Examining Return on Human Capital Investments in the Context of Offshore IT Workers

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Abstract

The rapid pace of technological innovation necessitates Information Technology (IT) services firms to continually invest in replenishing the skills of their key asset base, the human capital. We study the impact of human capital investments in the context of the Indian IT services industry, which has experienced double digit growth rates in the last decade. Indian IT services firms invest significant resources towards training and education of their employees. We examine whether these human capital investments directed towards employee training are effective in improving employee performance and productivity. Our rich employee level panel data set affords us the opportunity to link formal training with performance at the individual employee level. Controlling for unobservable employee characteristics and possible selection bias, we find significant a positive impact of training on employee performance. An additional training course, on an average, helps employees improve their performance by 3.6%. We also investigate the mediating role of employment related characteristics and the type of training on the link between training and performance. We find that employment characteristics such as work experience and whether the employee is a direct hire from an educational institution or a lateral hire from another IT services firm play a significant role in shaping the impact of training on performance. Interestingly, we find it that there is systematic superiority in the high experience laterals' ability to extract value from firm-provided training. We find significant differences between the impact of specific versus general training and domain versus technical training on performance. We also find that domain and technical training have a substitutive relationship. Taken together, these findings suggest that the value of training is conditional upon a focused curricular approach that emphasizes a structured competency development program. Our findings have both theoretical and practical significance, most important of which is that they justify increased human capital investments to fuel future growth of this important component of the global economy.

***Keywords**:* Training and productivity, offshore IT workers, employee performance, Indian IT industry, human capital theory

Acknowledgements

We thank Anitesh Barua, Prabhudev Konnana, Ashish Aggarwal and other seminar participants at UT-Austin for their valuable feedback. We thank Anindya Ghose, Il-Horn Hann, Anjana Susarla, and participants of 2009 SCECR conference at the Carnegie Mellon University, at INFORMS 2009 San Diego and at Erasmus University for their helpful comments on early versions of this work. The paper was also presented at the Carlson School Strategic Management Organization Department. We thank Aseem Kaul, Paul Valer, and Myles Shaver for their feedback. We also thank senior management at our research site for motivating us to undertake this study and for providing us with the panel data.

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 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 upon the technical and other expertise of the employees that require continuous overhaul due to the fast pace of technological change (Lee et al. 1995, Tambe and Hitt 2008), and workplace reorganization (Bresnahan et. al. 2002). The knowledge-based theory of the firm (Grant 1996) is particularly appropriate in characterizing firms in this 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 for firms in the IT services industry. Consequently, understanding the performance impacts of human capital investments in such industries becomes paramount and carries with it significant import for both theory and practice.

Despite a challenging global macro-economic environment, the market for IT and IT enabled Services (IT-ITeS) continues to grow at an above average rate of 6.3 percent, touching $967 billion in 2008.[1] These IT expenditures are occurring in an increasingly globalized production-consumption environment, with significant amount of white collar work being carried out in offshore locations such as India, Israel and Ireland. As of 2007, the Indian IT-ITeS industry accounts for $71.7 of the global $967 billion. It employs 2.23 million knowledge workers and has been growing by double digits for the last decade. The veneer of this growth in India masks the underlying 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

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[1] 2009 Nasscom Strategic Review Report, see http://www.nasscom.org/upload/60452/Executive_summary.pdf

US workforce when they join fresh from college,[2] in countries like India, the skills gap is widespread (Kapur and Mehta 2008). The consequence of these challenges is that Indian IT-ITeS firms are forced to make significant investments in providing education and training to their employees (Hatakenaka 2008). While the initial focus of the training investments were to bridge the skills gap of fresh college graduates, IT-ITeS firms have evolved to provide continuous training and education to cope with the dynamic demands of the global clientele and advances in technology. Our study examines whether these continuing training investments are linked to employee performance.

Our work is motivated by the observed trends of training investments by Indian IT firms. For instance, the bellwether company, Infosys, has been increasing training expenditure by close to 16% per annum per employee over the last five years. [3] 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. [4] Our primary research motivation is to ask whether these training investments yield any measurable performance benefits to the workers. In the context of IT offshoring, the answer to this question has productivity implications not just for the IT services firms making these massive-scale human capital investments, but also, in direct measure, to more favorable outcomes (lower costs and/or improved quality) for IT services consuming firms across the globe.

While there is significant interest in the human capital research community in measuring the returns to investment in employee training, there remain significant gaps in this literature. Blundell et al. (1999), in a review of the literature on the returns from human capital investments, point out that lack of

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[2] See "CIOs complain college grads aren't ready for IT work," available at http://www.computerworld.com/s/article/342347/Crossing_the_Skills_Gap?source=CTWNLE_nlt_mgmt_2009-09-21.
[3] Infosys annual reports from year 2002 to 2007.
[4] Price Waterhouse Coopers survey available at http://www.pwc.com/extweb/pwcpublications.nsf/docid/2711a28073ec82238525706c001eaec4

suitable data and methodological difficulties have resulted in a paucity of studies that have looked at the returns of human capital investments at the employee-employer level. We specifically address this gap in the literature in the context of IT services industry by using detailed archival training and performance data at the employee level from a leading Indian IT services firm that has global footprint. From the extant research it appears that the impact of training on human capital productivity gains depends on the industry context. For example, Ichniowski et al. (1997) find that training has an impact only in combination with complementary human resource practices in the context of steel finishing factories, whereas Ramasubbu et al. (2008) find that different types of skills training do have a significant impact on employee performance in the domain of enterprise software systems services. Our research differs from Ichniowski et al. (1997) in that in focuses on knowledge work and from Ramasubbu et al. (2008) in that it places no restriction on the type of software that the employees are working on. The firm in question in our study has an exemplary human resources practice, and has been a front-runner in investing heavily in training their employees. The data were provided to us by the senior management of this firm in return for a credible econometric analysis that examined the linkage 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 8000 employees over a three year period as well as detailed performance ratings for these employees. The company uses an industry-leading appraisal process (more on this in Section 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. Following Becker 1975 we distinguish between the differential impacts of general versus specific training in the context of IT workers. Motivated by the IS literature (Lee et al. 1995, Tambe and Hitt 2008, Joseph et al. 2009) 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 over-arching 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. Firstly, despite the fact that we obtain a random sample of approximately 8000 employees, potential selection bias in our data remains a concern. A variety of observed and unobserved factors could lead to why a given employee undergoes training in a given year, and a failure to account for this would lead to a biased estimate of the main effect. Secondly, the relationship between training and performance can potentially 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 a modified version of the Verbeek and Nijman (1996) extension of the basic Heckman selection model to correct for selection bias, and incorporate a bias-correcting term from the selection equation in a fixed effects model that washes out the impact of unobservable individual characteristics such as motivation and drive.

Controlling for unobservable employee characteristics and selection bias, we identify a significant positive impact of training on employee performance. Interestingly, we find that for employees with high experience, employer provided training generally has a higher impact on lateral-hires as compared to direct-hires. This suggests that lateral employees, who have the benefit of a wider work exposure, seem to be able imbibe training and translate the skill sets learnt from training towards their job responsibilities in an effective manner. The significant impact of training is observed in aggregate, as well as for general training (Becker 1975), or into categories of domain and technical as per the IS literature (Lee et al. 1995).

The senior management at the research site, based on the current industry needs,[5] was also interested in the structuring of the course curriculum a propos domain and technical training. The extant literature has not examined the combined effect of the two on performance, and thus this remains an empirical question. We investigate this by using interactions between domain and technical training, and find that they are mutually substitutable. This suggests that the value of training is conditional upon a focused curricular approach that emphasizes a structured competency development program. Firms have to be careful about not prescribing an ad hoc mixture of the various types of training to employees as such a practice could lead to canceling-out of the positive impacts of respective types of training. Our findings have theoretical and practical significance, most important of which is that 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 Section 3 we describe the key characteristics of our data. In Section 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

The strategic management literature, in particular the resource-based view of the firm, has established that intangible resources, such as human capital, are more likely than tangible resources to lead to competitive advantage (Grant 1996, Ghemawat 1986). Human capital has long been argued as a critical resource and a key driver of value for most firms (Pfeffer 1994). In the context of the growing global IT services industry, this perspective has added importance as the pool of knowledge workers constitutes *both* the primary tangible as well as the intangible resource. This paper examines the returns

[5] For example, Accenture Management Development Academy in India recently signed a multi-year, multi-million dollar deal with a leading educational institute in India to provide a curriculum and certification around existing training modules.

from human capital investments in the context of the Indian IT services industry. In particular, we focus on evaluating the impact of employer-provided training on employee performance. Providing training is one of the important components of the human resource planning activities firms have to pursue in maximizing the returns from this asset base (Malos and Campion 2000).

The conceptual framework of our study is illustrated in Figure 1. We first link employee training and performance. We then examine the impact on performance of different types of training, such as a) general versus specific, and b) technical versus domain. We also investigate the interactions between these different types of training, which allow us to examine complementarity or substitutability amongst these various training modules. Following literature that differentiates between employees who are direct versus lateral hires (e.g. Slaughter et al. 2007), we recognize that these employee types will differ in their capability to benefit from formal training programs. Finally, we reconcile the presence of significant identification challenges as exhibited by the bidirectional links between training and performance and observed and unobserved employee characteristics that could influence propensity to take training (which creates potential selection bias) into our sample as well as omitted variable bias. We elaborate on each of these aspects of the conceptual framework as we develop our hypotheses.

Our work primarily builds on emerging IS literature that points to the increased importance of skilled workers in IT industries. 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 we layer onto this the added dimension of offshore outsourcing of IT, where soft-skills and cultural differences playing 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 the various countries where offshore outsourcing is taking place or from IT services firms themselves.

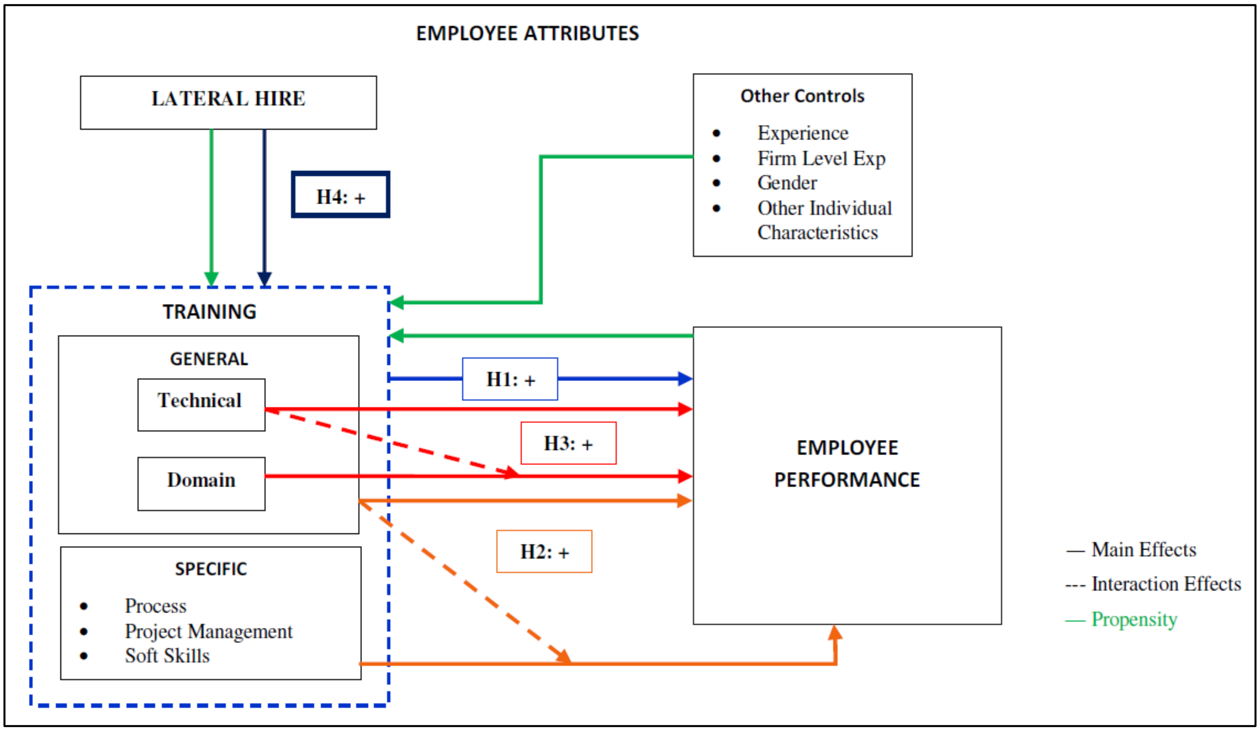

Figure 1: Conceptual Framework

In considering the relationship between training and performance our work relates and contributes to the broader human capital literature addressing this issue. As pointed out earlier, much of this analysis has been at the firm level. A notable exception is Bishop (1994), which 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. However, there has been no prior research in the context of IT services industry that establishes the link between employees' performance, the amount of employer provided training and the benefits accrued to employees from such training. Barrett and O'Connell (2001), using a firm-level dataset 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 non-knowledge work. 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 a knowledge intensive environment.

Generally speaking, and not surprisingly, a variety of researchers have suggested that training and education should be positively related to performance of knowledge workers. Banker et al 2009 suggest that both education and R&D investments are associated with a positive firm performance in IT industries, and that the interaction effects between R&D and education is positive, suggesting that IT firms which invest in highly skilled employees are in a better position to take advantage of R&D investments. Nelson and Phelps (1996) suggest that education enhances one's ability to receive, decode and understand information. Griliches (2000) points out that education can strengthen ability, reduce uncertainty and lead to better decision making. Motivated by the lack of studies examining the training performance linkage at the employee level (Blundell et al. 1999) and consistent with the views of Becker (1975), who views education as a strong indicator of the quality of human capital, we hypothesize:

H1: Employer provided training leads to improvement in overall employee performance in the context of IT services.

2.1 Differential Impacts of Types Training

Becker (1975) differentiates between two kinds of human capital investments – general and specific. For this study, we conceptualize general training as technical and domain knowledge (typically about industry verticals) courses. Employees have an incentive to undertake technical and domain knowledge training, such as on programming languages and industry processes, because they can utilize these skills even outside the current firm. In contrast, we characterize specific training to be firm contextual courses pertaining to behavioral skills, processes, and project management methodologies. These courses are of use only within a firm and do not accrue benefits outside the firm. Looking through the prism of human capital theory alone (Becker 1975) there is little room for employer funded general training, given that rents from this training accrue purely to the employees in the form of increased outside opportunities. For example, Tambe and Hitt (2009) find that mobility of IT workers leads to knowledge spillovers that can benefit other firms, making investments in IT workforce unattractive. Yet, in the Indian IT services industry, general training is provided and paid for in abundance along with specific training. Prior to hypothesizing the relative impacts of general and specific training in our context, we need to resolve the aforementioned departure (of employer *funded* general training), observed in practice, from the predictions of Becker's human capital theory.

The rationale behind employer funded general training is best captured through the lens of institutional theory (DiMaggio and Powell 1983 and Scott 1995). Institutional theory indicates that, in order to survive, organizations must conform to the rules and belief systems prevailing in the environment. Translated to our context, the simultaneous provision of general and specific training is best understood through the lens of their relationship to attrition and employability. Motivated by high attrition rates[6] as well as high training investments, Bapna et al. 2008 develop an analytical model to study the presence of general and specific training in the context of attrition of offshore IT workers. Their main theoretical finding is that it is optimal for IT services firms to provide both general and specific training. The intuition behind this result comes from understanding the micro-dynamics of general and specific training in the context of offshore IT services. While provision of specific training can potentially reduce the attrition rate (workers' marginal productivity outside the firm does not increase, but it does increase for the firm itself), they are forced by circumstances to provide general training to improve the workers' employability. If firms take on the onus of providing general training due to the dynamic nature of client requirements and technological advances, they end up with more productive employees but also make

[6] The high level of attrition in the Indian IT/ITeS industry is well documented in the popular press and is emphasized in a variety of industry reports. The industry consensus appears to be around 20% as per http://www.indiaattritionstudy.com.

their own employees more attractive to outside firms due to the general nature of training, thus potentially increasing the attrition rate. The other issue with providing general training is that firms don't benefit from it since the wages of programmers must be increased to match their increased outside opportunity, otherwise they will leverage their outside options and leave the firm. Since the benefits of general training are the same across all firms in the industry, the firms will compete to raise the wages until the net benefit to the firms (programmer productivity – wages paid) becomes zero. Hence, there is no ex-ante incentive for the firms to provide general training since provision of training is costly and the firms don't get any returns to their investments in training. Becker (1975) posits that the only way in which general training may be provided is when workers themselves accept lower current wages to compensate for the cost of training. They have an incentive to do so since they can expect increased wages once they are trained. However, our data reveals significant amount of general training being carried out for the institutional reasons mentioned above. Further, the wages offered by company from which we procured the data are among the highest in the industry and hence there is no reason to believe that firms are funding general training investments through paying lower wages to its employees. Thus there is an apparent conflict between predictions of human capital theory (Becker 1975) and the practice in the offshore IT services industry. Bapna et al. 2008 establish that this conflict can be resolved by realizing that firms may simultaneously provide both general and specific training. As pointed out earlier, provision of specific training raises the productivity of the employee only in the firm in which she works, and the employee is willing to stay on in the firm to reap the benefits of specific training. If the expected benefits by staying on in the firm due to specific training are superior to the expected benefits by leaving the firm to take advantage of higher wages due to general training, the employee will continue to stay with the firm. Thus the firm is able to retain the employee despite it not increasing the employee's wages to match her increased outside opportunity due to general training. This analytical finding and the existence of this symbiotic general-specific training equilibrium is further corroborated by an empirical analysis of attrition levels and training investments across a cross-section of Indian IT firms (Bapna et al. 2008).

Given this context, we expect both general and specific training to positively impact employee performance. However, the literature presents mixed evidence with respect to the ordering of the magnitude of the impact of general and specific training. While prior literature (Loewenstein and Spletzer 1999) finds that there is no difference in wages returns to specific and general training, 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. It could also be argued that a strong general foundation could serve as the basis for enhanced returns from specific training. In short, there isn't sufficient evidence based on the extant literature to argue for a directional difference between general and specific training, but we can hypothesize that:

H2: Both general and specific training contribute positively to employee performance in the context of offshore IT services.

Extant literature is clearer in the relative merits of domain versus technical training. Lee et al. (1995) assert that both technical and non-technical skills are needed by IT professionals; and that non technical 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 (for example, 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 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 not surprisingly find that for IT personnel, domain and business skills are increasingly becoming more important as compared to technical skills. This leads us to posit that:

H3a: Within general training, both domain and technical training contribute positively to employee performance.

H3b: 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 multi-year 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.

Finally, controlling for total work experience, we are also interested in examining whether the impact of training is felt equally by those that are hired directly out of college as compared to the lateral hires who have spent some portion of their work careers outside the focal firm. Laterals have the hindrance of not having gone through the foundation program provided to all college hires by the firm under consideration. More importantly, we expect the laterals to lack the within firm tacit knowledge, accumulated "at-the-water-cooler" over the years and perhaps strengthened through joint work on project teams and other formal or informal social networks, embodying networked learning effects of not-what-you-know-but-who-you-know (Reagans et al. 2005, Monge and Contractor 2003). From a learning perspective, firms rely on three kinds of mechanisms. Conventionally, these mechanisms include learning on-the-job and learning from formal training. However, more recently, the role of informal social networks, such as those existing between peers or team members, has also been recognized as an aid for learning. Such networks influence how intellectual capital is created and disseminated in workgroups (e.g. Boud and Middleton 2003, Liebeskind et al. 1996, Singh et al. 2009). Thus, individuals learn not only on-the-job and from formal training, but also by gaining contextual knowledge through informal social networks within the organization. Thus, it is very likely that lateral hires, who do not have the peer level networks to enhance their learning, would benefit more from formal training. To the extent that training could substitute for such tacit knowledge we hypothesize:

H4: The marginal impact of training is amplified for laterals relative to direct hires.

3. Background of Study and Data Description

In this section we describe our research setting, operationalization of our key constructs and the characteristics of the data.

3.1 Research Setting

To empirically validate our hypotheses, we conducted an in-depth study at a leading IT outsourcing vendor head-quartered 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, human resource 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 training programs include the 26 week foundation training program, which is mandated for all direct hires and is primarily designed to overcome the shortages of the educational system (Kapur and Mehta 2008). The vendor deploys stringent quality processes and has been assessed at CMM level 5; as a CMM level 5 organization, the company collects numerous metrics on projects, project personnel, and performance. The company was assessed at CMM level 5 during the entire time period in our study. In addition, the company has earned People CMM (PCMM) level 5 certification for its commendable Human Resources (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, Heffley, and Miller 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 the senior management revealed that enhancement in employees' potential is achieved through continuous training and competency building. For example, when new employees join the firm straight from college, they undergo a 26 week long foundation training course, which includes technical, domain, and process courses. Beyond the foundation training, the firm's dedicated education and research unit offers technical, domain, process, project management, and behavioral courses on a continuous basis. This continuous training and its impact is the focus of our study. Some examples of different kinds of courses (as coded by the manager of the participating firm) are provided in Table 1.

<< Insert table 1 about here>>

The firm has an elaborate performance evaluation process. It utilizes a "360 degree feedback" system on an annual basis to assess employees. This 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 data (CRR) between the scale 1 to 4, with 1 indicating the highest performance level and 4 the lowest. Employee's annual raises are a direct function of their CRR, and thus there is a strong incentive for an employee to boost the CRR.

While the firm encourages employees to undergo training, it did not have objective and convincing evidence that the efforts directed at training result in improved performance. In addition, it was not clear to the senior management how different kinds of training affect performance, and how this impact varies for different employee categories. These questions inspired senior management to participate in our study and to provide the staff resources and time commitment necessary to enable us to collect the detailed data required to answer these critical questions. We collect detailed training and performance data on 7399 employees between 2005 and 2007.

3.2 Data and Measurement

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

*Employee performance rating***:** As already noted, the firm has an exemplary evaluation process and thus employee ratings are a good proxy for employee performance. Therefore we use the annual employee rating as our dependent variable. Since a rating of 1 is better than a rating of 4, an increase in rating is equivalent to a decrease in employee performance, the coefficients would be difficult to interpret. Therefore, we use *PerformanceRating* (-1**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. 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. While the firm marked each course as pertaining to domain or technical training, categorization of courses into general and specific training courses posed some challenges. To aid us in this categorization, we held detailed discussions with the training unit management. We also examined what each course entailed. We found that while domain and technical courses, such as expertise in technologies like Java or knowledge of say the Sarbanes-Oxley Act, improved performance, these were the kinds of skills that an employee can use outside of the firm in question. In contrast, the process, project management, and behavioral courses were firm specific. The process or project management courses, for example, provided knowledge about internal processes or tools. Likewise, the behavioral courses are also tailored to the firm's context, and related to the notion of practical intelligence (Wagner and Sternberg 1985, Slaughter et al. 2007). Therefore, we include technical and domain courses in our definition of "general training," and process, project management, and behavioral courses in "specific training."

Other controls: We control for other employee specific characteristics in our model. Extant literature (e.g., Joseph et al. 2009) has found correlation between performance and experience. In addition, Slaughter et al. (2007) find that employees who have been longer with a firm 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 (Slaughter et al. 2007).

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. Since we use interactions in our model, we centered the relevant variables prior to 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 establish our identification strategy and present our analysis and results in the next section.

<<Insert tables 2 and 3 about here>>

4. Analysis, Results and Discussion

4.1 Analysis and Results

We develop a series of models to test our hypotheses. At the outset, since undertaking training is a choice decision made by the individual employee, existence of potential selection bias is an overarching concern. To test this we created a balanced panel of people who undertook training for two years and contrasted that with the unbalanced panel where some individuals undertook training for none of the two years, some undertook training for one year and others undertook training for both years. Following Verbeek (2001) we ran the identical fixed effects models on the balanced and unbalanced panel. If there was some systematic information in the selection of who undertook training, the vector of coefficients and the variance-covariance matrix of the balanced panel and the unbalanced panel should be significantly different. The test statistic value of 66.45 (> Chi Square = 4.5 with the appropriate degrees of freedom at p=0.05) reveals significant differences between the coefficients of the balanced and unbalanced panel. This confirms the existence of selection bias in the sample, which plays an influential role in shaping the relationship between training and performance (Verbeek 2001). To correct for this selection bias, we use a modified version of the Verbeek and Nijman (1996) extension of the basic Heckman procedure. Verbeek and Nijman (1996) use a two step random effects model. They 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 1986, Verbeek 2001).

While we can use the Verbeek and Nijman's (1996) two step random effects model for correcting the sample selection, another significant concern in our model is the presence of unobservable individual characteristics which can potentially bias our findings. Attributes such as motivation, drive, and persona are intangible and not directly observable in our data, but likely to be correlated with the errors of any model that links training with performance. To address this, we use a fixed effects model instead of a random effects model in the second step of the Verbeek and Nijman (1996) model. The random effects model in the selection equation takes advantage of time-invariant demographics, such as age, gender, whether the employees is a lateral hire or fresh out of college. The fixed effects model in the second step captures the additional unobserved effects which are directly related to the individual.

To estimate the inverse mills ratio and correct for the selection bias, we use the following random effects probit model for employee '*i*' for year '*t*' :

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

where $gotTraining_{i,t} = \begin{cases} 1 \text{ if an employee } 'i' \text{ takes training in year } 't', \text{ and} \\ 0 \text{ otherwise.} \end{cases}$

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

In the above equation, *PerformanceRating*$_{i,(t-1)}$ is the (transposed) performance rating of the employee for the previous year; this highly informative variable captures the influence of prior period performance in the likelihood of an employee taking training in the current period. *Age* is the employee's age in years, *FirmLevelExp* is the employee's work experience in years at the firm, *dGender* is a dummy variable that indicates whether the employee is a male (1) or a female (0), and *dDirectHire* is a dummy variable that indicates whether the employee is a direct (1) or a lateral (0) hire. Note that the exogenous variable *dGender* helps identify our model. Gender is likely to impact the propensity to take training, but unlikely to impact the performance of an individual. Prior studies have shown that women in particular are more likely to use training as a substitute to male dominated networks for accumulating expertise and improving performance (Ragins et al. 1998, Davies-Netzley 1998).

To test for the overall impact of training on employee performance, we test the following fixed effects model:

$$PerformanceRating_{i,t} = \beta_0 + \beta_1.TotalTrng_{i,(t-1)} + \beta_2.InvMills_{i,t} + u_i + \varepsilon_{2Ait}, \qquad \text{(2A)}$$

where $\varepsilon_{2Ait} \sim N(0, \sigma^2_{\varepsilon_{2A}})$, and where u_i is a full set of individual fixed effects

In above equation, $TotalTraining_{i,(t-1)}$ is the total number of courses that the employee took in the previous year, and *InvMills* is the (time variant) inverse mills ratio derived from the selection equation. 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 subsamples: a) direct hires with low experience,[7] b) lateral hires with low experience, c) direct hires with high experience, and) lateral hires with high experience.

To compare our results, we also estimate the following pooled OLS model that controls for observable employee characteristics. We also use interactions between total training, experience, and whether the employee is a direct or a lateral hire. This model is estimated hierarchically (Aiken and West 1991), that is, we estimate the baseline OLS first and then add the interactions.

---

[7] Below median

$$
\begin{aligned}
PerformanceRating_{i,t} = {} & \beta_0 + \beta_1.TotalTrng_{i,(t-1)} + \beta_2.InvMills_{i,t} + \beta_3.Age_{i,t} + \beta_4.TotalExp_{i,t} \\
& + \beta_5.FirmLevelExp_{i,t} + \beta_6.dDirectHire_i + \beta_6.PerformanceRating_{i,(t-1)} \\
& + \beta_7.TotalTrng_{i,(t-1)} XTotalExp_{i,t} + \beta_8.TotalTrng_{i,(t-1)} XdDirectHire_i \\
& + \beta_1.TotalTrng_{i,(t-1)} XTotalExp_{i,t} XdDirectHire_i + \varepsilon_{it}, \qquad (2B) \\
& \text{where } \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)
\end{aligned}
$$

where $TotalExp_{(i,t)}$ is the total experience of the employee in years.

To test for the differential impact of the types of training on performance, we estimate the following series of fixed effects models:

$$
\begin{aligned}
PerformanceRating_{i,t} = {} & \lambda_0 + \lambda_1.GeneralTrng_{i,(t-1)} + \lambda_2.SpecificTrng_{i,(t-1)} + \lambda_3.InvMills_{i,t} \\
& + \lambda_4.GeneralTrng_{i,(t-1)} XSpecificTrng_{i,(t-1)} + u_i + \varepsilon_{3it}, \qquad (3) \\
& \text{where } \varepsilon_{3it} \sim N(0, \sigma_{\varepsilon_3}^2), \text{ and where } u_i \text{ is a full set of individual fixed effects}
\end{aligned}
$$

Equation 3 allows us to compare the impact of general versus specific training on performance as well as the interaction between these two types of training. The model is estimated for the entire sample as well as for the different employee categories already specified.

$$
\begin{aligned}
PerformanceRating_{i,t} = {} & \gamma_0 + \gamma_1.DomainTrng_{i,(t-1)} + \gamma_2.TechnicalTrng_{i,(t-1)} + \gamma_3.InvMills_{i,t} \\
& + \gamma_4.DomainTrng_{i,(t-1)} XTechnicalTrng_{i,(t-1)} + u_i + \varepsilon_{4it}, \qquad (4) \\
& \text{where } \varepsilon_{4it} \sim N(0, \sigma_{\varepsilon_4}^2), \text{ and where } u_i \text{ is a full set of individual fixed effects}
\end{aligned}
$$

The model specified in Equation 4 compares the effect of domain versus technical training as well as their interaction. Again, this model is estimated for the entire sample as well as for the different employee categories already specified.

4.2 Results

What induces employees to take training?

We first discuss the insights from the random-effect probit selection model (equation 1). The estimated results from this analysis are presented in Table 4.

<<Insert table 4 about here>>

While the age of the employee and whether the employee was a direct hire did not exhibit a significant impact on the propensity to undertake training, other explanatory variables show a significant impact. The results indicate that the female employees are more likely to avail of opportunities for training than their male counterparts. Given the time constraints and other cultural considerations that inhibit female employees from engaging in skill and career advancement via avenues such as mentoring and social networking, our findings suggest that these employees find training as an attractive option (Ragins et al. 1998, Davies-Netzley 1998). Interestingly, we find that employees who have been with the firm longer are more likely to engage in training. This finding is consistent with the notion of depreciation of knowledge and hence the need to replenish and update the skill sets. This is particularly the case in high tech sectors such as IT Services where technology and business practices change rapidly. A somewhat surprising finding is that employees who have performed better on the job are more likely to undertake training. While conventional wisdom would suggest that poor performers should engage in training and use the skills obtained to enhance performance, our results run counter to this notion. Employees appear to perceive training as a 'luxury good' which they can less afford when the performance is sub-par. The focus is more on immediate 'on-the-job' efforts to improve performance. Training, whose perceived impact may be not as immediate, is deferred until the performance is improved.

Impact of training on performance

Table 5 presents the results for estimations of equation 2A and 2B that examine the results of the impact of training on performance.

<<Insert table 5 about here>>

Results from 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, and from the fixed effects model are presented for comparative purpose. Inverse Mills Ratio is significant in all specifications suggesting the existence of selection. The results consistently reveal a positive and economically and statistically significant impact of training on performance, and therefore support our primary research hypothesis. An additional training course, on an average, helps employees improve their performance by 3.6%. Additionally, the results suggest that while the overall years of work experience have a negative impact on performance, the number of years of firm-specific work experience enhances performance. The negative influence of overall work experience is indicative of the rapid obsolescence of skills in an employee, a unique characteristic of IT knowledge services industry. The positive influence of the within firm experience is indicative of the role of informal networks that enhance learning and thus performance (e.g. Boud and Middleton 2003).

In order to assess the relative performance impact of training we have conducted the fixed effects estimation along the dimensions of work experience and on whether an employee is a direct or a lateral hire.[8] We observe that for low experience employees there is no significant difference in the impact of training between direct hires and laterals. A stark result from this analysis is however, for high experience employees, training has a 3.5 times higher (based on a standardized test of coefficients and a 95% confidence interval) impact on laterals compared to fresh hires. Figure 2 illustrates the differential performance impacts across these two groups of employees. Particularly noteworthy from the figure is the steeper slope for laterals compared to direct hires as one moves from low to high experience (and

[8] While, for the sake of brevity and readability, we only the report 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 reflect the standardized coefficients.

conversely so for direct hires), which reveals that the laterals are better able to translate training to improved job performance.

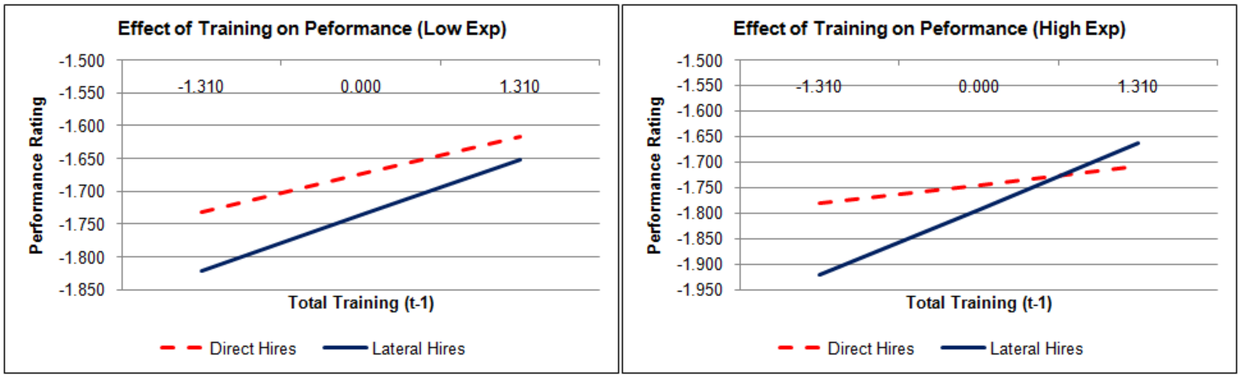

Figure 2: Comparative Training Impacts for Laterals and Direct Hires

Higher experience lateral hires, with a wider work exposure, seem to better imbibe training and translate the skill sets learnt from training towards their job responsibilities. Formal training is also a more credible source of knowledge and skills advancement for lateral hires since they are less likely to have deep organizational networks that they can leverage to improve their productivity and performance (Reagans et al. 2005, Monge and Contractor 2003). In addition, we posit that hiring of laterals with higher experience is based on a better set of information on the job candidate i.e., in addition to education and personality profile, information is also available about on-the-job performance than is the case for direct hires. This can lead to hiring of ‘superior’ employees who are more adept at translating training to performance. This effect is particularly pronounced when examined along the dimension of work experience; the effect of training on performance diminishes with experience for direct hires whereas it increases with experience for lateral hires. Our results indicate that training is a key lever that can be used by IT services firms to rapidly make-up for the lack of foundation training and firm specific tacit knowledge differential between laterals and direct hires.

Differential impact of general and specific training on performance

Table 6 presents the results of the performance impacts of type of training, split along the dimensions of specific versus general training (equation 3).

<<Insert table 6 about here>>

The results reveal that while general training has a significant positive impact, specific training does not have a significant impact on employee performance. This finding remains consistent regardless of how the data were partitioned. Examining the results from the OLS estimation, it is possible that experience, a proxy for on-the-job learning, renders the impact of formal specific training insignificant. More likely, however, firm specific training may not be a differentiating factor for employees, but creates value that is appropriated at the firm level. This is consistent with the predictions of human capital theory (Becker 1975), that firms will have incentives to invest in specific training in anticipation of economic returns. Likewise, the positive effect of general training is indicative of the increased marketability and exerts upward pressure on ratings, which proxy for wages.

For low experience employees there is no significant difference in the impact of general training between direct hires and laterals. However, for high experience employees, there are indications that general training has close to 1.5 times higher (based on a standardized test of coefficients and a 90% confidence interval) impact on laterals compared to fresh hires. We reiterate that this could be because of the wider work exposure of high experience laterals, their lack of organizational networks, and the fact that they are hired based on better information of their capabilities, as we reason previously.

The significantly positive impact of general training on performance motivates us to investigate these further.

Differential impact of domain and technical training on performance

Table 7 presents the results with the general training data bifurcated along the dimensions of technical versus domain training (equation 4).

<<Insert table 7 about here>>

The main result is that while both domain and technical training yield performance benefits, domain training is nearly 2.5 times more effective in boosting performance (test of coefficients is however significant at the 10% level). This is to be expected, given the increasingly strategic nature of IT applications. We also find that the interaction effects between the two types of training are uniformly and consistently negative. This is a clear indication that mixing technical and domain in a given year is counter-productive. Focus appears to be the key to reaping the optimal returns from training.

Similar to what we find in the case of the aggregate impact of training, there are stark contrasts in how domain and technical training affect performance for direct hires and lateral hires, especially for high experience employees. For low experience employees, technical training is highly beneficial for lateral hires, while domain training is not. The opposite is true for direct hires who realize positive benefits from domain training but not from technical training. This result is intuitive given the hiring practices of IT services companies. Fresh graduates, who constitute the typical direct hire pool, undergo foundation training in technology but often lack domain expertise. On the other hand, laterals are hired based on their knowledge and familiarity with a domain but do not have the benefit of foundation training. Therefore they derive significant benefits from technical training.

In contrast to the differential impacts of domain and technical training for low experience employees, both types of training are significant for high experience employees, whether laterals or direct hires. This indicates that training is serving the purpose of knowledge replenishment due to changes in both technology and client demands. In addition, at high experience level, 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). That is why the marginal benefit of domain training is also significantly positive. 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 high opportunity cost of training.

Our results also help analyze how training needs to change with employee profile. For direct hires, the returns from technical training become significantly positive with experience. Thus, technical skills diminish and need to be replenished. For laterals, both types of training become important with experience. A particularly piquant finding is that while domain training has little impact early on for laterals, it becomes important in later years. In fact, based on the formal analysis, for low experience employees there is no significant difference in the impact of domain training between direct hires and laterals. However, for high experience employees, there are indications that domain training has close to 2.5 times higher (based on a standardized test of coefficients and a 90% confidence interval) impact on laterals compared to fresh hires. This again suggests that domain skills, akin to technical skills, need to be replenished to reflect changes in the business climate. The key implication from our findings is that training program should be tailored to overcome significant gaps in knowledge required to perform competently, and should avoid knowledge redundancy. Thus, training should have the property of value-addition. This is the case with domain training for laterals and technical training for direct hires in their early years.

To the best of our knowledge ours is the first study to empirically corroborate the differential impacts of domain and technical training on direct versus lateral hires. 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 and 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

3.6%. We believe this effect to be economically significant, given that the employees, on average, takes 1.1 course per annum, and given that their appraisal reflects a broad assessment of their activities throughout the year. The effect is much larger in magnitude, on average, for high experience laterals, 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 of itself is not a differentiator for employees. Any value that is created through specific training is appropriated by the firm. We also find that both domain and technical training have significant positive main effects, but if taken together, can be detrimental. Our analysis takes care of possible selection bias as well as unobserved employee characteristics that could otherwise confound any linkage between training and performance.

The primary managerial implication of this research is that investment in training does lead to enhanced employee performance. However, our findings do point to the need for firms to effectively manage the training programs in order to reap optimal returns from these investments. The detailed analysis we conducted enable us to structure a set of 'best practices' for firms to extract the maximal returns from their training programs which are outlined below:

1. Focused training leads to better performance.
2. Tailor the training program to overcome significant knowledge gaps. Avoid repetitive and redundant training on skills that an employee already possesses.
3. Training should be a career-long endeavor as it is effective in boosting performance for junior as well as senior employees. The underlying rationale is that both domain and technical skill sets diminish and become outdated, and hence need to be replenished.
4. It can be beneficial to 'mandate' training for poor performers. Juxtaposing our finding that training positively impacts performance with the finding that employees who perform better undertake more training suggests the existence of 'positive feedback loop' between training and performance. However, the downside to this positive feedback loop is that poor performers are

excluded from getting into and benefitting from this loop. Mandating training for such employees may help them perform better.

Our work is limited by its reliance on data from a single company that has a highly regarded human resources practice. While on the surface this makes it hard to say anything generally about the average industry level impact of training on performance, it is worth recognizing that the employee pool (underlying population) that is accessible to this company is no different from that accessible to its two-three closest competitors. Further, these top three-four companies account for close to 80% of the Indian IT services market share. We speculate that our estimates should serve as lower bounds of the industry level estimates; given that the firm we studied has exemplary organizational and managerial practices that, while unaccounted for in this model, would be expected to complement the training investments. A cross-sectional analysis of this research question is a promising area for future research. We expect that such future work will also formally consider the impact of training investments on attrition and employee retentions.

The strength of our analysis comes from the depth of having micro employee level training and performance data, and therefore we are measuring economic activity at its most fundamental level. This makes our setting particularly well suited to the analysis of the differential impacts of the various types of training, in effect keeping firm characteristics constant and controlled for.

Given that software development is a complex group task, 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 the examination of the relative tradeoff between on the job learning and formal training. This falls into the unobserved time variant component of the error term in the present analysis.

Finally, we expect that future work will also consider social network analysis based knowledge diffusion and spill-over within and across software project teams. We expect this to further our understanding of the complementary or substitutive nature of on-the-job and formal training.

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Tables

Training Type	Course Type	Example
General	Domain Courses	• Foundation Course in Banking I • Overview of Derivatives
General	Technical Courses	• Analysis and Design Certification • J2EE Analysis and Design
Specific	Process Courses	• Quality Foundation • Internal Auditors Certification
Specific	Project Management Courses	• PM Elite Foundation Level • Project Management Professional (PMP) at
Specific	Behavioral Courses	• APAC Business Communication • Soft Skills | Managing Team | Team Building

Table 1: Examples of Training Courses Offered

Variable Name	Variable Description	Mean (SD)
PerformanceRating	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).	1.676 (0.699)
Age	Age of the employee in years.	28.224 (2.813)
TotalExp	An employee's total IT work experience in years.	5.144 (2.414)
FirmLevelExp	An employee's work experience at ITV in years.	4.307 (2.132)
dGender	Dummy variable indicating employee's gender (1: Male; 0: Female)	0.766 (0.424)
dDirectHire	Dummy variable indicating whether employee is a direct or lateral hire (1: Direct; 0: Lateral).	0.442 (0.497)
TotalTrng	The total number of training courses taken by an employee in a year.	1.197 (1.31)
GeneralTrng	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 and include technical training courses and domain training courses.	1.043 (1.173)
SpecificTrng	The total number of general training courses taken by an employee in a year. These courses add to the specific skills set of an employee and include project management courses, soft skills courses and process courses.	0.155 (0.398)
TechTrng	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,	0.532 (0.697)

Variable Name	Variable Description	Mean (SD)
	C++, etc.	
DomainTrng	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.	0.511 (0.691)

Table 2: Data Dictionary and Summary Statistics

		1	2	3	4	5	6	7	8	9	10	11
1	PerformanceRating											
2	PerformanceRating (t-1)	0.184										
3	FirmLevelExp	0.035	0.003									
4	TotalExp	0.131	0.113	0.720								
5	Age	0.140	0.127	0.628	0.885							
6	TotalTrng (t-1)	-0.032	-0.097	0.330	0.242	0.210						
7	DomainTrng (t-1)	-0.038	-0.094	0.307	0.216	0.188	0.874					
8	TechTrng (t-1)	-0.026	-0.080	0.214	0.166	0.146	0.773	0.478				
9	GeneralTrng (t-1)	-0.038	-0.102	0.311	0.226	0.197	0.963	0.910	0.799			
10	SpecificTrng (t-1)	0.008	-0.013	0.170	0.130	0.109	0.446	0.162	0.162	0.188		
11	dDirectHire	-0.085	-0.100	0.144	-0.298	-0.291	0.038	0.042	0.014	0.035	0.020	
12	dGender	-0.069	-0.072	0.057	0.078	0.079	0.002	0.004	-0.006	0.000	0.008	-0.033

Table 3: Correlation Matrix

GotTraining	Coefficient (Std. Error)
PerformanceRating (t-1)	0.217 (0.017)**
Age	-0.002 (0.007)
FirmLevelExp	0.284 (0.011)**
dGender	-0.086 (0.028)**
dDirectHire	-0.01 (0.027)

Table 4: Selection Equation[9]

PerformanceRating	OLS		Fixed Effects				
	Baseline Model	+ Interactions	Overall	Low Exp		High Exp	
				Direct Hire	Lateral Hire	Direct Hire	Lateral Hire
TotalTrng (t-1)	0.026 (0.007)**	0.03 (0.009)**	0.064 (0.008)**	0.044 (0.016)**	0.065 (0.023)**	0.027 (0.015)+	0.098 (0.016)**
InvMills	0.633 (0.139)**	0.639 (0.148)**	0.4 (0.051)**	0.913 (0.088)**	0.652 (0.116)**	-0.291 (0.123)*	0.148 (0.09)
Age	-0.027 (0.005)**	-0.027 (0.005)**					
TotalExp	-0.039 (0.008)**	-0.039 (0.008)**					
FirmLevelExp	0.127 (0.021)**	0.127 (0.022)**					
dDirectHire	-0.006 (0.015)	-0.002 (0.015)					
PerformanceRating (t-1)	0.23 (0.018)**	0.232 (0.019)**					
TotalTrng (t-1) X TotalExp		0.003 (0.003)					
TotalTrng (t-1) X dDirectHire		-0.061 (0.016)**					
TotalTrng (t-1) X dDirectHireX TotalExp		0.006 (0.007)					

Table 5: Impact of Training on Performance[9]

[9] Note for all estimation tables: + Significant at 10%; * significant at 5%; ** significant at 1%.

PerformanceRating	Overall	+ Interactions	Low Exp		High Exp	
			Direct Hire	Lateral Hire	Direct Hire	Lateral Hire
GeneralTrng (t-1)	0.072 (0.009)**	0.031 (0.008)**	0.052 (0.017)**	0.069 (0.024)**	0.047 (0.017)**	0.099 (0.017)**
SpecificTrng (t-1)	0.011 (0.029)	-0.059 (0.036)+	-0.089 (0.114)	-0.208 (0.151)	-0.012 (0.061)	0.063 (0.08)
InvMills	0.413 (0.051)**	-0.012 (0.029)	0.923 (0.089)**	0.64 (0.116)**	-0.241 (0.125)+	0.146 (0.092)
GeneralTrng (t-1) X SpecificTrng (t-1)		0.024 (0.026)	0.04 (0.081)	0.199 (0.109)+	-0.044 (0.043)	0.025 (0.058)

Table 6: Impact of General vs Specific Training on Performance[9]

PerformanceRating	Overall	+ Interactions	Low Exp		High Exp	
			Direct Hire	Lateral Hire	Direct Hire	Lateral Hire
DomainTrng (t-1)	0.087 (0.014)**	0.045 (0.012)**	0.107 (0.028)**	0.03 (0.044)	0.06 (0.024)*	0.151 (0.029)**
TechTrng (t-1)	0.049 (0.021)*	0.036 (0.022)+	0.048 (0.047)	0.227 (0.059)**	0.12 (0.06)*	0.12 (0.046)**
InvMills	0.412 (0.051)**	0 (0.029)	0.974 (0.09)**	0.686 (0.119)**	-0.183 (0.126)	0.197 (0.095)*
DomainTrng (t-1) X TechTrng (t-1)		-0.041 (0.026)	-0.126 (0.061)*	-0.148 (0.08)+	-0.147 (0.059)*	-0.113 (0.056)*

Table 7: Impact of Domain vs. Technical Training on Performance[9]