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Ravi Bapna, Nishtha Langer, Amit Mehra, Ram Gopal, Alok Gupta,

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# Human Capital Investments and Employee Performance: An Analysis of IT Services Industry

Ravi Bapna

Carlson School of Management, University of Minnesota, Minneapolis, Minnesota 55455; and  
SRITNE, Indian School of Business, Hyderabad 500032, India, [rbapna@umn.edu](mailto:rbapna@umn.edu)

Nishtha Langer, Amit Mehra

Indian School of Business, Hyderabad 500032, India {[nishtha\\_langer@isb.edu](mailto:nishtha_langer@isb.edu), [amit\\_mehra@isb.edu](mailto:amit_mehra@isb.edu)}

Ram Gopal

School of Business, University of Connecticut, Storrs, Connecticut 06269, [ram.gopal@business.uconn.edu](mailto:ram.gopal@business.uconn.edu)

Alok Gupta

Carlson School of Management, University of Minnesota, Minneapolis, Minnesota 55455, [agupta@csom.umn.edu](mailto:agupta@csom.umn.edu)

The rapid pace of technological innovation necessitates that information technology (IT) services firms continually invest in replenishing the skills of their key asset base, the human capital. We examine whether human capital investments directed toward employee training are effective in improving employee performance. Our rich employee level panel data set affords us the opportunity to link formal training with performance at the individual employee level. Using a dynamic panel model, we identify a significant positive impact of training on employee performance. A unit increase in training is linked to a 2.14% increase in an employee's performance. Interestingly, we find that in the IT sector, skills atrophy and consequently high-experience employees reap higher returns from training, which highlights the uniquely dynamic nature of IT knowledge and skills. We also find that general training that an employee can utilize outside the focal firm improves employee performance. However, specific training pertinent to the focal firm is not positively linked to performance. On the other hand, although domain and technical training both enhance employee performance individually, the interaction between the two suggests a substitutive relationship. Thus, our findings suggest that the value of training is conditional on a focused curricular approach that emphasizes a structured competency development program. Our findings have both theoretical and practical significance. Most important, they justify increased human capital investments to fuel future growth in this important component of the global economy.

**Key words:** training and productivity; IT services; dynamic panel model; employee performance; Indian IT industry; human capital theory

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## 1. Motivation and Background

In today's knowledge economy, firms need to continually nurture their human capital to gain lasting competitive advantage. This is especially true for the information technology (IT) services industry where employee costs and associated productivity are the major determinants of gross profits. The productivity of human capital in this industry crucially depends on the employees' expertise, which requires continuous overhaul due to the fast pace of technological change (Joseph and Ang 2010, Lee et al. 1995, Tambe and Hitt 2010a), and workplace reorganization (Bresnahan et al. 2002). The knowledge-based theory of the firm (Grant 1996) is particularly appropriate in characterizing firms in the IT services industry. Such a view conceptualizes the firm as an institution for integrating knowledge, where knowledge is viewed as residing

within the individual, and the primary role of the organization is knowledge application. Viewed from this perspective, human capital emerges as the key tangible and intangible resource likely to provide sustainable competitive advantage for firms in the IT services industry (Hatch and Dyer 2004). Becker (1962, 2003) and Mincer (1962) suggest that investment in human capital through employee training improves the quality of human capital and thus has major productivity implications. Consequently, understanding the performance impacts of human capital investments in the form of employer-funded training has significant import for both theory and practice.

Our research is set in the context of the Indian IT services industry. Despite a challenging global macroeconomic environment, the market for IT services continues to grow at an above average rate of 6.3%,

and is nearly \$967 billion in 2008 (NASSCOM 2009). As of 2007, the Indian IT services industry accounts for \$71.7 billion of the global \$967 billion industry. It employs 2.23 million knowledge workers and has been growing by double digits for the last decade. However, the veneer of this growth in India masks the underlying structural weaknesses of a higher education system in crisis where a majority of college graduates are unemployable (see Irani 2008 for views from the Indian popular press). While studies have shown that there is disillusionment with skills gap even in the U.S. workforce when they join fresh from college (see King 2009) in countries such as India, the skills gap is significantly wider (Kapur and Mehta 2007). The consequence of these challenges is that Indian IT services firms are forced to make significant investments in providing education and training to their employees (Hatakenaka 2008). In addition to the training investments that bridge the skills gap of new college graduates, IT services firms also provide continuous training and education to cope with the dynamic demands of the global clientele and rapid advances in technology.

The increasing need for training investments by Indian IT firms motivates our study. For instance, the bellwether company, Infosys, has been increasing its training expenditure by close to 16% per annum per employee over the last five years.<sup>1</sup> In contrast to 2002 when training expenses were a mere 3.3% (1.52%) of wages (revenues), Infosys currently spends the equivalent of 8% (3.52%) of wages (revenues) on employee training and education. More broadly, industry surveys show that IT firms are increasing investments in training at close to double digits in percentage terms (Price Waterhouse Coopers 2009). Our primary research question is whether these continuing training investments yield any measurable performance benefits to the employees. In the context of IT offshoring, the answer to this question has productivity implications not just for the IT services firms making these substantial human capital investments, but also for more favorable outcomes (lower costs and/or improved quality) for IT services consuming firms across the globe.

There is significant interest in the human capital research community in measuring the returns on training investments. Extant literature has advanced our understanding of the relationship between training investments and human capital improvement. However, many such studies have used self-reported (survey) or aggregate level data (see Blundell et al. 1999 for more discussion on this). This impedes understanding of more nuanced aspects of this research strand, for instance, the effect of different

types of training across different employee types. Generalizability of prior studies is also constrained by the methodological constraints inherent in this research problem, namely, employee motivation and drive, which may otherwise confound the results. We specifically address this gap in the literature in the context of IT services industry by using rich, detailed archival training and performance data at the employee level from a leading Indian IT services firm with a global footprint. Our work is in line with emerging information systems (IS) research that examines the returns to education and occupation-specific experience (IT versus non-IT experience) in terms of compensation (Mithas and Krishnan 2008). Extant research posits that the impact of training on human capital productivity gains depends on the industry context. Barring a few exceptions (Mithas and Krishnan 2008, Mithas and Lucas 2010, Ramasubbu et al. 2008), existing studies have been carried out in nonknowledge work contexts (e.g., Ichniowski et al. 1997). For example, Ichniowski et al. (1997) find that training has an impact only in combination with complementary human resource (HR) practices in the context of steel finishing factories. Likewise, Ramasubbu et al. (2008) find that different types of skills training have a significant impact on employee performance in the domain of enterprise software systems services. In contrast, we extend human capital literature by focusing on knowledge work and placing no restrictions on the type of software that the employees are working on.

The firm in our study has an exemplary HR practice, and has been a front runner in employee training investments. The data were provided by the senior management of this firm in return for a credible econometric analysis that examined the link between their growing training outlays and economic returns. We were fortunate in having access to details about every firm-provided training module taken by a random selection of close to 8,000 employees over a five year period as well as detailed performance ratings for these employees. The company uses an industry-leading appraisal process (more on this in §3, where we discuss our constructs); therefore, the performance rating gives us a highly credible, reliable, and objective measure of performance, and serves as our dependent variable. While our primary interest is in measuring the aggregate effect of training on employee performance, the richness of our data also permits us to examine more nuanced aspects of human capital theory. Given the rapid rate of technological innovation in IT we draw on the literature on obsolescence and forgetting (Joseph and Ang 2010, Pazy 1996) to examine whether there are differences in the performance benefits of training between high and low-experience employees (Underwood 1957).

<sup>1</sup> Infosys annual reports from year 2002 to 2007.

Following Becker (2003), we distinguish between the differential impacts of general versus specific training in the context of IT workers. Motivated by IS literature (Lee et al. 1995, Tambe and Hitt 2010a, Joseph et al. 2010) on skills development of IT workers, we further seek to distinguish the performance impact of technical and domain knowledge training. In making these distinctions we are interested not just in the relative main effects of the different types of training, but also their interactions. In particular, we ask whether the different types of training are complementary or substitutive in nature and whether the lack of focus or the presence of an overarching curriculum has a moderating influence on the main effect of training (van der Hulst and Source 2002).

While the richness of our data affords us the opportunity to ask these hitherto unaddressed questions, there are significant econometric challenges in identifying the performance impact of training. First, despite the fact that we obtain a random sample of approximately 8,000 employees, endogeneity in our data remains a concern. A variety of observed and unobserved factors could determine why a given employee undergoes training in a given year, and failure to account for this would lead to a biased estimate of the main effect. Second, the relationship between training and performance could be confounded by unobserved individual characteristics, such as motivation and drive, which could be correlated with the errors in our primary model. To overcome these identification challenges, we use an Arellano–Bover/Blundell–Bond (Arellano and Bover 1995, Blundell and Bond 1998) dynamic panel model to construct unbiased and efficient estimators based on moment equations constructed from lagged levels of the dependent variable and the first-differenced errors. A combination of detailed archival data and a sophisticated econometric model make our findings robust.

We identify a significant positive impact of training on employee performance: Taking one additional course results in a 2.14% increase in performance for an average employee. Critically, the positive link justifies continued investments in employer-funded employee training. Consistent with the obsolescence effect of IT knowledge, we find that employer provided training has a higher impact for employees with high experience. It is thus likely that training replenishes the knowledge losses from interference or obsolescence for these employees, and that the high-experience employees seem to imbibe training and to effectively translate the skill sets learned from training to their job responsibilities. Looking deeper into the relative merits of the different types of training using the lens of human capital theory (Becker 1962, 2003), we find a significant positive impact of general

training but no discernible differentiation to employees from specific training. Furthermore, motivated by the IS literature that examines the relative merits of domain and technical training (Lee et al. 1995, Mithas and Krishnan 2008, Mithas and Lucas 2010), we find significant positive and statistically equivalent impacts for both domain and technical training.

The senior management at the research site, based on current industry needs, was also interested in obtaining insights into structuring of the course curriculum with respect to the different types of training. The extant literature has not examined the combined effect of the different types of training (general/specific and domain/technical) and their interactions on performance; thus, this remains an empirical question. While there is no evidence of an interaction effect between general and specific training (with the exception of a subsample of low-experience employees), we find that domain and technical training may be mutually substitutable under certain conditions. For instance, our results indicate that domain and technical training are largely substitutive for high-experience employees as well as for low-experience employees with low levels of technical training. Hence, mixing these two types of training would diminish employee performance. The value of training is thus conditional on a focused curricular approach that emphasizes a structured competency development program. It is evident that focusing training effort in either domain or technical skills would yield optimal training efficacy. Firms must be careful not to prescribe an ad hoc mixture of the various types of training to employees. Such a practice could nullify the positive impacts of the respective types of training. Our findings have both theoretical and practical significance. Most important, they justify increased human capital investments to fuel future growth of this important component of the global economy.

In the next section we present our conceptual model and the underlying theoretical base. In §3 we describe the key characteristics of our data. In §4 we present our econometric analysis and discuss our key findings. Section 5 concludes with managerial implications and fruitful directions for future research.

## 2. Conceptual Framework and Hypotheses

Our research is set in the context of both the strategic management literature that speaks to the importance of human capital in creating competitive advantage and the labor economics literature that relies on identifying general HR principles. In addition, we draw on the theories of obsolescence and skills replenishments from the IS literature, given the high rate of



technological innovation and the consequent low half-life of IT skills and knowledge. We draw on each of these motivating theories to form our hypotheses.

The strategic management literature has established that intangible resources, such as human capital, are more likely than tangible resources to lead to competitive advantage (Grant 1996, Ghemawat 1986, Hatch and Dyer 2004). Human capital has long been argued as a critical resource and a key driver of value (Pfeffer 1994).<sup>2</sup> In the context of the growing global IT services industry, this perspective has added importance as the pool of knowledge workers constitutes the primary tangible as well as the intangible resource. Training is one of the important components of HR planning activities in maximizing the returns from this asset base (Malos and Campion 2000). In a recent survey on personnel economics, Lazear and Shaw (2007) point out that training can be a tool to not only enhance productivity, but also to attract better talent. Our work also relates to the emerging IS literature that points to the increased importance of skilled workers in IT industries (Levina and Xin 2007, Mithas and Krishnan 2008, Mithas and Lucas 2010). Ang et al. (2002) suggest that this can be attributed to the complexity of IT jobs that arises from the need to master relatively difficult technical concepts such as data modeling, process discipline, and systems design theory. The challenge intensifies when one considers the added dimension of offshore IT outsourcing, where soft skills and cultural differences play an equally important role (Langer et al. 2008, Levina and Vaast 2008). This overall complexity raises the need for significant education inputs either from the education systems of countries where offshore outsourcing is taking place or from the IT services firms themselves.

Recent human capital literature has examined the benefits of training at the firm level (e.g., Almeida and Carneiro 2009), as well as at the employee level (e.g., Blundell et al. 1999). For example, Bishop (1994) uses matched pair data from the National Federation of Independent Business Survey (NFIB) to examine whether and to what extent variations in productivity across workers doing the same job at the same firm can be predicted by prior training. He reports a significant tendency of new hires with relevant previous work experience and relevant school-based formal training to require less training and to be more productive. Barrett and O'Connell (2001), using a firm-level data set of Ireland based construction, manufacturing and related services, distinguish between

general and specific training and test for the relative effects of the two types of training on productivity growth. They find that although general training has a statistically positive effect on productivity growth, no such effect is observable for specific training. Both Bishop (1994) and Barrett and O'Connell (2001) use survey based perceptual measures of employee productivity in work that can be classified as nonknowledge. However, there is a dearth of prior research in the context of IT services that establishes the link between employees' performance and the amount of employer provided training. In addition, our work builds on the prior literature by relying on archival data, which are more objective and immune to survey response rates and biases (Espinosa et al. 2007), in the context of knowledge intensive environment pertinent to the IT services industry.

Generally speaking, and not surprisingly, a variety of research has suggested that education should be positively related to performance of knowledge workers. Banker et al. (2009) suggest that both education and research and development (R&D) investments are associated with a positive firm performance in IT industries, and that the interaction effect between R&D and education is positive, suggesting that IT firms who employ highly skilled employees are in a better position to take advantage of R&D investments. Nelson and Phelps (1966) suggest that education enhances one's ability to receive, decode, and understand information. Griliches (2000) points out that education can lead to better decision making. These abilities are very useful in the context of the complex nature of IT jobs (Ang et al. 2002). Firm provided training is expected to be well directed toward specific job requirements. Hence, one can expect that firm provided training will also, like education, have a positive effect on employee performance. Consistent with this idea, we hypothesize the following:

**HYPOTHESIS 1 (H1).** *Employer provided training is positively related to improvement in overall employee performance.*

While we anticipate the positive effects of training on employee performance, we are also interested in examining whether this effect varies across employees, given our research context. Specifically, we ask whether there are significant differences in returns to training between high and low-experience employees. First, the various factors that contribute to human capital depreciation, such as skills obsolescence, interference, and forgetting, differ across employees. Second, employees may also differ in their ability to absorb and benefit from training.

In particular, training may help contain the effects of skills obsolescence, a major contributor to human capital depreciation (de Grip and van Loo 2002). Skills

<sup>2</sup> This phenomenon is not limited to firm level growth. A recent report by the European Commission Directorate General for Employment and Social Affairs stressed the role of investment in human capital as a lever for wider economic growth (see de la Fuente and Ciccone 2002).

obsolescence can happen for several reasons. The IT services sector is witness to fast paced technological, domain, and process changes leading to rapid skills obsolescence, unless these skills are updated often (Joseph and Ang 2010, Pazy 1996). At the individual level, human capital can also depreciate due to interference (Underwood 1957), that is, other things interfere with an employee's cognitive processes. In the context of IT, newer computing artifacts such as languages, operating systems, domains, and interfaces interfere with previous learning, leading to depreciation. Finally, a significant literature on organizational and individual productivity points to the effect of forgetting and its impact on performance (e.g., Argote et al. 1990, Thompson 2007). Thompson (2007) suggests that individual skills can atrophy naturally over time leading to skills depreciation and the need for renewed training. We thus argue that high-experience employees are more prone to skills depreciation than low-experience employees. Hence, the potential upside of training on their productivity is expected to be higher.

It can also be argued that experienced employees better assimilate new courses than novices. For instance, Chase and Simon (1973) suggest that (past) acquired knowledge allows experts (in our case, more experienced employees) to exhibit intuitive decision making and faster information processing, contributing positively to the effect of training on their performance. Experienced employees may also have higher absorptive capacity, that is, the ability "to recognize the value of new, external information, assimilate it, and apply it" (Cohen and Levinthal 1990, p. 128). Therefore, experienced employees can assimilate and deploy new knowledge quickly, thereby making them more productive.

We thus expect that compared to low-experience employees, high-experience employees can absorb employer provided training more and can better replenish their human capital, leading to significant performance gains. Hence, we posit the following:

**HYPOTHESIS 2 (H2).** *The marginal impact of training is higher for high-experience employees compared to low-experience employees.*

### 2.1. Differential Impacts of Types of Training

Becker (1962, 2003) differentiates between two kinds of human capital investments: general and specific. General human capital increases an employee's productivity not only within the current firm, but also with other firms as well. In contrast, (firm) specific human capital investments increase employee productivity only within the focal firm. The perceived value of these two types of human capital investments is different for the employee and the employer, resulting in dichotomous incentives and gains appropriation.

We first consider the effect of specific training on performance. Extant human capital literature (e.g., Becker 1962, 2003) suggests that specific training, by increasing employee productivity within the firm, should be particularly useful in increasing performance. In conformity with this idea, Slaughter et al. (2007) underline that specific training relating to superior context sensitivity and soft skills are associated with a higher valuation of the employee by the employer. Bapna et al. (2008) provide yet another reason: Because the provision of specific training raises the productivity of the employee only in the firm in which she works, the employee is willing to stay on in the firm to reap the benefits of specific training. Thus, the firm has lower turnover rates resulting in lower forgetting rates and hence higher productivity (Argote et al. 1990).<sup>3</sup> Accordingly, we expect that specific training investments improve employee performance.

The effect of general training on employee performance is subtler. On one hand, human capital theory (Becker 1962, 2003) suggests that there is little room for employer funded general training because benefits from this training accrue purely to the employees in the form of increased outside opportunities. For example, Tambe and Hitt (2010b) find that mobility of IT workers leads to knowledge spillovers that can benefit other firms, making investments in IT workforce unattractive. On the other hand, in the dynamic and rapidly changing IT services context, firms need to provide general training to make their employees productive, but which also makes their own employees attractive to outside firms. This makes general training less useful for firms because they cannot realize the productivity benefits of their investments. However, recent literature recognizes this apparent paradox of observed employer-funded general training and has suggested some reasons why firms may still be able to realize productivity improvement benefits from general training. For instance, Lazear (2009) argues that an employee's portfolio of general skills may have firm-idiosyncratic weights. These skills may then be combined using differing weights such that the employee's skill portfolio is useful only within the firm. In contrast to productivity improvement, Cappelli (2004) argues that the provision of general training helps firms attract better quality employees who stay on the job longer. These employees improve their labor market value through general training and benefit from it in the future. Signaling

<sup>3</sup> Employee retention is particularly attractive to Indian IT services: The high level of attrition in the Indian IT services industry is well documented in the popular press and is emphasized in a variety of industry reports. Deloitte (2012) estimates the attrition rate to be around 16% for the Indian ITes industry.

of talent is far easier in the context of IT employees, aided by various mechanisms such as open source software (e.g., Mehra et al. 2011). Likewise, it is possible that general training is also a credible signal to the labor market.<sup>4</sup>

To summarize, we argue that firms simultaneously provide both general and specific training to make their employees more productive. Accordingly, we hypothesize the following:

**HYPOTHESIS 3 (H3).** *Both general and specific training contribute positively to employee performance.*

Extant literature is clearer on the relative merits of domain versus technical training. Lee et al. (1995) assert that both technical and nontechnical skills are needed by IT professionals; and that nontechnical skills are more valued and better rewarded by employers. We note two trends in the demand and supply of skills in IT workforce that manifest the importance of domain training. First, research has found higher payoffs when IT applications are more aligned with strategy (e.g., see Weill and Aral 2006). Second, many firms are moving up the architecture maturity curve (Ross and Beath 2006), necessitating transformational outsourcing partnerships (Cohen and Young 2006). Thus, there is a need for the IT human capital supply—whether procured in-house or through outsourcing—to be adept in domain and business skills. Zweig et al. (2006) investigate trends in the demand and supply of IT workforce and find that for IT personnel, domain and business skills are becoming more important compared to technical skills. This leads us to posit the following:

**HYPOTHESIS 4A (H4A).** *Both domain and technical training contribute positively to employee performance.*

**HYPOTHESIS 4B (H4B).** *The contribution of domain training is higher in magnitude than that of technical training.*

We are also interested in investigating whether the different types of training interact with each other in a significant way. Extant literature (e.g., Lee et al. 1995, van der Hulst and Source 2002) suggest breadth, depth, and relevance to IT curricula by advocating a focused and holistic approach to a multiyear training program. However, they do not discuss whether these different training dimensions would be substitutive or complementary. Thus, we approach the relationship between domain and technical training as an empirical question, and cautiously avoid a directional hypothesis with respect to the interaction effects.

<sup>4</sup> Extending Cappelli's (2004) argument, while we expect general training to improve performance, we need to identify its effect, taking into account the fact that potentially high performers are attracted to firms that provide general training. We discuss this in detail in the analysis section.

### 3. Background of Study and Data Description

In this section we describe our research setting, operationalize our key constructs, and elaborate on the data characteristics.

#### 3.1. Research Setting

To empirically validate our hypotheses, we conducted an in-depth study at a leading IT outsourcing vendor headquartered in India. The study involved gaining access to the company and its resources, and interviewing key managers to learn more about the organization as well as its training environment. We held extensive discussions with these managers to become familiar with the company's training structure, HR systems, and performance evaluation processes.

The vendor provides an ideal setting for our study. The company employs tens of thousands of IT personnel and has an extensive training program. The vendor deploys stringent quality processes and has been assessed at capability maturity model (CMM) level 5 during the entire period of our study. As a CMM level 5 organization, the company collects numerous metrics on projects, project personnel, and their performance. In addition, the company has earned people CMM (PCMM) level 5 certification for its commendable HR practices. This certification aims at improving workforce capabilities and thus entails continuous workforce innovation through training, appraisals, mentoring, and performance alignment with organizational goals (Curtis et al. 2001).

The company recognizes that human capital is its most significant asset, and that its employees play a crucial role in achieving organizational goals. Our interviews with senior management revealed that enhancement of employees' potential is achieved through continuous training and competency building. For example, when new employees join the firm immediately after graduating from college, they undergo a mandatory 26-week foundation training course, which includes technical, domain, and process courses. This program is primarily designed to overcome the shortages of the educational system (Kapur and Mehta 2007). Beyond the foundation training, the firm's dedicated education and research unit offers continuous training courses. This training and its impact is the focus of our study.

The firm has an elaborate performance evaluation process. It uses a "360 degree feedback" system to annually assess employees. The evaluation rubric includes feedback from team members, peers, subordinates, and supervisors leading to a holistic assessment of the employee performance. The appraisal process scores each employee relative to others to yield a consolidated relative rating (CRR) on a scale of 1 to 4, with 1 indicating the highest performance



level and 4 the lowest. Employees' annual raises are a direct function of their CRR, and thus there is a strong incentive for them to boost their ratings. We collected detailed training and performance data on 7,918 employees between 2002 and 2007. Our data are restricted broadly to software engineer and programmer analyst categories of employees with the average experience in the data set being six years. Based on our discussions with the senior management at the research site, we found these employees to be ideal for our study: they are not only at a critical stage in the human capital development process, but they also form the largest layer of the employee pyramid.

### 3.2. Data and Measurement

In addition to the employee performance data (CRR), we have employee demographic data on age and gender, and total as well as firm level experience, and whether the employee is a direct or a lateral (hired from another firm) hire. We also have data on the complete training history of each employee.

*Employee Performance Rating.* Employee ratings are a good proxy for employee performance because the firm has an exemplary evaluation process. We therefore use the annual employee rating as our dependent variable. Because a rating of 1 is better than a rating of 4, an increase in rating is equivalent to a decrease in employee performance. Consequently, the coefficients would be difficult to interpret. Therefore, we use *PerformanceRating* (defined as  $-1 \times \text{CRR}$ ) as our dependent variable (see Espinosa et al. 2007).

*Training Variables.* The data set included detailed information on the courses taken by each of the employees. While the firm categorized each course as pertaining to (i) domain, (ii) technical training, (iii) behavioral, (iv) process related, and (v) related to project management methodologies, categorization of courses into general and specific training posed some challenges. To further categorize these courses into general and specific, we used a three-pronged approach. First, we used extant literature to guide us conceptually (Slaughter et al. 2007). We posit that while behavioral (e.g., communication or leadership skills), domain (e.g., knowledge of the Sarbanes-Oxley Act or the retail vertical), and technical courses (e.g., expertise in technologies such as Java) improved employee performance, these were the kinds of skills that an employee can use outside of the firm, and hence can be classified as general. In contrast, process content and project management courses indicated them to be firm specific. The process or project management courses, for example, provided knowledge about internal processes or tools (e.g., a proprietary software designed to help estimate resources and timelines for a given software project). Second, we corroborated our categorization from the senior

management at our research site. We held detailed discussions with training unit managers and examined what each course entailed to understand the content and its implication, and used their input to help us categorize courses into general and specific.

Finally, we recruited a panel of five experts, all of whom had familiarity and experience in the Indian IT services industry and all had a master's degree in computer science or engineering. We provided these experts with course names and descriptions, as well as definitions of general and specific training (Becker 1962). We then asked the experts to rate each course description based on the rating scale of 1 (specific training) to 7 (general training); the expert evaluators were first asked to rate a pilot instrument to get some practice. Once we obtained the experts' responses, we checked for the interrater reliability using Cohen's kappa (Cohen 1960) for evaluating the courses as general or specific, where the kappa value manifests agreement between the raters. We found that the measures of agreement all exceeded 0.8. Conventionally, a kappa of  $< 0.2$  is considered poor agreement, 0.21–0.4 is fair, 0.41–0.6 is moderate, 0.61–0.8 is strong, and more than 0.8 near complete agreement (Kvalseth 1989). Based on these tests, we find our experts to be in agreement. We next averaged the ratings across the experts to arrive at a final rating for the course. Finally, we categorized courses that were rated 4 or above as general, and the rest as specific.

We provide some examples of these courses in Table 1. The amount of training in each category (domain/technical and general/specific) in a given year is computed as the total number of relevant courses taken in that category, normalized by the course duration.

*Other Controls.* We control for other employee specific characteristics in our model. Extant literature (e.g., Joseph et al. 2010) has found correlation between

**Table 1** Examples of Training Courses Offered

| Training type | Example  |
|---------------|--|
| General       | <ul style="list-style-type: none"> <li>J2EE analysis and design</li> <li>Overview of derivatives</li> <li>Business communication</li> </ul>                |
| Specific      | <ul style="list-style-type: none"> <li>ITIL quality foundation course—frameworks and processes</li> <li>Introduction to ITIL PM elite processes</li> </ul> |
| Domain        | <ul style="list-style-type: none"> <li>Foundation course in banking I</li> <li>Insurance company operations</li> </ul>                                     |
| Technical     | <ul style="list-style-type: none"> <li>OS basic programming for C++</li> <li>IBM certified database associate DB2</li> </ul>                               |

*Notes.* J2EE refers to the Java 2 Platform Enterprise Edition. ITIL refers to the Information Technology Infrastructure Library. PM and OS are abbreviations for project manager and operating system, respectively. DB2 is a relational model database server developed by IBM.



**Table 2** Data Dictionary and Summary Statistics

| Variable name             | Variable description  | Mean (SD)         |                   |                   | Min (Max)       |                |                 |
|---------------------------|---|-------------------|-------------------|-------------------|-----------------|----------------|-----------------|
|                           |   | Overall           | Low exp.          | High exp.         | Overall         | Low exp.       | High exp.       |
| <i>Performance Rating</i> | Performance rating of the employee. The consolidated relative rating (CRR) ranges from 1 (excellent) to 4 (poor). To ease interpretation, we use $-1 * CRR$ as our dependent variable (see Espinosa et al. 2007).               | −1.776<br>(0.734) | −1.597<br>(0.456) | −1.906<br>(0.489) | −4 (−1)         | −4 (−1)        | −4 (−1)         |
| <i>Age</i>                | Age of the employee in years.   | 28.224<br>(2.813) | 26.428<br>(1.901) | 30.026<br>(2.397) | 23 (60)         | 23 (48)        | 25 (60)         |
| <i>TotalExp</i>           | An employee's total IT work experience in years.  | 6.145<br>(2.273)  | 4.402<br>(0.702)  | 7.892<br>(1.936)  | 0.08<br>(40.97) | 0.08<br>(5.53) | 5.54<br>(40.97) |
| <i>FirmLevelExp</i>       | An employee's work experience at the focal firm in years.   | 4.307<br>(2.132)  | 3.703<br>(1.350)  | 4.914<br>(2.558)  | 0.08<br>(13.35) | 0.08<br>(5.44) | 0.13<br>(13.35) |
| <i>dGender</i>            | Dummy variable indicating employee's gender (1: male; 0: female)  | 0.766<br>(0.424)  | 0.735<br>(0.441)  | 0.796<br>(0.403)  |                 |                |                 |
| <i>dDirectHire</i>        | Dummy variable indicating whether employee is a direct or lateral hire (1: direct; 0: lateral).   | 0.442<br>(0.497)  | 0.161<br>(0.489)  | 0.718<br>(0.449)  |                 |                |                 |
| <i>TotalTrng</i>          | The total number of training courses taken by an employee in a year.  | 0.599<br>(1.103)  | 0.595<br>(1.084)  | 0.603<br>(1.121)  | 0 (14)          | 0 (8)          | 0 (14)          |
| <i>GeneralTrng</i>        | The total number of general training courses taken by an employee in a year. These courses add to the general skills set of an employee.  | 0.524<br>(0.985)  | 0.522<br>(0.970)  | 0.527<br>(0.999)  | 0 (14)          | 0 (8)          | 0 (14)          |
| <i>SpecificTrng</i>       | The total number of specific training courses taken by an employee in a year. These courses add to the specific skills set of an employee.  | 0.074<br>(0.284)  | 0.072<br>(0.272)  | 0.076<br>(0.295)  | 0 (5)           | 0 (4)          | 0 (5)           |
| <i>DomainTrng</i>         | The total number of domain training courses taken by an employee in a year. This category includes courses that impart domain specific knowledge. For example, the financial domain included courses on the Sarbanes–Oxley Act. | 0.256<br>(0.552)  | 0.251<br>(0.533)  | 0.261<br>(0.569)  | 0 (14)          | 0 (7)          | 0 (14)          |
| <i>TechTrng</i>           | The total number of technical training courses taken by an employee in a year. For example, this category includes core and advanced courses on technologies such as Java, Net, C, C++, etc.                                    | 0.266<br>(0.560)  | 0.269<br>(0.557)  | 0.263<br>(0.564)  | 0 (6)           | 0 (5)          | 0 (6)           |

performance and experience. In addition, Slaughter et al. (2007) find that employees who have been with a firm longer are more valued. We therefore control for both total and firm level experience. We also control for age and examine the impact of whether the employee was a direct or a lateral hire.

*Subsamples.* We divide the data into two subsamples of employees. One subsample consists of employees below median total experience (i.e., low-experience employees) and the other consists of those above median total experience (i.e., high-experience employees). These subsamples are useful in analyzing H2;

they also provide deeper insights into the other hypotheses.

The detailed description and the summary statistics of the variables are presented in Table 2. Table 3 presents the correlation matrix between the dependent and explanatory variables. Because we use interactions in our model, we centered the relevant variables before our analysis, making it easier for us to interpret our results, and alleviating collinearity issues in models using interaction effects (Aiken and West 1991).

We formulate our identification strategy and present our analysis and results in the next section.

**Table 3** Correlation Matrix

|                                  | 1       | 2       | 3      | 4       | 5       | 6      | 7      | 8      | 9      | 10      | 11      |
|----------------------------------|---------|---------|--------|---------|---------|--------|--------|--------|--------|---------|---------|
| 1 Performance Rating             |         |         |        |         |         |        |        |        |        |         |         |
| 2 Performance Rating ( $t - 1$ ) | 0.236*  |         |        |         |         |        |        |        |        |         |         |
| 3 FirmLevelExp                   | -0.044* | 0.068*  |        |         |         |        |        |        |        |         |         |
| 4 TotalExp                       | -0.167* | -0.078* | 0.564* |         |         |        |        |        |        |         |         |
| 5 Age                            | -0.260* | -0.257* | 0.335* | 0.740*  |         |        |        |        |        |         |         |
| 6 TotalTrng ( $t - 1$ )          | 0.077*  | 0.183*  | 0.229* | 0.200*  | -0.116  |        |        |        |        |         |         |
| 9 GeneralTrng ( $t - 1$ )        | 0.083*  | 0.188*  | 0.212* | 0.188*  | -0.129* | 0.969* |        |        |        |         |         |
| 10 SpecificTrng ( $t - 1$ )      | 0.003   | 0.040*  | 0.138* | 0.104*  | 0.010*  | 0.427* | 0.191* |        |        |         |         |
| 7 DomainTrng ( $t - 1$ )         | 0.075*  | 0.171*  | 0.221* | 0.185*  | -0.110* | 0.880* | 0.910* | 0.166* |        |         |         |
| 8 TechTrng ( $t - 1$ )           | 0.069*  | 0.155*  | 0.133* | 0.135*  | -0.115* | 0.796* | 0.819* | 0.166* | 0.506* |         |         |
| 11 dDirectHire                   | 0.118*  | 0.101*  | 0.149* | -0.391* | -0.358* | 0.012* | 0.011* | 0.010* | 0.017* | -0.002* |         |
| 12 dGender                       | 0.057*  | 0.055*  | 0.035* | 0.073*  | 0.085*  | -0.012 | -0.011 | -0.006 | -0.008 | -0.012  | -0.036* |

\*Denotes that the correlation is significant at  $p < 0.05$ .

## 4. Analysis, Results, and Discussion

### 4.1. Analysis and Results

To draw any link between training and performance, we have to consider possible endogeneity. Employees self-select into training, hence great care has to be taken in linking training with performance. A variety of observed and unobserved factors could explain why an employee undergoes training in a given year; failure to account for this would lead to a biased estimate of the main effect. Furthermore, the relationship between training and performance could be confounded by unobserved individual characteristics, such as motivation and drive. Highly motivated employees may decide to take more training courses, and hence, the number of courses may be correlated with the error term. It may also be that firms that provide general training attract high performers (Cappelli 2004) who perceive training as a credible signal to the labor market. To overcome these identification challenges, we use an Arellano–Bover/Blundell–Bond (Arellano and Bover 1995, Blundell and Bond 1998; hereafter, AB–BB) dynamic panel model using robust standard errors (see the appendix for more details on the suitability of this model to our context).

To determine the impact of training on employee performance, we use the following dynamic panel model structure (exhibited here for brevity only for the aggregate training, and fully specified for precision sake along with each of the results table):

$$\begin{aligned} \text{PerformanceRating}_{i,t} &= \beta_0 + \beta_1 \cdot \text{TotalTrng}_{i,(t-1)} \\ &+ \beta_2 \cdot \text{PerformanceRating}_{i,(t-1)} + \varepsilon_{it}, \end{aligned} \quad (1A)$$

where  $\text{TotalTrng}_{(t-1)}$  is the endogenous variable representing the (lagged and normalized) total number of courses that employee “ $i$ ” took in the previous year;

$\text{PerformanceRating}_{(t-1)}$  is the lagged performance rating of the employee for the previous year (this highly informative variable captures the influence of earlier performance in the likelihood of an employee taking training in the current period); and  $\varepsilon_{it}$  is the error term. We estimate this model for the overall sample. To assess how the coefficients vary for different employee categories, we also estimate the same model for the two subsamples of low-experience and high-experience employees.<sup>5</sup>

### 4.2. Robustness Checks

For robustness purposes, and to compare our results, we also estimate the following selection-corrected pooled ordinary least squares (OLS) model that controls for observable employee characteristics and includes an inverse mills term that models the selection process for employee propensity to take training. We use interactions between total training and experience and also account for the effect of nonlinearity of total experience on performance by including a quadratic term (Becker 1962, 2003). This model is estimated hierarchically (Aiken and West 1991); that is, we estimate the baseline OLS first and then add the interactions.

$$\begin{aligned} \text{PerformanceRating}_{i,t} &= \beta_0 + \beta_1 \cdot \text{TotalTrng}_{i,(t-1)} + \beta_2 \cdot \text{PerformanceRating}_{i,(t-1)} \\ &+ \beta_3 \cdot \text{Age}_{i,t} + \beta_4 \cdot \text{TotalExp}_{i,t} + \beta_5 \cdot \text{TotalExpSq}_{i,t} \\ &+ \beta_6 \cdot \text{FirmLevelExp}_{i,t} + \beta_7 \cdot \text{dDirectHire}_i \\ &+ \beta_8 \cdot \text{InvMills}_{i,t} + \beta_9 \cdot \text{TotalTrng}_{i,(t-1)} \times \text{TotalExp}_{i,t} \\ &+ \varepsilon_{it}, \quad \text{where } \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2), \end{aligned} \quad (1B)$$

where  $\text{Age}$  is the employee’s age in years,  $\text{TotalExp}_{(i,t)}$  is the total experience of the employee in years,

<sup>5</sup> To test H2 and H3, we estimate similar models for general and specific training (H2) and domain and technical training (H3), details of which are included in the results tables.

$TotalExpSq_{(i,t)}$  is the total experience squared,  $FirmLevelExp_{(i,t)}$  is the employee's work experience in years at the firm,  $dDirectHire_{(i)}$  is a dummy variable that indicates whether the employee is a direct (1) or a lateral (0) hire, and  $InvMills_{(i,t)}$  is the (time variant) inverse mills ratio derived from the following selection equation for employee "i" for year "t":

$$\begin{aligned} \Pr(\text{gotTraining} = 1)_{i,t} \\ = \Phi(\alpha_0 + \alpha_1 \cdot PerformanceRating_{i,(t-1)} + \alpha_2 \cdot Age_{i,t} \\ + \alpha_3 \cdot FirmLevelExp_{i,t} + \alpha_4 \cdot dGender_i \\ + \alpha_5 \cdot dDirectHire_i + u_{it}), \end{aligned} \quad (2)$$

where

$$\text{gotTraining}_{i,t} = \begin{cases} 1 & \text{if an employee "i" takes} \\ & \text{training in year "t" and,} \\ 0 & \text{otherwise,} \end{cases} \quad (3)$$

and  $u_{it} = \alpha_i + \eta_{it}$ ;  $\alpha_i \sim N(0, \sigma_\alpha^2)$ ,  $\eta_{it} \sim N(0, 1)$ .

Here,  $dGender$  is a dummy variable that indicates whether the employee is a male (1) or a female (0).

Our method is based on a modified version of the Verbeek and Nijman (1996) extension of the basic Heckman procedure, in which we first estimate a probit model for sample selection, and then incorporate the correction term from the selection equation into the main model (inverse mills ratio; Maddala 1983, Verbeek 2004). We use a random effects model in the selection equation to take advantage of time-invariant demographics, such as age, gender, whether the employee is a lateral hire or fresh out of college, etc. Although get qualitatively similar results for the major hypotheses using this approach, it is possible that the model is identified only due to the nonlinearity introduced by the first step correction. Therefore, we believe that the dynamic panel model provides a cleaner way to address both the selection and the endogeneity issues in our model (Arellano and Bond 1991).

We also test for the validity of generalized method of moments (GMM) in our dynamic panel model. In particular, we test whether the resulting model is specified correctly.<sup>6</sup> The test results are reported (for

<sup>6</sup> It is recommended that we carry out the Arellano–Bond test for no serial correlation in the first-differenced disturbances. This test is applied to the residuals in differences to test for autocorrelation aside from the fixed effects. Note that while normally for this purpose we use the Sargan's test ( $H_0$ : instruments as a group are exogenous) to check whether the model and overidentifying conditions are correctly specified, the Breusch–Pagan/Cook–Weisberg test (Greene 2002, Cook and Weisberg 1983) indicates heteroscedasticity in our model ( $H_0$ : constant variance,  $\chi^2(1) = 194.97$ ; Prob >  $\chi^2 = 0.0000$ ), requiring us to estimate our parameters using robust standard errors. In such cases, distribution of the corresponding test statistics is not specified and cannot be estimated, and hence Sargan's test cannot be conducted.

**Table 4** Selection Equation

| Got training                         | Coefficient (std. error) |
|--------------------------------------|--------------------------|
| <i>PerformanceRating</i> ( $t - 1$ ) | 0.146 (0.024)**          |
| <i>Age</i>                           | −0.609 (0.019)**         |
| <i>FirmLevelExp</i>                  | 1.256 (0.032)**          |
| <i>dGender</i>                       | 0.004 (0.072)            |
| <i>dDirectHire</i>                   | −1.809 (0.079)**         |

\*\*Significant at 1%.

the major models in the interest of brevity) at the bottom of the results (Tables 5–7). The results indicate that our model specifications are indeed based on instruments that are exogenous and that there is no serial correlation in the first-differenced disturbances.<sup>7</sup> Furthermore, as we show in our results in the following section, the coefficient for the lagged performance variable is positive and significant, indicating that past performance is a good predictor of current performance, and hence pertinent to our model.

### 4.3. Results

**4.3.1. Impact of Training on Performance.** Table 4 presents the results of the estimation from Equation (2), and Table 5 presents the results for estimations of Equations (1A) and (1B) that examine the results of the impact of training on performance.

Results from the dynamic panel effects model are presented along with the pooled OLS with the lagged training variables (the use of the one-lag is based on Frazis and Loewenstein 2005) with and without interaction terms for comparative purposes. Note that in the OLS specification, the Inverse Mills Ratio is significant, suggesting the existence of selection. *R*-square values from the OLS base and interaction models are close to 10%. The results consistently reveal a positive and economically and statistically significant impact of training on performance, and therefore support our primary research hypothesis. Our unbiased and efficient estimate from the AB–BB dynamic panel model suggests that an additional training course, on average, helps employees improve their performance rating by 2.14%.<sup>8</sup> This supports H1.

While the positive link of training to performance is qualitatively similar to the selection corrected OLS result, we worry about other sources of endogeneity

<sup>7</sup> In particular, rejecting the null hypothesis of no serial correlation at order one, as we do in the first-differenced errors, implies that the model is not misspecified. See Stata Press (2009) for more details.

<sup>8</sup> The dynamic panel model results (Table 5) suggest that a unit increase in overall training improves the *PerformanceRating* by 0.038. An additional course taken by an average employee (with rating 1.77555, from Table 2) improves this rating by 0.038, or 2.14%.

**Table 5** Impact of Training on Performance

| Performance rating                                    | OLS                 |                     | Dynamic panel model |                   |                    |
|---|---------------------|---------------------|---------------------|-------------------|--------------------|
|   | Baseline model      | With interactions   | Overall             | Low exp.          | High exp.          |
| <i>TotalTrng</i> ( $t - 1$ )                          | 0.0134<br>(0.006)*  | −0.000<br>(0.008)   | 0.038<br>(0.005)**  | −0.005<br>(0.008) | 0.050<br>(0.007)** |
| <i>PerformanceRating</i> ( $t - 1$ )                  | 0.176<br>(0.007)**  | 0.176<br>(0.007)**  | 0.094<br>(0.012)**  | −0.034<br>(0.024) | 0.124<br>(0.014)** |
| <i>Age</i>  | −0.069<br>(0.005)** | −0.069<br>(0.005)** |                     |                   |                    |
| <i>TotalExp</i>                                       | −0.019<br>(0.007)** | −0.018<br>(0.007)** |                     |                   |                    |
| <i>TotalExpSq</i>                                     | 0.002<br>(0.000)**  | 0.002<br>(0.000)**  |                     |                   |                    |
| <i>FirmLevelExp</i>                                   | 0.027<br>(0.008)**  | 0.025<br>(0.008)**  |                     |                   |                    |
| <i>dDirectHire</i>                                    | −0.003<br>(0.016)   | −0.000<br>(0.016)   |                     |                   |                    |
| <i>InvMills</i>                                       | 0.034<br>(0.13)**   | 0.032<br>(0.13)**   |                     |                   |                    |
| <i>TotalTrng</i> ( $t - 1$ ) $\times$ <i>TotalExp</i> |                     | 0.006<br>(0.002)*   |                     |                   |                    |

Specification for dynamic panel model for overall training impact:

$$\text{PerformanceRating} = L \cdot \text{PerformanceRating} + I \cdot \text{TotalTrng} + e.$$

- The dynamic model takes  $I \cdot \text{TotalTrng}$  as an endogenous variable and specifies number of instruments = 29.
- Instruments for differenced equation: GMM-type:  $L(2/-) \cdot \text{PerformanceRating}$ ,  $L(2/-) \cdot \text{TotalTrng}$ , i.e., all available lags from lag2 onward.
- Instruments for level equation: GMM-type:  $LD \cdot \text{PerformanceRating}$ ,  $LD \cdot \text{TotalTrng}$ , i.e., first difference of explanatory endogenous variables.

Arellano–Bond tests results for zero autocorrelation in the first differences errors

| Overall |          |                 | Low exp. |          |                 | High exp. |          |                 |
|---------|----------|-----------------|----------|----------|-----------------|-----------|----------|-----------------|
| Order   | <i>z</i> | Prob > <i>z</i> | Order    | <i>z</i> | Prob > <i>z</i> | Order     | <i>z</i> | Prob > <i>z</i> |
| 1       | −32.821  | 0               | 1        | −32.821  | 0               | 1         | −32.821  | 0               |
| 2       | −1.345   | 0.179           | 2        | −1.345   | 0.179           | 2         | −1.345   | 0.179           |

Notes. We use the two steps estimation method. As is conventional in dynamic panel models, \**L* or *I* denotes lag and \**D* denotes first difference.

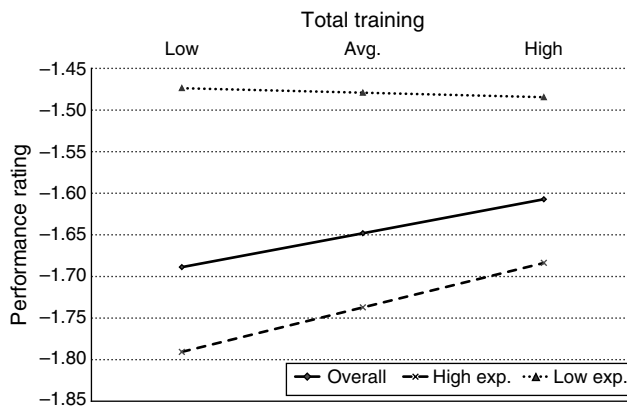
\*Significant at 5%; \*\*significant at 1%.

in the OLS specification (as described in the prior subsection). Nevertheless, it is interesting to discuss the effects of some of the time-invariant factors that the OLS model allows us to capture (which the dynamic panel model does not). For instance, we find a significant quadratic relationship between employee experience and performance, suggesting that there is certain threshold after which experience is on its own positively linked to performance; a partial derivative of the OLS equation (Table 6) suggests that this minima occurs at approximately 4.5 years. Interestingly, this idea is reinforced in the model in which training interacts with experience. The positive sign on the interaction effect coupled with the lack of significance of the main effect of training suggest that high-experience

employees gain more from training. Note that there is a negative main effect on the experience variable, which while counterintuitive at a glance, has to be viewed in conjunction with the positive interaction effects it is a part of. We discussed this with our counterparts at the research site. They suggested that with experience roles and responsibilities become more complex, which leads to increased challenges in manifesting high performance. These findings, albeit from OLS, motivate us to further examine subsamples of our data based on low (below median) and high-experience (median and above) employees using the dynamic panel (AB–BB) approach.

We observe that high-experience employees derive significantly higher returns from training than



**Figure 1** Training Has Different Performance Implications for Low- vs. High-Experience Employees

low-experience employees, for whom there is no significant effect.<sup>9</sup>

Figure 1 illustrates the interaction between total training and experience. While overall training improves performance, this effect is differentiated based on the experience level of the employees. High-experience employees accrue significant gains from overall training, whereas those with low experience do not. Figure 1 illustrates a slight decrease in performance with overall training for low-experience employees though this downward trend is not statistically significant. This is consistent with the skills depreciation and obsolescence logic we associated with the rapidly changing world of IT sector innovations (Joseph and Ang 2010, Pazy 1996). Thus, our findings are in contrast to the classic learning curve literature that assumes the cumulative effects of learning (e.g., Yelle 1979), and more in line with the literature on forgetting and its impact on performance (e.g., Argote et al. 1990, Thompson 2007, de Grip and van Loo 2002). It can also be argued that experienced employees may have higher absorptive capacity (Cohen and Levinthal 1990), and hence can better assimilate new courses than novices (Chase and Simon 1973). Given these findings, we expect firms to provide a renewed emphasis on employer provided training for high-experience employees. Such a practice better replenishes the human capital and contributes significantly to employee performance. This supports H2.

#### 4.3.2. Differential Impact of General and Specific Training on Performance. Table 6 presents the

<sup>9</sup> For the sake of brevity and readability, we only report the unstandardized coefficients in the tables. In differentially analyzing our data, we were careful to make meaningful comparisons based on (separate) standardized versions of these models. To be precise, the comparisons are based on the standard errors from the unstandardized models and where significant differences are found the magnitude of differences reflects the standardized coefficients.

results of the performance impacts of type of training split along the dimensions of specific versus general training.

The results reveal that general training overall has a significant positive impact. This finding is reinforced by the subsample of high-experience employees. The positive effect of general training is indicative of the increased marketability and exerts upward pressure on ratings, which proxy for wages. Our findings are particularly pertinent to more experienced employees. Recall that according to the classical human capital theory, there is no incentive for firms to provide general training. Only recently has human capital literature attempted to theoretically answer this paradox by laying out possible conditions under which general training may be provided by the firm. Thus, our findings as they relate to general training fit into the emerging nuance of human capital theory. Our empirical results complement the theoretical work of Lazear (2009) and Cappelli (2004). Together, our results provide new research impetus on the rationale behind and impact of employer funded general training.

Specific training does not have a significant impact on employee performance. This finding is surprising because firms can reinforce their competitive advantage using firm specific processes. Hence, firm value should be created when employees are cognizant of firm specific knowledge. However, it is likely that these benefits would be at the firm level, e.g., better adherence to project deadlines and cost projects, higher client satisfaction, etc. Thus, although these specific skills are necessary for the employee to create value, they may not be rewarded at an individual level because, consistent with human capital theory, the firm does not need to reward performance based on specific skills. Hence, the performance implication of these skills is also not reflected in the employee performance measure. Thus, H3 is only partially supported.

Our results also indicate that for low-experience employees, the performance impact of general training is contingent on the amount of specific training they undergo. Although we only find the interaction effect to be significant for these employees (Table 6), we surmise that for low levels of specific training, general training is substitutive; that is, taking more general training is counterproductive in terms of performance. In contrast, for high levels of specific training, general training is complementary; that is, taking more general training enhances the performance rating. These findings point to the importance of specific training for low-experience employees who are yet to be assimilated into the firm processes and its culture. Once these employees have the firm specific skills to a sufficient extent, the general training then begins to impact employee performance. These

**Table 6** Impact of General vs. Specific Training on Performance

| Performance rating  | Overall            |                    | Low exp.          |                   | High exp.          |                    |
|---|--------------------|--------------------|-------------------|-------------------|--------------------|--------------------|
|   | Baseline model     | With interactions  | Baseline model    | With interactions | Baseline model     | With interactions  |
| <i>GeneralTrng</i> ( $t - 1$ )                                      | 0.043<br>(0.006)** | 0.043<br>(0.006)** | −0.003<br>(0.008) | 0.001<br>(0.009)  | 0.056<br>(0.008)** | 0.055<br>(0.008)** |
| <i>SpecificTrng</i> ( $t - 1$ )                                     | −0.038<br>(0.027)  | −0.037<br>(0.037)  | −0.037<br>(0.050) | −0.126<br>(0.088) | −0.012<br>(0.032)  | 0.020<br>(0.040)   |
| <i>PerformanceRating</i> ( $t - 1$ )                                | 0.094<br>(0.012)** | 0.094<br>(0.012)** | −0.035<br>(0.024) | −0.034<br>(0.024) | 0.123<br>(0.014)** | 0.123<br>(0.014)** |
| <i>GeneralTrng</i> ( $t - 1$ ) ×<br><i>SpecificTrng</i> ( $t - 1$ ) |                    | 0.004<br>(0.026)   |                   | 0.093<br>(0.056)+ |                    | −0.033<br>(0.030)  |

Specification for baseline dynamic panel model for general and specific training:

$$PerformanceRating = L \cdot PerformanceRating + I \cdot GeneralTrng + I \cdot SpecificTrng + e.$$

- The dynamic model takes  $I \cdot GeneralTrng$  and  $I \cdot SpecificTrng$  as endogenous variables and specifies number of instruments = 35.
- Instruments for differenced equation: GMM-type:  $L(2/\cdot) \cdot PerformanceRating$ ,  $L(2/\cdot) \cdot GeneralTrng$ ,  $L(2/\cdot) \cdot SpecificTrng$ , i.e., all available lags from lag2 onward.
- Instruments for level equation: GMM-type:  $LD \cdot PerformanceRating$ ,  $LD \cdot GeneralTrng$ ,  $LD \cdot SpecificTrng$ , i.e., first difference of explanatory endogenous variables.

Specification for dynamic panel model for general and specific training with interactions:

$$PerformanceRating = L \cdot PerformanceRating + I \cdot GeneralTrng + I \cdot SpecificTrng + I \cdot GeneralTrng \times SpecificTrng + e.$$

- The dynamic model takes  $I \cdot GeneralTrng$ ,  $I \cdot SpecificTrng$ , and  $I \cdot GeneralTrng \times SpecificTrng$  as endogenous variables and specifies number of instruments = 38.
- Instruments for differenced equation: GMM-type:  $L(2/\cdot) \cdot PerformanceRating$ ,  $L(2/\cdot) \cdot GeneralTrng$ ,  $L(2/\cdot) \cdot SpecificTrng$ ,  $L(2/\cdot) \cdot GeneralTrng \times SpecificTrng$ , i.e., all available lags from lag2 onward.
- Instruments for level equation: GMM-type:  $LD \cdot PerformanceRating$ ,  $LD \cdot GeneralTrng$ ,  $LD \cdot SpecificTrng$ , i.e., first difference of explanatory endogenous variables.

Arellano–Bond tests results for zero autocorrelation in the first differences errors (baseline model)

| Overall |         |          | Low exp. |         |          | High exp. |         |          |
|---------|---------|----------|----------|---------|----------|-----------|---------|----------|
| Order   | z       | Prob > z | Order    | z       | Prob > z | Order     | z       | Prob > z |
| 1       | −32.753 | 0        | 1        | −14.569 | 0        | 1         | −30.343 | 0        |
| 2       | −1.344  | 0.179    | 2        | 0.949   | 0.343    | 2         | −0.639  | 0.523    |

Arellano–Bond tests results for zero autocorrelation in the first differences errors (with interactions)

| Overall |         |          | Low exp. |        |          | High exp. |        |          |
|---------|---------|----------|----------|--------|----------|-----------|--------|----------|
| Order   | z       | Prob > z | Order    | z      | Prob > z | Order     | z      | Prob > z |
| 1       | −32.836 | 0        | 1        | −14.62 | 0        | 1         | −30.36 | 0        |
| 2       | −1.3248 | 0.185    | 2        | 0.842  | 0.4      | 2         | −0.675 | 0.5      |

Notes. We use the two steps estimation method. As is conventional in dynamic panel models, \*L or I denotes lag and \*D denotes first difference.

+Significant at 10%; \*\*significant at 1%.

results suggest the importance of a focused curricular approach to training, i.e., directing the training focus based on employee experience and the right portfolio of skill sets.

**4.3.3. Differential Impact of Domain and Technical Training on Performance.** Table 7 presents the results for technical and domain training. Broadly our analysis indicates that training replenishes knowledge due to changes in both technology and domain. Our main finding is that while both domain and technical training yield performance benefits, there is no clear indication on the relative merits of the two in the data. Therefore, H4A is supported whereas H4B

is not. Given the increasingly strategic nature of IT applications, the extant literature seems to suggest that domain training should matter more, but this is not supported by our data.

A comparison of low- versus high-experience employees reveals interesting insights. Domain training shows a significant negative link to low-experience employees and a significant positive link to high-experience employees. Figure 2 depicts the interaction between domain and technical training for low-experience employees. For these employees, domain training has a deleterious impact on performance except when the technical training levels

**Table 7** Impact of Domain vs. Technical Training on Performance

| Performance rating   | Overall            |                    | Low exp.           |                     | High exp.          |                    |
|--|--------------------|--------------------|--------------------|---------------------|--------------------|--------------------|
|  | Baseline model     | With interactions  | Baseline model     | With interactions   | Baseline model     | With interactions  |
| <i>DomainTrng</i> ( $t - 1$ )                                  | 0.040<br>(0.010)** | 0.041<br>(0.010)** | −0.035<br>(0.016)* | −0.042<br>(0.016)** | 0.071<br>(0.015)** | 0.072<br>(0.016)** |
| <i>TechTrng</i> ( $t - 1$ )                                    | 0.050<br>(0.014)** | 0.069<br>(0.017)** | 0.041<br>(0.020)*  | 0.022<br>(0.023)    | 0.038<br>(0.021)   | 0.065<br>(0.026)*  |
| <i>PerformanceRating</i> ( $t - 1$ )                           | 0.094<br>(0.012)** | 0.094<br>(0.012)** | −0.036<br>(0.020)  | −0.034<br>(0.024)   | 0.122<br>(0.014)** | 0.122<br>(0.014)** |
| <i>DomainTrng</i> ( $t - 1$ ) ×<br><i>TechTrng</i> ( $t - 1$ ) |                    | −0.040<br>(0.021)+ |                    | 0.058<br>(0.032)+   |                    | −0.057<br>(0.032)+ |

Specification for baseline dynamic panel model for domain and technical training:

$$\text{PerformanceRating} = L \cdot \text{PerformanceRating} + \cdot \text{DomainTrng} + I \cdot \text{TechTrng} + e.$$

- The dynamic model takes  $I \cdot \text{DomainTrng}$  and  $I \cdot \text{TechTrng}$  as endogenous variables and specifies number of instruments = 35.
- Instruments for differenced equation: GMM-type:  $L(2/\cdot) \cdot \text{PerformanceRating}$ ,  $L(2/\cdot) \cdot \text{DomainTrng}$ ,  $L(2/\cdot) \cdot \text{TechTrng}$ , i.e., all available lags from lag2 onward.
- Instruments for level equation: GMM-type:  $LD \cdot \text{PerformanceRating}$ ,  $LD \cdot \text{DomainTrng}$ ,  $LD \cdot \text{TechTrng}$ , i.e., first difference of explanatory endogenous variables.

Specification for dynamic panel model for domain and technical training with interactions:

$$\text{PerformanceRating} = L \cdot \text{PerformanceRating} + I \cdot \text{DomainTrng} + I \cdot \text{TechTrng} + I \cdot \text{DomainTrng} \times \text{TechTrng} + e.$$

- The dynamic model takes  $I \cdot \text{DomainTrng}$ ,  $I \cdot \text{TechTrng}$  and  $I \cdot \text{DomainTrng} \times \text{TechTrng}$  as endogenous variables and specifies number of instruments = 38.
- Instruments for differenced equation: GMM-type:  $L(2/\cdot) \cdot \text{PerformanceRating}$ ,  $L(2/\cdot) \cdot \text{DomainTrng}$ ,  $L(2/\cdot) \cdot \text{TechTrng}$ ,  $L(2/\cdot) \cdot \text{DomainTrng} \times \text{TechTrng}$ , i.e., all available lags from lag2 onward.
- Instruments for level equation: GMM-type:  $LD \cdot \text{PerformanceRating}$ ,  $LD \cdot \text{DomainTrng}$ ,  $LD \cdot \text{TechTrng}$ ,  $LD \cdot \text{DomainTrng} \times \text{TechTrng}$ , i.e., first difference of explanatory endogenous variables.

Arellano–Bond tests results for zero autocorrelation in the first differences errors (baseline model)

| Overall |         |          | Low exp. |         |          | High exp. |         |          |
|---------|---------|----------|----------|---------|----------|-----------|---------|----------|
| Order   | z       | Prob > z | Order    | z       | Prob > z | Order     | z       | Prob > z |
| 1       | −32.759 | 0        | 1        | −14.566 | 0        | 1         | −30.353 | 0        |
| 2       | −1.345  | 0.179    | 2        | 0.0345  | 0.973    | 2         | −0.664  | 0.507    |

Arellano–Bond tests results for zero autocorrelation in the first differences errors (with interactions)

| Overall |         |          | Low exp |         |          | High exp |         |          |
|---------|---------|----------|---------|---------|----------|----------|---------|----------|
| Order   | z       | Prob > z | Order   | z       | Prob > z | Order    | z       | Prob > z |
| 1       | −32.815 | 0        | 1       | −14.582 | 0        | 1        | −30.437 | 0        |
| 2       | −1.326  | 0.185    | 2       | −0.3203 | 0.749    | 2        | −0.646  | 0.518    |

Notes. We use the two steps estimation method. As is conventional in dynamic panel models, \*L or I denotes lag and \*D denotes first difference.

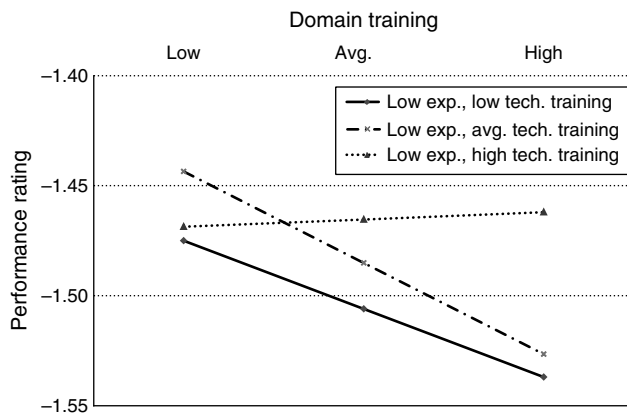
+Significant at 10%; \*\*significant at 1%.

are high, suggesting the relative importance of technical training for low-experience employees. Mixing domain training with technical training when employees do not have sufficient technical training proves to be counterproductive. However, when these employees have high levels of technical training, domain training begins to exhibit performance gains over and above those available only through technical training.

For high-experience employees, the value creation potential of the employee is closely linked to the strategic alignment of IT with business objectives for their clients (Weill and Aral 2006, Cohen and Young 2006). This provides the rationale for the marginal

benefit of domain training, which is also significantly positive. By contrast, technical training has consistently positive links to both low and high-experience employees. The latter finding reinforces the technology obsolescence and replenishments arguments first highlighted in H2. However, the significance of the main effects for both technical and domain training has to be interpreted cautiously given the significantly large negative effect of the interactions. It is evident that focusing training effort in either domain or technical skills would yield optimal training efficacy. This is even more imperative for the high-experience employees, given their higher opportunity cost of training.

**Figure 2** Domain Training Benefits Low-Experience Employees Only When Technical Training Is High



To summarize, our overall results in this sub-analysis indicate that both types of skills training are beneficial to employees with the caveat that the differential impact of each skill category depends on experience and focus. To the best of our knowledge, ours is the first study to empirically corroborate these differential impacts. Clearly one size does not fit all when it comes to training IT services employees!

## 5. Conclusions and Directions for Future Research

In this study we investigate the impact of human capital investments made by a large Indian IT services firm on employee performance. We find that an additional training module leads to a significant increase in performance. For the average employee, an additional training course helps improve performance by 2.1%. Mithas and Krishnan (2009) show that IT professionals with an MBA earn 47% more than those without. The average employee in our data takes about 0.6 courses, which would give her a 1.4% boost relative to her peers. However, the unit course duration in our setting is normalized to two working days, i.e., 16 contact hours, which is roughly equal to two MS-IS (master of science in information systems; the nature of training in our context is closer to an MS-IS program than to an MBA) credit hours. Assuming 32 credits hours in a typical MS-IS program, it appears that the returns are roughly of comparable orders of magnitude (44.8% for an equivalent 32 credit program). Of course this has to be cautiously interpreted because of a variety of contextual differences, and the fact that training in our context is spread over multiple years. Still, it is encouraging to find that the courses are in the same order of magnitude.

We believe this effect to be economically significant, given that the employees, on average, take 0.6 courses per year, and given that their appraisal reflects a broad assessment of their activities throughout the

year. The effect is much larger in magnitude for high-experience employees, suggesting significant differences in their ability to translate their learning into firm valued performance. While general training has a significant positive effect across the board, we find a lack of significance for specific training. This indicates that specific training in and of itself is not a differentiator for employees; any value that is created through specific training appears to be appropriated by the firm. We also address the paradox of employer funded general training (Becker 1962, 2003), complementing the theoretical work of Lazear (2009) and Cappelli (2004). We hope future work can focus on breaking down the possible mechanisms that yield this outcome. Finally, we find that although domain and technical training have significant positive main effects, if taken together, the effects can be detrimental. We believe that the strength, robustness, and validity of our findings result from (a) use of micro-employee level training and performance data which captures economic activity at its most fundamental level; and (b) explicitly dealing with possible endogeneity that could otherwise confound any link between training and performance.

The primary managerial implication of this research is that investment in training enhances employee performance. However, our findings point to the need for firms to effectively manage the training programs to reap optimal returns from these investments. The detailed analysis we conducted enable us to structure a set of “best practices” for firms: (i) It is important to tailor the training program to the employee profile; focused training leads to better performance. (ii) Training is particularly useful for experienced employees because their skills may diminish or become obsolete, or because they are more adept in absorbing training; thus, training should be a career-long endeavor. (iii) It can be beneficial for firms to impress on poor performers the benefits that can accrue from training or even “mandate” training for poor performers.

Our work is limited by its reliance on data from a single company with highly regarded HR practices. On the surface this makes generalizations about the average industry level impact of training on performance difficult. Note, however, that the employee pool (underlying population) that is accessible to this company is no different from that accessible to its two-three closest competitors. Furthermore, these top three or four companies account for close to 80% of the Indian IT services market share. We believe that our estimates should serve as lower bounds of the industry level estimates. Although unaccounted for in the current model, the firm’s exemplary organizational and managerial practices could be expected to complement training investments. Furthermore, we



are limited in not having data on employee education (as this was considered highly confidential in a tough recruiting environment) as well as on project characteristics. We hope that future work can overcome these limitations and shed new light on the relevant contingencies.

A number of critical issues are worthy of further study. A cross-sectional analysis of our research question can help generalize our findings and also provide insights on the firm level effects of training impacts on performance. The performance metric should also be expanded to incorporate employee retention and promotion. Given that software development is a complex group based endeavor, we expect future work to examine the impact of training on team and project performance as well as client satisfaction. More detailed information on employee project characteristics will also facilitate examination of the relative trade-off between on the job learning and formal training.

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### Appendix. Dynamic Panel Modeling

To overcome the identification challenges in our model, we use an Arellano–Bover/Blundell–Bond (Arellano and Bover 1995, Blundell and Bond 1998) dynamic panel model using robust standard errors. This approach gives us unbiased and efficient estimators based on moment equations constructed from further lagged levels of the dependent variable and the first-differenced errors. The Dynamic Panel data model involves use of dynamic effects by adding a lagged dependent variable to explanatory variables. Arellano–Bond (Arellano and Bond 1991) and Arellano–Bover/Blundell–Bond (Arellano and Bover 1995, Blundell and Bond 1998) dynamic panel estimators are general, designed for situations with (1) “small  $T$ , large  $N$ ” panels; (2) a linear functional relationship; (3) one left-hand-side

variable that is dynamic, depending on its own past realizations; (4) independent variables that are not strictly exogenous, which could be correlated with the past and possibly current realizations of the error term; (5) fixed individual effects; and (6) heteroskedasticity and autocorrelation within, but not across, individuals. Thus, they are particularly suited to our context.

This model is estimated using GMM, which works in a similar way to two-stage least squares; however, the instruments are based on moment equations constructed from further lagged levels of the dependent variable and the first-differenced errors (Holtz-Eakin et al. 1998). Arellano and Bond (1991) showed that the moment conditions are formed by assuming that particular lagged levels of the dependent variable are orthogonal to the differenced disturbances and are known as GMM-type moment conditions. As discussed earlier, we use the following dynamic panel model:

$$\begin{aligned} \text{PerformanceRating}_{i,t} &= \beta_0 + \beta_1 \cdot \text{TotalTrng}_{i,(t-1)} \\ &\quad + \beta_2 \cdot \text{PerformanceRating}_{i,(t-1)} + \varepsilon_{it}. \end{aligned}$$

To reiterate, in our estimation process we rely on Arellano–Bond (Arellano and Bond 1991) and Arellano–Bover/Blundell–Bond (Arellano and Bover 1995, Blundell and Bond 1998) dynamic panel estimators. Arellano–Bond estimation starts by transforming all regressors, usually by differencing, and uses the GMM. It is called the difference GMM. The Arellano–Bover/Blundell–Bond estimator augments the Arellano–Bond estimator by making an additional assumption that first differences of instrument variables are uncorrelated with the fixed effects. This allows for the introduction of more instruments and dramatically improves efficiency. It builds a system of two equations—the original equation and the transformed one—and is known as system GMM. Instead of transforming the regressors to expunge the fixed effects, it transforms, i.e., differences, the instruments to make them exogenous to the fixed effects. In short, where Arellano–Bond instruments differences (or orthogonal deviations) with levels, Blundell–Bond instruments levels with differences.

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