that teams that stay together become more isolated from information sources and that this tendency counteracts the benefits of familiarity and internal communication. Therefore, the relationship between tenure and performance exhibits a curvilinear or inverted-U-shaped relationship. Using data from professional sports, Berman et al. (2002) also find support for a curvilinear relationship. Both of these studies examine longstanding teams. The inflection point at which performance degrades in Katz's study does not occur until after greater than five years together as a team (Katz 1982). This suggests that project teams whose lifetimes are measured in months rather than years may be less likely to see a negative effect.

Therefore, we predict:

HYPOTHESIS 1. *Team familiarity is positively related to team operational performance.*

2.2. Team Structure and Roles

Changes in the internal structure of teams (i.e., roles of individual members) represent another aspect of team experience that becomes relevant once one assumes that teams are not perfectly stable entities. Our interest in this case is not in socially constructed roles and the conflict or confusion that may arise from changes in them, but rather in individuals' formal roles within teams. For example, in product development, a team made up of individuals with diverse backgrounds may maintain consistent membership but choose a different leader for subsequent projects based on which member has the most industry-specific experience relevant to a project (Sutton and Hargadon 1996). Alternatively, a team may consist of a project manager, middle managers, and team members. After completion of a project, the project manager may leave the team, and one of the middle managers may be promoted to project manager. Here both membership and structure change. In each of the cases described, the change in structure or roles may impact performance.

To capture these distinctions we introduce the concept of *role experience*—the experience that individuals have operating in their current role on the team. Our concept is related to, but not identical to, the idea of task-specific human capital (Gibbons and Waldman 2004, 2006). Much of the human capital amassed in a job may be specifically related to the task repeated as opposed to being general or firm specific. When examining task experience it is common to measure it as the total time someone has been generating a particular output. This measure ignores the fact that an individual will gain different knowledge and experience based on the role that she holds within the focal production unit. For example, in a software team, the skills a manager needs to motivate individuals and interact with customers are likely not entirely the same as those she needed when writing code. In our measure of role experience, we capture the bundle of tasks that make up each hierarchical role within a firm and create a measure useful for studying fluid teams, in particular, and evaluating experience accumulation more generally.

If changes in roles are more than just changes in titles and require learning and using different skills, then a change in role may reset—or at least set backward—the experience “clock.” We predict:

HYPOTHESIS 2. *Role experience is positively related to team operational performance.*

Further insight may be gained in studying the impact of role changes by separately examining managers and team members. Because of the different skill requirements for each role, the magnitude, and perhaps even the existence, of a relationship between experience and performance may differ between managers and team members. Theoretically, however, we expect a positive relationship between role experience and performance for both managers and team members. Therefore, we predict:

HYPOTHESIS 3A. *Manager role experience is positively related to team operational performance.*

HYPOTHESIS 3B. *Team member role experience is positively related to team operational performance.*

3. Setting, Data, and Empirical Strategy

3.1. Setting

Wipro Technologies is a leading supplier of outsourced software services headquartered in Bangalore, India. Wipro provides customized services throughout the world in areas including application development, engineering services, IT infrastructure management, maintenance, and testing. Wipro offers these services across multiple industries, software languages, and technologies. At the end of 2006, Wipro had annual revenues greater than three billion dollars and more than 66,000 employees.

Between 2001 and 2005, the Indian software services industry grew 29% annually—from \$8 billion to \$22 billion (NASSCOM 2005). In this context of rapid growth, adding new employees while retaining qualified employees is a challenge. While the size and complexity of deals are increasing, pricing is not keeping pace with wage inflation because of gains in supplier efficiency and competition in the marketplace (Moore 2007). Allocating existing experience and building new expertise is vital because of these conditions of growth, turnover, and pressure on cost and price.

We focus on software development projects because they offer the opportunity to use numerous controls across projects. Development involves capturing customer requirements, designing a solution, writing code to meet these objectives, and testing the final output. Capturing the lines of new code, effort used, and software language (among other factors) allows us to control for complexity across projects.

The median development project at Wipro during our sample period lasted six months and had a team size of 12 people. When a project is completed, the team typically breaks up and is distributed to new projects as opportunities arise. Some team members might shift to a project to fix bugs and

add enhancements to the previous project, and some might end up working together again, but development project teams typically do not stay together in their entirety over multiple projects.

Organizationally, Wipro is divided into multiple business units, each of which contains subunits. Both marketing and staffing typically take place within the subunit. Wipro's utilization rate is close to the maximum sustainable utilization when time for vacation, training, and transitions is considered. Given the firm's growth rate, involuntary employee turnover is low at Wipro. Within a project team, there are both middle managers and project engineers in addition to one or more project managers (PMs). Project engineers write software code, and middle managers are typically "player-coaches" who manage portions of projects and write code. PMs manage overall projects and typically do not write code.

3.2. Data

Our sample begins with the universe of 1,004 development projects completed at Wipro from January 2004 to September 2006. We have human capital data for each of the 11,376 individual employees on these project teams. In addition, we have historical data on Wipro employees back to the year 2000 for all types of projects (development, maintenance, etc.), yielding a total of approximately 350,000 project-person records. The additional historical data do not include project outcome data but do provide us with employees' previous project experience. Using this information, we create individual work-experience histories and track the other individuals who worked on project teams with a given employee over time. After removing small projects with fewer than five team members and those with missing data, we are left with 543 projects for our analysis.¹ The subsample on which we conduct our analyses is, therefore, effectively all development projects completed by teams that use kilolines of code as their unit of measurement. Comparing projects missing data to those not missing data on observable criteria revealed no meaningful differences in our variables of interest.

Like other leading firms in the Indian software services industry, Wipro has achieved Capability Maturity Model Integrated (CMMI) Level Five status (SEI 2001). As part of reaching this status, an organization must accurately track its operational performance. Project and employee information at Wipro is recorded using an internally developed Web-based

system. The system not only contains project performance information but also provides life cycle models, project documentation, and reference tools. Project managers enter data in monthly, quarterly, and end-of-project reports. Employees record which projects they are working on each week, and these reports undergo rigorous quality assurance and are subject to random audits. Typically employees work on one project at a time. Employee demographic information, such as birth date and start date at Wipro, is drawn from the firm's multiple HR systems.

3.2.1. Dependent Variables. Identifying objective measures of performance in information technology has proven difficult (Banker and Kemerer 1989), forcing researchers to rely appropriately on survey data (e.g., Faraj and Sproull 2000). We focus on two objective, customer-facing measures of operational performance: (1) output quality and (2) adherence to schedule and effort estimates. We choose these measures because they are used for internal performance measurement, are important to Wipro's customers, and are outcomes over which the team has substantial control. For example, when Wipro administers its customer satisfaction survey, it includes separate questions related to quality and adherence.

Output Quality. Our first dependent variable measures the quality of Wipro's output through a count of *post-delivery defects*. Customer acceptance testing occurs as a final step in most development projects and is the point at which code is tested against the project's predetermined objectives. The customer (or a third party representing the customer) performs the testing, so the results are not open to manipulation by Wipro. In software engineering, the number of defects in acceptance testing is a common measure of quality (Boehm 1981, Jones 1986). The Wipro audit group checks all projects showing no defects to confirm that customer acceptance testing took place.

Adherence. A measure of team performance, or efficiency, is whether the team delivers the project on time and on budget (Boehm 1981, Faraj and Sproull 2000). Sales personnel estimate both the schedule and effort required for a project prior to its start.² These estimates are confirmed with the customer and are formally recorded. Wipro operates in a competitive marketplace, so the company is not able to build significant slack into these estimates, because customers could move their business to other firms. During a project, either estimate may be modified, primarily because of scope changes by the customer. Any

¹ Four hundred eleven projects are missing the variable kilolines of code (KLOC). Many projects do not track KLOC and instead use another unit of measurement. Also, some projects do not include a coding component and are naturally excluded from our analysis. Thirteen other projects are missing one of the variables of interest.

² An important question is whether there is any bias in the creation of estimates. Including customer controls in the models accounts for circumstances unique to specific customers. Additionally, the data do not show clear signs of bias because, for example, estimated effort is not correlated with the deviation between actual and estimated effort.

revisions must be justified by a customer-approved change request. Prior to changing the estimate, both business and quality managers at Wipro must also approve the request to make sure that no manipulation is taking place. The revision process is not an opportunity for a PM to game the system, and a PM cannot revise estimates because a project is not making adequate progress. We use the revised estimate in our analysis because it more fully incorporates a project's final objectives.

Because we have estimates and actual values for both schedule and effort, it is possible to construct continuous variables to measure performance. For effort we create the variable *effort deviation* by subtracting estimated effort from actual effort and dividing by estimated effort. We normalize the measure because we would expect larger absolute differences for larger projects. We do not analyze schedule deviation because the data suggest that it is not, in fact, a continuous measure—more than 70% of the projects in our data deliver on the day the project is due.³ This suggests that, at least in some cases, teams may finish before the delivery date but wait to deliver the code, perhaps because the client is not ready for delivery.

Discussions with project personnel at Wipro suggest that there is a discontinuous jump between delivering a project on time (or on budget) and failing to do so. All things being equal, earlier delivery or less effort is better, though delivering as expected is the most important criterion. During an interview with a Wipro project manager, he noted, "The target is what we're really looking at. My job is to make sure that there isn't slippage [in schedule] or overrun [in effort]."⁴ To capture the importance of meeting these targets, we create dichotomous variables, *effort adherence* and *schedule adherence*, each of which equals one if a project delivers at or better than the estimate and zero otherwise.

Finally, we consider the impact of adhering to both the effort and schedule estimates. Though the measures can be evaluated separately, our fieldwork suggests that Wipro personnel view them jointly with a team being either on plan or not on plan. During a different interview, a Wipro manager noted, "A project must have no schedule deviation and no effort deviation. If you fail there then the customer thinks you are a criminal." These areas are included jointly in the delivery section of Wipro's project customer satisfaction surveys. To address this issue, we construct a joint variable, *adherence*, which equals one if a project delivers at or better than its schedule and effort estimates and zero otherwise.

³ While 76% of projects finish at or below their effort budget, only 2% of projects finish with zero effort deviation.

⁴ During a visit to Wipro's development centers in Bangalore, India in February 2008 we interviewed 17 project managers.

3.2.2. Independent Variables.

Team Familiarity. Similar to Reagans et al. (2005), we measure team familiarity by first calculating the number of times each pairing of team members i and j has worked together on a project at Wipro within the two years⁵ prior to the current project. We sum this value, PW_{ij} , over every unique pair on a team to capture team-specific experience, $\sum_{i=1}^N \sum_{j=1}^N PW_{ij} / (N(N-1)/2)$, where N is team size.

Role Experience. We calculate the average role experience—measured in years—across individuals on each team. For project managers, we identify the first day that the individual appears in the Wipro data set as a project manager and subtract that date from the project's start date. For this calculation, we look at all types of Wipro projects (e.g., maintenance, development, conversion, testing) to identify the role experience for a project manager. We repeat the same process for middle managers, identifying when they first became middle managers. Role experience for project engineers is the same as Wipro or firm experience because project engineer is the most junior role at the firm. We then calculate an overall project variable—role experience—as the weighted average of role experience across all team members. We weight by the number of days each individual spends on the project.

Fewer than 5% of the PMs in our data are left censored for role experience, because they were promoted to their managerial positions prior to the start of our historical data (none of the middle managers are left censored). To correct for this censoring, we calculate a revised value for role experience. In particular, we examine first-time PMs in our data to identify the distribution of time at Wipro prior to promotion. We then add the median value of this distribution to the censored individual's start date at Wipro to determine the estimated date of promotion to manager. This estimated date is then used to calculate revised role experience. As a robustness check, we also use the 25th and 75th percentile values of time at Wipro prior to promotion and find no meaningful differences in the results.⁶

⁵ Establishing the time period over which team familiarity is calculated is an important issue. Similar to the decay of learning (Argote et al. 1990, Benkard 2000), it is likely that the impact of team familiarity also decreases over time. Given that the average project lasts six months, we use a two-year window. We run all models with team familiarity calculated over three years and get similar results. We also conduct sensitivity analyses at higher values and obtain qualitatively similar results, although for these higher values we lose projects from our sample due to censoring because our historical data start in 2000.

⁶ We run two further robustness checks on all models. First, we remove all projects with a censored PM. Second, we add an indicator set to one if a project has a censored PM. Both approaches generate the same pattern of results.

In addition to the overall role experience measure, we calculate separate weighted-average role experience variables for all PMs on a team and for all project engineers on a team, but not for middle managers on a team. We focus on just PMs and project engineers for two reasons. First, the split is theoretically “clean” because it allows us to consider pure managers and pure team members. As noted above, middle managers (e.g., a module lead) hold a “player-coach” role in that they both oversee portions of the project (as managers) and write code (as team members). Second, if we add role experience for middle managers, we lose observations, because many projects do not have middle managers.

Though we have discussed team familiarity and role experience as conceptually distinct components of experience, it is important to note that they are also practically separable. Individuals can gain role experience without increasing team familiarity by continuously changing the team members with whom they work. Similarly, an increase in team familiarity may occur as individuals are shifting across roles, thereby resulting in low role experience.

3.2.3. Control Variables. We control for numerous variables that could impact operational performance. Table 1 provides summary statistics and correlations for the key variables in our analysis.

Firm Experience. For each team, we calculate firm experience as the weighted average of the Wipro work experience across all team members. We weight each individual’s experience by the number of days spent on the project. We use firm experience instead of general experience because the data available for analysis are more complete. Our database includes the firm start date as well as previous experience for Wipro employees. However, approximately 10% of Wipro projects use outside contractors as team members, and

for these individuals we have only the contractor’s Wipro start date. If we were to use general experience, we would need to exclude each of these projects because of missing data. We expect firm experience and total experience to have a similar impact on performance, because more than 47% of Wipro’s employees in our sample have no previous work experience upon joining the firm and more than 65% have less than two years of prior experience.

Fixed Price Contract. Typical of the industry, most contracts at Wipro take one of two forms: time and materials (T&M) or fixed price (FPP) (Banerjee and Duflo 2000). With a T&M contract (known elsewhere as cost-plus), the customer pays a negotiated rate for the hours that Wipro engineers spend on the project. For an FPP contract, the customer and Wipro agree on the requirements and a flat payment. With a T&M contract, the customer traditionally bears the risk of effort overage and benefits of underage, whereas with an FPP contract, Wipro bears the risks and benefits. In our analysis, we use an indicator variable, fixed price contract, set to one if a project has a FPP contract and zero if it has a T&M contract.

Offshore Percentage. Using employee data, we determine the percentage of work completed in Wipro’s Indian locations (offshore) versus that completed at the customer’s location (onsite). We construct a measure of the offshore hours as a percentage of the total hours on a project. Increasing offshore hours could improve performance if Wipro operated more efficiently at its India locations than at customer locations. Alternatively, increasing offshore hours could negatively impact operational performance if it created a disconnect from the customer, making it more difficult for Wipro to obtain client feedback.

Complexity. Our primary measure of project complexity is kilolines of new source code (KLOC). This measure is not without its flaws, but it is the most

Table 1 Summary Statistics and Correlation Table of Dependent, Independent, and Control Variables of Interest

Variable	Mean	σ	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Post-delivery defects	27	113	0	1,396															
2. Effort deviation (%)	-4.6	20.5	-63	274	0.10														
3. Effort adherence	0.77	0.42	0.00	1.00	-0.12	-0.47													
4. Schedule adherence	0.85	0.36	0.00	1.00	-0.13	-0.34	0.37												
5. Adherence	0.72	0.45	0.00	1.00	-0.11	-0.42	0.86	0.66											
6. Team familiarity	0.40	0.44	0.00	2.80	-0.09	-0.12	0.12	0.14	0.15										
7. Role experience	1.25	0.57	0.13	3.71	-0.08	-0.04	0.06	0.04	0.08	0.19									
8. PM role experience	1.19	1.17	0.00	5.63	-0.06	0.00	0.03	-0.06	0.03	0.03	0.36								
9. Project engineer role experience	1.36	0.70	0.01	3.69	-0.08	-0.02	0.04	0.03	0.06	0.17	0.89	0.06							
10. Firm experience	2.10	0.85	0.15	6.23	-0.16	-0.10	0.05	0.05	0.06	0.15	0.70	0.25	0.67						
11. Fixed-price contract	0.69	0.46	0.00	1.00	-0.12	-0.03	0.07	-0.06	0.04	0.10	0.13	0.01	0.12	0.14					
12. Offshore percentage	0.85	0.15	0.23	1.00	-0.03	0.06	-0.07	-0.08	-0.10	0.02	-0.20	-0.03	-0.22	-0.14	-0.09				
13. log(manual KLOC)	3.51	1.21	-1.24	7.66	0.36	0.08	-0.03	-0.10	-0.08	-0.16	-0.09	-0.01	-0.12	-0.23	-0.02	-0.10			
14. log(estimated effort)	8.76	1.04	6.23	12.55	0.38	0.00	0.06	-0.12	-0.02	-0.19	-0.06	-0.01	-0.08	-0.27	-0.16	-0.09	0.68		
15. log(team size)	2.66	0.70	1.61	5.02	0.32	0.12	-0.03	-0.11	-0.09	-0.20	-0.03	-0.01	-0.02	-0.23	-0.17	-0.07	0.60	0.85	
16. log(estimated duration)	5.25	0.62	3.76	7.01	0.19	0.08	0.00	-0.04	-0.03	-0.17	-0.07	-0.05	-0.05	-0.13	-0.13	-0.06	0.45	0.70	0.56

Note. $N = 474$, except for post-delivery defects, where $N = 309$. Bold denotes significance of less than 5%.

common measure of size and complexity in software engineering (Boehm 1981, Scacchi 1995). Many of the traditional drawbacks of KLOC—such as defining what qualifies as a line of code and how to count thousands of lines of code—are mitigated in our case, because we consider only one organization that uses a consistent counting methodology (Jones 1986, Low and Jeffery 1990). Software development has been shown to exhibit scale effects, so we use the logarithm of KLOC (Banker and Kemerer 1989). We also add indicators for seven groups of software languages that appear in the data⁷ to address the potential for systematic differences in adherence or quality across different languages. We also include an additional control for whether the project used one or more than one software language (70% and 30% of projects, respectively), because a project using multiple languages could be more complex than one of the same size involving only one language.

Team Size. Increasing a team's size at low levels may improve performance because of the capacity and experience of the additional member. However, increasing team size above a context-specific maximum may increase coordination challenges resulting in decreased performance (Brooks 1975, Hackman 2002). Team scale-up varies at Wipro, as some teams staff up at once whereas others do so more gradually. We thus measure team size as the log of the total people who participated in the team over its existence.⁸

Effort. To capture the size of a project, we use the log of the estimated total person-hours dedicated to the project. We use the estimate rather than the realized value to avoid potential endogeneity because a project that misses its estimate would by definition use more effort than an identical project that does not miss its estimate. Similar to KLOC and team size, we would expect projects with more effort to be more difficult to manage. We thus expect increasing effort to have a negative impact on performance.

Duration of Project. We include the estimated duration of a project (measured in log days), because longer projects may perform worse given the challenges already discussed or because they risk additional employee attrition (Ethiraj et al. 2005). We use the estimated value to avoid concerns of endogeneity.

Start Year. To control for potential learning and environmental conditions (such as changes in employee attrition) at the firm level, we include indicators for the year the project started. Substituting indicators for the year the project ended does not meaningfully change our results.

⁷ C, C++, Java, C#, query (e.g., SQL), markup (e.g., HTML), BASIC, and other is the "excluded" category.

⁸ We log team size, effort, and duration to control for outliers. Our results do not change with unlogged variables.

3.3. Empirical Strategy

3.3.1. Output Quality. With our dependent variable bounded by zero, linear regression may yield results that are inconsistent, biased, or inefficient (Long 1997). Additionally, our database has multiple projects per customer, so we need to control for time-invariant characteristics of customers that may impact quality. Models for count data can address both of these issues, and, because our data exhibit overdispersion, we use a conditional fixed-effects negative binomial model (Hausman et al. 1984, Cameron and Trivedi 1998). This model conditions on the total count within a given subgroup (e.g., customer). The model eliminates all instances with one observation per group and those groups where the dependent variable does not vary from zero. Because not all projects complete acceptance testing, we are left with a sample of 309 projects for analysis.

3.3.2. Effort Deviation. For effort deviation, we control for customer attributes using a generalized least squares (GLS) random-effects regression model.⁹ After eliminating projects from customers with only one project in the database, we are left with 474 projects for our analysis.

3.3.3. Adherence. Given that effort, schedule, and overall adherence are dichotomous variables, we use a logistic regression model. We cannot simply add customer indicators to the logistic regression model, because the unconditional maximum-likelihood estimator is inconsistent when the number of units (in our case, projects per customer) is small (Greene 2003). Although the bias has been found to be small in unit values as low as eight, our data include unit values as low as two (Heckman 1981, Katz 2001),¹⁰ so we use the conditional logit. When using the conditional logit, we lose not only projects from customers with only one project in the database but also those from customers for whom the outcome of interest does not vary. This restriction leaves us with a sample of 393 projects from which our estimates are generated.

4. Results and Discussion

We now examine our models for each of the two classes of dependent variables.

⁹ Hausman's specification test fails to reject the null hypothesis that the random-effects model is consistent.

¹⁰ We test our model specification using Hausman's specification test. In particular, if there are no customer effects then the estimators from the logit (unconditional maximum likelihood) and conditional logit (conditional maximum likelihood) are consistent, but the conditional maximum likelihood estimator is inefficient. Our alternative hypothesis is that the conditional maximum likelihood estimator is consistent and efficient and the maximum likelihood estimator is inconsistent (Greene 2003). The test rejects the null hypothesis at $p < 0.05$.

Table 2 Results of the Regressions of Post-Delivery Defects and Effort Deviation, Respectively on Wipro Experience, Role Experience, and Team Familiarity ($n = 309$ and 474 , Respectively)

	Dependent variable: Post-delivery defects			Dependent variable: Effort deviation		
	(1)	(2)	(3)	(4)	(5)	(6)
Team familiarity	−0.469** (0.242)	−0.438* (0.243)	−0.458* (0.241)	−2.687** (1.282)	−2.945** (1.335)	−3.096** (1.345)
Firm experience	−0.129 (0.112)			−2.507 (1.779)		
Role experience		−0.278* (0.158)			−1.734 (2.281)	
Project manager role experience			−0.027 (0.069)			−0.316 (0.916)
Project engineer role experience			−0.221* (0.132)			−0.860 (1.923)
Fixed-price contract	0.324 (0.214)	0.331 (0.213)	0.336 (0.213)	−0.707 (2.251)	−0.790 (2.299)	−0.834 (2.194)
Offshore %	0.180 (0.541)	0.063 (0.551)	0.091 (0.549)	−0.692 (6.699)	0.084 (7.103)	0.462 (7.136)
log(manual kilolines of new code)	−0.002 (0.196)	0.037 (0.194)	0.033 (0.195)	2.927*** (0.982)	2.880*** (1.007)	2.912*** (1.008)
log(estimated project effort)	0.424*** (0.119)	0.409*** (0.119)	0.405*** (0.119)	−11.228*** (3.476)	−10.483*** (3.089)	−10.496*** (3.296)
log(maximum group size)	−0.056 (0.223)	−0.025 (0.224)	−0.028 (0.224)	11.118*** (4.000)	11.329*** (4.147)	11.310*** (4.291)
log(estimated duration)	−0.024 (0.192)	−0.076 (0.189)	−0.076 (0.194)	6.567** (2.919)	6.070** (2.609)	6.070** (2.822)
Constant	−2.322* (1.220)	−2.240* (1.198)	−2.237* (1.204)	33.408** (15.053)	26.615** (13.189)	25.721** (12.968)
No. of languages indicator	Not sig	Not sig	Not sig	Not sig	Not sig	Not sig
Start year indicators	Not sig	Not sig	Not sig	**	***	***
Language indicators	**	**	**	Not sig	Not sig	Not sig
Observations	309	309	309	474	474	474
Log likelihood	−637.3	−636.4	−636.4	—	—	—
Overall R^2	—	—	—	0.1305	0.1191	0.1188
Wald chi-squared	54.05***	56.16***	56.16***	70.03***	69.19***	70.45***

Notes. Post-delivery defect models are conditional fixed-effects negative binomial models that condition on the customer. Effort-deviation models are GLS random-effects models with heteroskedasticity robust standard errors, clustered on the customer.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.1. Output Quality

Table 2 shows the results of our conditional negative binomial regression models testing the relationship between experience and post-delivery defects.

In column 1 we run a model with controls, firm experience, and team familiarity and find that the coefficient on firm experience is negative (implying a positive relationship with quality) but not significant at conventional levels. The coefficient on team familiarity is negative and significant, providing support for Hypothesis 1. An increase of one standard deviation in overall team familiarity results in an 18.6% decrease in expected defects. In column 2 we again find that the coefficient for team familiarity is negative and significant at the 10% level. When we substitute role experience for firm experience, the coefficient for role experience is negative and significant at the 10% level, providing support for Hypothesis 2. An increase of one standard deviation in overall average role experience yields a 14.7% decrease in expected defects. In column 3 the coefficient on team familiarity remains negative and significant at the 10% level. The coefficient on PM role experience is effectively zero, whereas that on project engineer role experience is negative and significant at the 10% level. An increase of one standard deviation in project engineer

role experience results in a 14.3% decrease in expected defects. These results provide support for Hypothesis 3B but not Hypothesis 3A.

4.2. Deviation and Adherence

As discussed above, we have multiple measures to evaluate the efficiency with which a project is delivered. Columns 4–6 in Table 2 show the results from regressions with effort deviation as the dependent variable. The independent and control variables in the three models are the same as those in the quality analysis. We find that team familiarity is a significant predictor of superior performance for effort deviation. A one-standard-deviation change in team familiarity is related to an 18%, 30%, and 36% decrease in effort deviation for columns 4, 5, and 6, respectively. Whereas team familiarity is significant in each of the models, providing support for our first hypothesis, firm experience, overall team role experience, PM role experience, and project engineer role experience have their expected signs but are not significant.

We next examine effort adherence instead of effort deviation. Table 3 presents the results from each of the conditional logistic regressions. Column 1 presents a model with all of the controls, firm experience, and team familiarity. The coefficient on team familiarity is positive and significant at the 10% level,

Table 3 Results of the Conditional Logistic Regression of Effort Adherence, Schedule Adherence, and Adherence on Wipro Experience, Role Experience, and Team Familiarity
 ($n = 365, 344, \text{ and } 393, \text{ Respectively}$)

	Dependent variable: Effort adherence			Dependent variable: Schedule adherence			Dependent variable: Adherence		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Team familiarity	0.721* (0.424)	0.713* (0.431)	0.770* (0.435)	0.731 (0.551)	0.704 (0.588)	0.748 (0.563)	0.829** (0.382)	0.792** (0.393)	0.790** (0.386)
Firm experience	0.466* (0.248)			0.066 (0.223)			0.288 (0.189)		
Role experience		0.557** (0.239)			0.143 (0.325)			0.461** (0.230)	
Project manager role experience			0.256* (0.148)			-0.097 (0.181)			0.206* (0.118)
Project engineer role experience			0.360** (0.177)			0.008 (0.236)			0.303* (0.160)
Fixed-price contract	0.104 (0.435)	0.176 (0.432)	0.166 (0.441)	-0.690 (0.505)	-0.682 (0.503)	-0.699 (0.523)	-0.098 (0.414)	-0.066 (0.416)	-0.112 (0.428)
Offshore %	-0.573 (1.460)	-0.521 (1.457)	-0.548 (1.478)	-2.659* (1.549)	-2.631* (1.562)	-2.724* (1.536)	-1.181 (1.311)	-1.097 (1.332)	-1.161 (1.266)
log(manual kilolines of new code)	-0.419** (0.173)	-0.414** (0.183)	-0.435** (0.189)	-0.060 (0.223)	-0.062 (0.227)	-0.051 (0.225)	-0.373** (0.170)	-0.370** (0.176)	-0.384** (0.176)
log(estimated project effort)	1.143*** (0.403)	1.018*** (0.361)	0.976*** (0.341)	-0.445 (0.358)	-0.451 (0.365)	-0.427 (0.361)	0.781** (0.336)	0.714** (0.317)	0.709** (0.304)
log(maximum group size)	-0.719 (0.485)	-0.789 (0.496)	-0.779 (0.495)	-0.080 (0.423)	-0.088 (0.423)	-0.114 (0.432)	-0.765* (0.418)	-0.800* (0.423)	-0.890** (0.447)
log(estimated duration)	-0.534 (0.365)	-0.404 (0.329)	-0.332 (0.303)	0.328 (0.384)	0.335 (0.393)	0.309 (0.375)	-0.208 (0.325)	-0.161 (0.315)	-0.111 (0.299)
No. of language indicator	*	Not sig	*	Not sig	Not sig	Not sig	*	*	*
Start year indicators	Not sig	Not sig	Not sig	Not sig	Not sig	Not sig	Not sig	Not sig	Not sig
Language indicators	Not sig	Not sig	Not sig	Not sig	Not sig	Not sig	Not sig	Not sig	Not sig
Observations	365	365	365	344	344	344	393	393	393
McFadden's pseudo R ²	0.1220	0.1197	0.1285	0.1587	0.1592	0.1601	0.1180	0.1211	0.1319
Wald chi-squared	42.77	71.23	64.24	38.79***	41.52***	54.59***	47.47***	72.14***	74.05***

Notes. All models condition on the customer (i.e., include customer fixed effects). Standard errors are heteroskedasticity robust. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

and a one-standard-deviation change in team familiarity increases the odds of effort adherence by 37%. Also, the coefficient on firm experience is positive and significant at the 10% level, and a one-standard-deviation change in experience increases the odds of effort adherence by 49%. We note that this is the only model where the coefficient on firm experience is significant at less than 10%. In columns 2 and 3 we run the same model first substituting overall role experience and then substituting PM role experience and project engineer role experience for firm experience. In each model, the coefficient on team familiarity is positive and significant at the 10% level. In column 2 role experience is significant, and an increase of one standard deviation in role experience yields a fitted odds ratio of 1.38. In column 3 the coefficients on both PM and project engineer role experience are positive and significant at the 10% level.

Columns 4–6 in Table 3 show the models for schedule adherence. In each model, the coefficient on team familiarity is positive and close to the values in the corresponding models for effort adherence, although they are not significant at conventional levels. The coefficients on firm experience (column 4) and overall team role experience (column 5) are positive but not significant. Whereas the coefficient for project engineer experience is positive (column 6), the coefficient for project manager role experience is negative, though neither is statistically significant.

Finally, we examine the relationship between our predictors and overall adherence (whether a project meets both its effort and schedule estimate). In column 7 our model includes controls and both firm experience and team familiarity. The coefficient on firm experience is positive, though not significant at conventional levels. The coefficient on team familiarity is positive and significant, providing support for Hypothesis 1. Interpreting this latter coefficient, we note that an increase of one standard deviation in team familiarity increases the odds of adherence by 44%.¹¹

Column 8 substitutes overall role experience for firm experience. The coefficient for team familiarity remains positive and significant, and that for role experience is also positive and significant, providing support for Hypothesis 2. An increase of one standard deviation in overall role experience yields a fitted odds ratio of 1.30. When we divide role experience into separate components for PMs and project engineers, we find support for Hypotheses 3A and 3B

(column 9). The coefficient on team familiarity is positive and significant, and an increase of one standard deviation yields a fitted odds ratio of 1.42. In this model the coefficients on both PM role experience and project engineer role experience are positive and significant at the 10% level. An increase of one standard deviation in each variable yields odds ratios of 1.27 and 1.24, respectively.

4.3. Alternative Explanations

We now examine alternative explanations for our findings on team familiarity and role experience. In a study that examines the relationship between the frequency with which individuals work together and performance, selection of team members is an important concern. Typically, Wipro's presales personnel are responsible for estimating the effort and schedule requirements for a project with a customer. Once the estimates for a project are frozen, the PM—sometimes multiple PMs for large projects—is assigned. The estimates are used to staff the project team. In general, PMs cannot select specific individuals for their teams. PMs receive potential team members from a subunit's HR function, and, if resources are not available within the subunit, the search is expanded first across the firm and then outside of it. The PM can exert control by rejecting potential team members, but he or she does not select the pool from which potential team members are chosen. This ability to reject team members could be problematic if exercised often. To examine this question empirically we use a Cox proportional hazards model to analyze every dyad of individuals who worked together in our sample (Cleves et al. 2004). We define failure as the pair not working together on their next project, and we examine whether poor team performance increased the hazard rate.

As seen in Table 4, neither adherence nor quality performance is a significant predictor of the likelihood of a dyad not staying together. Furthermore, the signs of these variables are not all consistent with the selection story (e.g., effort adherence in column 1), increasing our confidence that selection is not driving our results.

We now turn to alternative explanations of our findings with respect to role experience. The first is that, with increasing role experience, a PM is better able to build slack into initial project estimates, thereby improving the chances of adherence. Because a PM is not responsible for her project's estimates, this manipulation is not possible. The second alternative explanation is that, with increasing role experience, a team is able to manipulate the revision process, thereby "tricking" the customer

¹¹ Given the work of Katz (1982) and others we test for curvilinearity for all independent variables in all models. We find no evidence of a curvilinear effect in our data (results not shown). Given that project teams do not stay together over long periods of time this result is not surprising.

Table 4 Summary Results of Cox Hazard Models to Examine the Potential Selection Effects Due to Project Performance

	(1)		(2)	
Post-delivery defects	0.00005	(0.00004)	0.00005	(0.00004)
Effort adherence	0.0086	(0.0312)		
Schedule adherence	-0.0271	(0.0207)		
Adherence			-0.0020	(0.0222)
Fixed-price contract	0.0211	(0.0239)	0.0248	0.0247
Offshore %	-0.0140	(0.0931)	-0.0212	(0.0962)
log(manual kilolines of new code)	0.0011	(0.0094)	-0.0001	(0.0098)
log(estimated project effort)	-0.0349**	(0.0160)	-0.0330**	(0.0159)
log(maximum group size)	0.0546**	(0.0211)	0.0521**	(0.0208)
log(estimated duration)	0.0576***	(0.0179)	0.0575***	(0.0173)
Observations	114,401		114,401	
Log likelihood	-1,209,524		-1,209,526	

Notes. The following variables are included in the regressions but are not shown in the table: project start year, software language, number of languages, and customer fixed effects. Standard errors are clustered by project.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

into a revision.¹² Wipro has mechanisms to prevent this from occurring, but we still test whether such behavior occurs. Specifically, we find no relationship between any of our measures of role experience and changes in effort or schedule estimates. We also consider only positive revisions—those revisions where additional effort or schedule is added to a project—and again find no relationship. These results give us confidence that increased role experience is not related to increased manipulation in this setting.

Another alternative explanation could be that our measures of experience and team familiarity capture repeated interaction with a given customer. Increased experience with a customer could lead to improved understanding of project requirements or an exchange of tacit knowledge resulting in better performance. As such, we repeat the models in columns 2 and 3 of Table 2 and columns 8 and 9 of Table 3 including a measure of the team’s customer experience (i.e., the average number of times that each team member has previously worked with the focal customer). We do not include this measure in our base models because it is highly correlated with team familiarity (0.68). We show only the results with overall adherence because it is the most comprehensive measure of delivery performance, although other measures show similar results.

Comparing the adherence results from the first two columns of Table 5 to the analogous models in Table 3 we see that the coefficients on both team familiarity and role experience are changed only slightly and that

¹² Because there are not original and revised estimates for acceptance testing, we do not have to consider manipulation by managers as the cause of our quality findings.

Table 5 Summary Results of the Regressions of Adherence and Post-Delivery Defects on Role, Team, and Customer Experience ($n = 393$ and $n = 309$, Respectively)

	Adherence		Quality	
	(1)	(2)	(3)	(4)
Team familiarity	0.775* (0.456)	0.779* (0.449)	-0.310 (0.297)	-0.336 (0.296)
Role experience	0.460** (0.234)		-0.270* (0.160)	
Project manager role experience		0.192* (0.115)		-0.038 (0.069)
Project engineer role experience		0.278* (0.156)		-0.197 (0.133)
Customer experience	0.011 (0.172)	0.030 (0.167)	-0.086 (0.097)	-0.083 (0.098)
Observations	393	393	309	309
McFadden’s pseudo R^2	0.1211	0.1250	—	—
Log likelihood	—	—	-633.9	-634.1
Wald chi-squared	72.52***	77.00***	61.75***	61.17***

Notes. All models condition on the customer (i.e., include customer fixed effects). The following variables are included in the regressions but are not shown in the table: contract type, offshore, log(manual kilolines of new code), log(estimated project effort), log(maximum team size), log(estimated duration), project start year, software language, and number of languages.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

the coefficient on customer experience is not significantly different from zero. The story is slightly different with respect to quality. The coefficient for team familiarity in each model has decreased and is no longer significant. The values for the overall team role experience and project engineer role experience coefficients are similar to Table 2, although the project engineer role experience coefficient is no longer significant at conventional levels. The coefficient on customer experience is negative, but not significant in either case. This robustness check supports our role experience findings, although it does suggest that, in the case of quality, we cannot conclusively distinguish the effects of team familiarity and customer experience because of their collinearity. Separating these effects represents an area for potential future research.

4.4. Discussion

Consistent with Hypothesis 1, we find that familiarity among team members is positively and significantly related to both quality and adherence (with the exception of schedule adherence on its own). Wipro software-development teams tend to be hierarchical in nature, with PMs being responsible for the assignment of work. It is possible that, as the PM gains experience with a team, she is better able to allocate responsibilities among team members and manage interdependencies. Also, a project engineer’s experience with other project engineers may prove helpful for identifying and managing interdependencies. These coordination benefits likely impact both quality and adherence. The potential for an increasing willingness to engage in a relationship with an

increase in team familiarity may be particularly helpful for improving quality. Given the difficulty in making in-process quality visible, familiarity among project engineers may be valuable as they build informal advice-seeking networks (Leonardi 2007). With growing familiarity, project engineers also might be increasingly willing to put their reputations at risk by asking questions and sharing errors earlier in the process (Edmondson 1999).

We find partial support for Hypothesis 2. Although the average firm experience of team members is not significantly related to quality or project efficiency in all but one of our models, overall role experience is associated with better performance in terms of quality and two of the four measures of project efficiency. Changes in roles at Wipro are more than just changes in titles and necessitate learning and the use of different skills. For example, the PM is responsible for allocating project work, interacting with the customer, and monitoring progress but is rarely directly involved in writing code. Therefore, a change in role may reset, or at least set backward, the experience “clock” of a new PM in some cases.

Reagans et al. (2005) find a curvilinear relationship between an individual surgeon’s experience and her performance; increases in experience are first negatively related to performance, before eventually shifting over to a positive relationship. Among their potential explanations is that roles could be changing within teams of surgeons. Although our work cannot conclusively say that role changes were the causal mechanism in their study, our findings provide support for that hypothesis.

We further explore the impact of role experience by introducing separate measures for project managers and project engineers. We find evidence of differential effects of PM role experience and project engineer role experience on project efficiency and quality. Although both measures are positively and significantly related to effort adherence and overall adherence, only project engineer role experience is positively and significantly related to quality. With respect to engineer experience, this result is likely due to a traditional learning-curve story—with repetition, project engineers become more effective coders and are able to monitor their own progress, manage their own interdependencies, and deal more effectively with the inevitable changes that most projects encounter.

Given that the PM role is different from that of a project engineer, it is not surprising that PM role experience is differentially related to these measures of project performance. After follow-up discussions with Wipro personnel, we think that an important distinction may be one of observability. Because the overall effort and the elapsed days for a project are

both metrics that are easily and routinely monitored while a project is in progress, PMs are able to follow performance and adjust in response. To the extent that greater PM role experience provides more know-how in dealing with uncertainty and problems as they arise, we would expect—and find—PM role experience to be positively related with adherence.

On the other hand, our quality variable is an end-state measure, which is difficult to track in process. It is hard to know the quality of a project until it nears its end. For a PM, additional role experience may help in structuring work more effectively, but, given the difficulty in monitoring progress and making mid-course corrections, the overall benefit of experience for a PM may be more muted with respect to quality as opposed to adherence. Our findings thus suggest that experience as a manager is positively related to performance measures that can, in fact, be more easily managed in process.

4.5. Limitations

Like any study, ours has limitations, and one should be careful in applying its results. First, it is possible that any nonrandom assignment of individuals to teams might bias our results. The approach used by Wipro to determine project teams and conversations with Wipro personnel indicate that, typically, project managers are not able to choose specific team members. Our hazard analysis suggests that members of unsuccessful teams are not less likely to work together in the future than members of more successful teams. Nevertheless, we cannot categorically rule out the possibility of bias. Second, there is the possibility that teams with more team familiarity or role experience are assigned to projects with a higher priority with respect to adherence or quality. Assuming that we are adequately controlling for project complexity and any other characteristics of higher-priority projects that are correlated with experience, this effect should be diminished. Table 1 supports this view, because neither role experience nor PM role experience is significantly correlated with measures of size and complexity (KLOC, effort, team size, and duration). Furthermore, interviews suggest that this is not how Wipro generally assigns projects.¹³

Third, our results are from one firm in one industry, and it is possible that they will not generalize to other settings. Compensating for this drawback is the detailed information we have about team composition and quantitative performance measures. In this context, we are able to combine deep knowledge of a single firm with large-scale empirical tests of our hypotheses.

¹³ In a discussion with a senior manager on this topic, he said that when he examined PM experience and project value in his business he found that his vertical had not assigned its most senior PMs to its largest projects.

5. Conclusion

Our study begins by setting aside the assumption that teams are stable over time and uses unique data to examine how team familiarity and role experience impact team performance. Our setting is a useful backdrop for exploring this question because we can link data on team members to verifiable team outcomes.

We shed light on how changes in team composition affect performance. First, we examine a measure of team familiarity that accounts for the degree to which each member of a team has worked with every other team member on previous projects. This measure allows us to avoid the assumption that team membership remains constant from one project to the next. We find that overall team familiarity is positively related to both of our measures of operational performance. Second, we examine the impact of what we term *role experience*—the experience that individuals have operating in their current roles of team member or team manager—on team performance. We find partial support for this hypothesis, as role experience is positively related to some, but not all, of our measures of operational performance. Looking more closely at role experience, we find a differential relationship between project manager and project engineer role experience and our measures of operational performance.

Our work has implications for the academic study of teams and organizations. First, our findings underscore the need to use caution in assuming that team membership is constant from one project to the next. Second, our results build on previous work on team familiarity by considering longitudinal data on the individual members of teams. We, therefore, are able to view team familiarity as a continuous, rather than dichotomous, measure. We do not simply measure whether a team has familiarity or not but rather capture the difference between a team where 75% of team members have previously worked with other team members and a team where only 25% of team members have done the same. Future work should explore further decompositions of team familiarity. For example, it is possible that the team familiarity of specific subgroups (e.g., PMs and project engineers) may be related to different measures of performance.

Third, our findings suggest the importance of considering role experience. Further work should both evaluate this effect in different empirical settings and explore additional questions, such as when a role is different enough to reset the experience “clock.” Fourth, our results highlight the value of studying multiple measures of experience at different levels (Reagans et al. 2004). By getting into the black box linking experience and operational performance, we see that task characteristics may play a key role in

determining the value of different types of experience. In our case, PM role experience is positively related to some measures of project efficiency, but not quality, perhaps because of differences in observability. Future work should explore these linkages further. Both of these points suggest that there may be something special about managerial roles. Many writers have noted that not all individual contributors are good managers (e.g., Charan et al. 2000). Some of this could be innate, but these results suggest that experience within a given role and the characteristics of the task itself may significantly impact a manager’s ability to do her job effectively.

Prior work (e.g., Reagans et al. 2005) has hypothesized about the value of having knowledge about how to carry out a role (role experience) and the value of coordinating across and among roles (team familiarity), but these two constructs are often confounded empirically. Separating the two, as we have done in our analyses, is important both empirically and theoretically. By identifying and separating further the theoretical constructs that make up the experience of fluid teams, we are able to understand in more detail how each impacts team performance.

Our work also has important implications for managers. In many industries, fluid project teams are the rule rather than the exception (Edmondson and Nembhard 2008). In contexts such as product development, consulting, investment banking, and service delivery, project teams are formed to produce a definable output and then are disbanded, with members being assigned to new teams. Our findings suggest that managers should adopt a more nuanced view of experience in which they explicitly consider both experience within a given role and experience with other team members when making staffing decisions. For example, rather than just assigning a programmer with three years of experience to a given project, a manager may want to assign a programmer with three years of experience (with at least one year as a project manager) who has worked with at least 25% of the other project team members on previous projects. Though it may require firms to track additional data, this approach places new, and potentially important, levers of control in the hands of the manager.

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