CLIMBING THE ORGANIZATIONAL LADDER: INVESTIGATING THE ROLE OF ON-THE-JOB TRAINING AND GENDER ON EMPLOYEE PROMOTIONS

ABSTRACT

In this study, we examine the effect of formal training and gender on the likelihood of employee promotions. We examine not only the effect of gender on promotions, but also whether gender moderates the effect of training on promotions. We analyze archival promotions and human capital data (on-the-job training) for 7,918 employees from 2002-2007 for multiple levels of promotions. We utilize a dynamic panel model to overcome a number of empirical challenges associated with identifying the effect of training and performance on the likelihood of promotion. We find that training as well as past performance have a positive impact on the likelihood of promotions. We also find that the average performance of other employees in the same role is negatively associated with the likelihood of promotions, making promotions akin to tournaments. Our results also indicate that ceteris paribus, general training, as opposed to specific training, is more likely to aid in promotions. Further, high performing employees benefit more from training. Additionally, we find that women are more likely to be promoted, and benefit more from training, especially when being promoted to managerial roles. While these results may seem counter-intuitive to prior literature, our results advocate the nuanced effects of formal training, performance, gender, and their interactions on employee promotion.

Key words: Formal Training, IT Human Capital, Gender, Promotions, IT Services Industry

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1. Introduction

How do employees climb the organizational ladder? While employee performance has long been understood to be one of the primary factors determining promotions (Gibbons and Waldman 1999, see also Prendergast 1993, DeVaro 2006a, Melero 2010), investments in human capital also seem prescriptive for employees seeking promotions (Sheridan et al. 1997).

Classic human capital theory posits that employees make education and training investments to improve future payoffs (Becker 1962). This is particularly true for knowledge workers such as those in the Information Technology (IT) sector, where human capital is an innate part of the firm’s production function (Mehra et al. 2014). IT professionals “perform complex, technical assignments that require originality, independent judgment, and analytical skills,” (Ang et al. 2002, p. 1428). To stay attuned to the changing technological and functional landscape, IT professionals need to constantly update their human capital so that they can perform the aforementioned tasks and remain productive (Bapna et al. 2013). Extant research has shown positive returns to education and training investments in not only improving employees’ performance (Bapna et al. 2013) but also their wages (Sicherman and Galor 1988).

Human capital investments not only affect worker performance, but also the way they are perceived relative to other workers. Prior literature suggests that promotions mimic tournaments in an organization’s internal labor market (Lazear 1992, DeVaro 2006a, b). Lazear and Rosen (1981) designate promotions to be non-wage incentives that are aimed at identifying and retaining high-ability employees. Because most “human capital investments takes place within firms in the form of training” (Acemoglu 1997, pp. 445), we examine the effect of formal training on the likelihood of promotion.
Furthermore, the earlier literature on labor economics has largely focused on performance and human capital investments, it is only now that a systematic examination of the effect of gender on promotions has begun. DeVaro et al. (2007) point out that while discrimination based on gender in hiring decisions and wage inequality has been studied extensively, discrimination in promotion decisions has not been studied as comprehensively. Numerous articles in academia as well as popular press have decried the underrepresentation of women in IT (Vara 2014, MacMillan 2012) as well as the lack of promotions for women (Ibarra et al. 2010). In a somewhat contrasting study, Booth et al. (2003) utilize data from British Household Panel Survey (BHPS) and report that women are as likely as men to be promoted. In this study, we seek to resolve this dichotomy in literature in the context of IT services. We also find extant literature to be unclear on whether the interplay between gender and human capital investments affects employee promotions. Consequently, we examine not only the effect of gender on promotions, but also whether gender moderates the effect of training on promotions.

The current literature that assesses the relationship between employee promotions and their human capital investments remains tenuous when it comes to empirical validation. First, much of this literature is theoretical and follows the seminal works of Lazear and Rosen (1981), Becker (1962, 2003), and Prendergast (1993) to provide incentive driven contracts that identify optimal human capital investments, wages, and promotions (see Gibbons and Waldman 2006 for a detailed discussion). Second, the few studies that do provide some empirical support rely on self-reported, survey data (e.g., Melero 2010), or are rooted in contexts other than that of knowledge work (e.g. Sheridan et al. 1997). While some of the findings from the past research may be applied to the IT industry, it should be noted that unlike other industries, knowledge that is critical to firm’s production function is tacit, that is, embedded within employees and cannot be separated into either processes or technology (Mehra et al. 2014), thereby meriting a closer examination. Finally,
prior literature may also be constrained by methodological concerns intrinsic to this problem, such as employee motivation and innate capability, which may otherwise confound the results. Together, these may hinder a more thorough understanding of how human capital investments, together with performance and gender, affect promotions for knowledge workers.

We address this gap in the literature by analyzing detailed, archival promotions, demographic, and human capital data for 7,918 IT professionals from 2002-2007 for multiple levels of promotions. The firm, focal in this study, is a leading IT services firm with stellar HR practices that invests heavily in formal employee training. Using this detailed data, we are not only able to parse out the effect of training and performance on promotions, but also whether there are differences between men and women in how training affects the likelihood of their promotions. We further draw on the human capital theory and utilize Becker’s delineation of general versus specific training to distinguish between the effect of general and specific training on promotions. We can thus examine whether gender and/or employee performance moderate the effect of training on promotion.

We find that training as well as past performance have a positive impact on the likelihood of promotions. Additionally, we find that women are more likely to be promoted, and benefit more from training, especially when being promoted to managerial roles. We also find that the average performance of other employees in the same role is negatively correlated with the likelihood of promotions, thus promotions are akin to tournaments. We also find that general training, as opposed to specific training, is associated with a higher likelihood of promotions. Further, we find that performance moderates the effect of training on promotions, such that training and performance are complementary. Employees who have performed better benefit even more from training. Together, our results reveal a nuanced effect of gender, formal training, performance, and their interactions on employee promotions.
Our study also speaks to the importance of promotions as a way to conserve human capital for knowledge firms. MacCrory et al. (2014) propose the use of promotions as a way to mitigate turnover of IT employees and the consequent loss of human capital. DeVaro (2006b) draws on the resource based view of the firm (Porter 1985) to argue that managing its human capital is of strategic importance to the firms; because this capital represents a resource “embodied in the firm’s workers, that is both superior to that of competitors and also difficult to replicate by other firms (p. 722-723).” Given the high turnover rates and potential spillovers to competitors in IT sector (Tambe and Hitt 2014), it becomes imperative to understand the mechanisms that affect employee promotions.

We contribute to the extant literature in multiple ways. First, we contribute to the literature on human capital by examining granular, archival data that connects training, gender, and promotions for multiple levels of promotions, in a context where human capital investments are critical. Our model accounts for endogenous self-selection into training. After controlling for performance as well as the endogenous motivation to take training, ours is one of the first studies to provide unequivocal, empirical validation of the efficacy of training on promotion. Second, we contribute to the growing body of research on gender issues in organizations. Our findings on the ameliorating effect of training for women’s promotions should help not only women as they navigate organizational promotional ladders but also inform knowledge firms’ human resources policy.

We organize the paper as follows. In the next section, we provide the theoretical framework we utilize and propose the hypotheses. In section 3, we discuss the research setting and also expound on the empirical challenges associated with research on human capital investments. In section 4, we present the empirical model that validates the hypotheses and results from the analysis. We conclude with a discussion of results and directions for future research.
2. Conceptual Framework and Hypotheses

To examine how of training, performance, and gender influence the likelihood of promotions, we draw on human capital, social sciences, and labor economics literature. We utilize the central tenets from each of these theories to frame our hypotheses. The underlying assumption that connects these theories is that promotions in an organization are merit driven. Therefore, the link between employee behavior and associated rewards and penalties should be explicit. In addition, these contracts should be “... linked clearly and directly to the firm’s strategic goal in a way that is transparent to workers...” (DeVaro 2006b, p. 724). Promotions are, therefore, analogous to rank-order tournaments within an organization and represent non-wage, incentive driven rewards schemes that direct employees to desirable levels of performance and skills acquisition (Lazear and Rosen 1981).

Sheridan et al. (1997) examine several factors that affect employee promotions. They suggest that human capital investments such as education and training may increase the likelihood of promotions in three ways. First, human capital theory suggests that these investments are made to influence future income and improve labor market outcomes (Becker 1962) and speak to the supply side economics in an organization. That is, training would improve their skills and therefore improve any future performance. An organization can hire for positions within its hierarchy in two ways: (i) it may utilize the internal labor markets, wherein employees are hired into entry level jobs and promoted to higher levels of the organizational ladder, or (ii) it may hire employees from the external labor markets, paying competitive market wages (Lazear and Oyer 2004). Because of such fluidity in hiring and employment decisions, existing employees will invest in training only “... in expectation that their organization will utilize their potential with a faster career path,” (Sheridan et al. 2007, p. 374).
Similar to human capital theory, credentialist theory (Thurow 1972) proposes an alternate explanation between training and employee mobility. Given the context of IT services, this view presupposes that skills acquisition is necessary for enhanced performance (Bapna et al. 2013). Thus, when an employee takes training, it can be viewed as a credible indication of further trainability, and that the amount and kind of training would determine the upward mobility of that particular employee.

In contrast, screening theories (Stiglitz 1975) argue for the demand side economics at play in an organization. Even when the past performance of an employee is known, managers would rarely have complete information about his/her future potential and value to the firm. Therefore, training investments can be seen as signals for future success and can be used by managers to screen high performing workers from the low performing ones and promote them to faster career paths.

While these theories advocate alternate perspectives, they point in unison to the importance of training as a means to achieve career mobility, over and above performance (Sundstrom 1988, Melero 2010). Therefore, we posit that

**H1: An increase in on-the-job formal training is associated with a higher likelihood of promotions**

While the role of training is essential for career mobility, extant literature posits performance to be critical for growth as well. Consider this, as employees improve their performance, they become more valuable to their employers (Bapna et al. 2013). Ng et al. (2005) discuss the objective measures of career success such as promotions, which are tenable only when an organization instills the contest-mobility perspective into its HR strategy. This perspective argues that in an organization where objective – rather than subjective, sponsorship-mobility – practices are followed, employee performance would be a strong predictor of the probability of promotions. Literature has also likened promotions to competitive tournaments (Nalebuff and Stiglitz 1983,
Gibbs 1994, Eriksson 1999) and argues that employees can get ahead in the various stages of the promotion tournament only on the basis of their own performance and contribution to an organization’s strategic goals. More interestingly, while absolute performance is desirable, it is only the relative evaluation of this performance that induces optimal levels of effort in knowledge workers such as those in the IT sector (Rosen 1986, MacCrory et al. 2014). Employees compete with one another in a fair contest for career advancements; with those who perform better than others are “deemed victorious” and promoted to the next stage. In sum, labor economics literature posits that as a result of performance improvements, employees are rewarded by promotions (Gibbons and Waldman 1999, Melero 2010). Consequently, any differences in promotion probabilities should reflect differences in employee productivity (Medoff and Abraham 1980). From the tournament theory perspective, promotions are considered to be an incentive for the high performing employee to keep up their accomplishments in the future (DeVaro 2006b).

Furthermore, consider the thick labor markets that exist for IT professionals. If there is a vibrant external labor market, high performing employees would have multiple outside options. Any increase in their performance relative to other employees makes them more attractive to other firms. In such a scenario, not promoting a high performing employee will have a negative spillover that may result in employee turnover and consequent transactions costs of hiring and training a replacement (Bidwell and Keller 2014). Therefore, promotions can also be an incentive to increase the longevity of an employee within an organization, and stemming turnover of a firm’s high performing employees (MacCrory et al. 2014). We hypothesize that:

\[ H2A: \text{An increase in an employee's relative performance is associated with an increase in the likelihood of promotions.} \]

As a corollary to the above, we propose that
H2B: An increase in other employee’s relative performance is associated with a decrease in the likelihood of promotions.

The above hypotheses manifest the tournament aspects of promotions within organizations. While both training and performance are credible predictors of employee promotions, an interesting question to then ask is: how does performance moderate the effect of training on the likelihood? In other words, do high performing employees benefit more or less from training?

The effort in taking and completing training is costly to employees. Signaling theory (Spence 1973) postulates that training sends a stronger signal for high ability (and therefore high performance) employees because their marginal effort to undergo training is lesser. Extant literature takes advantage of the Spence’s signaling model to suggest that productivity rises faster for workers of higher innate ability (Gibbons and Waldman 2006). Becker (1962) in particular notes the positive correlation between innate ability and human capital investments. However, beyond the fact that employees with higher performance take more training (see Bapna et al. 2013), their marginal productivity is also higher. It is likely that such employees are better able to utilize their training into improving future productivity, send stronger signals, or indicate their future trainability and hence enhance their chances of a promotion. Therefore, we argue that the performance and training are complementary, that is:

H3: Performance interacts positively with training, such that employees with high performance benefit even more from training in increasing the likelihood of promotions.

Human capital literature also distinguishes between two types of on-the-job training: general and specific (Becker 1962). General training is useful to the employee not only within the firm that provides the training, but for other firms as well. In essence, general training increases an employee’s marginal product in both current and future firms. For instance, consider a training
course in data base administration, or a programming language such as Java. Any training procured in these areas would be of use not only to the current employer but to others as well. As a result, the employee becomes attractive in both internal and external labor markets. In contrast to this, specific training is useful only within the firm that provides that training. In the context of IT services, these would include any firm specific processes and frameworks. In other words, specific training that increases the productivity of an employee within the focal firm but has not such commensurate productivity gains in the external labor market. In addition, the gains from specific training are more difficult to quantify and hence it is difficult to compensate the employee for acquisition of firm specific human capital (Prendergast 1993).

The divergent appropriation of gains from general and specific training for both the firm and its employees is reflected in the incentives to take or provide these trainings. Because general training increases an employee’s marginal product and consequently their wages in both internal and external markets, firms have minimal incentives to provide general training (Becker 1962). In contrast, only the firm gains from provision of specific training, employees do not benefit from it. Prendergast (1993) posits “it is difficult to repay the employee after skills are collected as the firm has an incentive to renego,” (p. 523). Thus, employees have little inducement to take specific training (Becker 1962, Prendergast 1993).

Slaughter et al. (2007) suggest that firm specific training is contextual, therefore the employees who acquire firm specific skills are considered more valuable. Prasad and Tran (2012) examine an employee’s incentive to acquire costly human capital (whether general or specific) when any skills gained cannot be verified in the external labor market and therefore cannot be contracted on. They suggest that a firm can provide dichotomous incentives to its employees for their human capital investments: increasing wages for acquisition of general skills, and promoting an employee for
acquisition of specific skills. Prendergast (1993) also advocates the use of promotions as a way to induce and compensate an employee for taking specific training. In keeping with this, we posit that

\[ H4: \text{Within general and specific training, specific training is associated with higher likelihood of promotions.} \]

Finally, the social science and management literature presents mixed evidence with respect to gender and promotions. Overwhelmingly, this literature suggests that men are more likely to be promoted compared to women (e.g., Darity Jr. and Mason 1998, Gneezy et al. 2003, Ibarra et al. 2010). However, more recent literature proposes that once differences between motivation and capability are accounted for, women are at least as likely to be promoted (Lewis 1986, Booth et al. 2003, Buchan et al. 2008). In particular, Lewis (1986) analyzed data for 10,000-12,000 federal employees in white-collar jobs but found that no significant differences between the promotion probabilities for men and women, once the demographic and occupational attributes were controlled for. The effect of gender on promotions, especially for IT professionals, is ambiguous and therefore an open empirical question.

Literature also does not provide a theoretical perspective on whether human capital investments such as training benefit women more or less. If discrimination witnessed in labor markets arises from gender stereotyping and the consequent preconceptions about gender and productivity (Bennett 1976, Darity Jr. and Mason 1998), training can help clear away any such information asymmetries and result in more benefits from training for women, the gender that has been observed to be discriminated against. Nonetheless, we do not hypothesize about either the effect of gender on promotions or whether gender moderates the effect of training on promotions. Thus, we are unable to predict either a complementary or substitutive relationship between gender and training.
Given the lack of theory to guide us, we purposely avoid a directional hypothesis with respect to the interaction effects. However, these issues are of academic importance to research as well have managerial implications for the IT industry (Trauth et al. 2009). We are thus motivated to examine the relationship between training and gender in the context of knowledge workers in the IT industry. We are also interested in examining the ‘pure gender’ effect, in that after controlling for other factors, is there any empirical evidence for women (men) to be promoted earlier? Further whether females tend to undertake more training than their male counterparts to access promotion opportunities, and whether they tend to leverage their training better to procure promotions are also assessed.

There are a number of empirical challenges associated with identifying the effect of training and performance on the likelihood of promotion. For instance, as Bapna et al. (2013) point out, training and performance can be correlated with unobservables such as an employee’s motivation and drive, and can confound any analysis that does not take these factors into account. We discuss the research setting and our empirical strategy next.

3. RESEARCH SETTING AND DATA DESCRIPTION

Research Setting: To evaluate our hypotheses, we conducted an extensive, in-depth study at a leading IT services vendor headquartered in Bangalore, India. We were able to connect with the senior management at the company to enable this research. We held interviews with managers responsible for human resources (HR) practices as well as employees’ learning and development, so that we could understand the firm’s promotion policies, organizational dynamics, and performance evaluation processes.

The firm employed around 70,000 people at the time of data collection, since then it has grown to around 160,000 employees. The firm has a dedicated education and research department to
provide in-depth training to its employees. In addition to incorporating the stringent quality processes that enabled it to be assessed at level 5 of the capability maturity model (CMM) since 1999, it has been assessed at level 5 for the people CMM (pCMM). This stupendous growth in its employee strength necessitated that the firm put in place objective HR management policies that allowed it to improve workforce capabilities through adequate training, performance evaluations, appropriate employee incentives such as promotions, and human capital alignment with the firm’s strategic goals (Curtis et al. 2009).

The firm understands that investing in its human capital is critical for its growth and invests in employee training to attain these organizational goals. To that end, it has instituted a 26 weeklong, foundational training program that is mandatory for all employees who join immediately after graduation. This program incorporates courses that build technical, domain, and process competencies and seeks to make these employees “work ready” (Kapur and Mehta 2008). Beyond the foundational training, the firm continues to provide training courses to its employees. In this study, we examine the effect of this on-the-job training on promotions.

The majority of the projects delivered by the company adapt the waterfall methodology for software production, such that there are distinct phases for design, analysis, programming, testing and implementation (Royce 1970). Dedicated project teams deliver these software projects. The typical career path at this firm reflects this, such that an employee progresses along the corporate hierarchy from being software engineer to programmer analyst to project manager and further on. Our discussions with the senior management at the focal firm suggested that we focus our analysis to these three categories for the following reasons: (i), these three rungs constitute the largest layer of the employee pyramid, and (ii) these three categories are most critical to human capital development and directly responsible for the success and failure of various projects. We detail the roles and expectations for these below:
The entry-level position in the organization is that of a software engineer. Software engineers help code and test the software. They also provide help with implementation and post-production support. To accomplish these tasks, they require knowledge of the underlying technology and the programming language needed to code the software. They would also need to understand the processes and frameworks that the organization uses to ensure quality and timeliness of the developed software.

The next step on the organizational ladder is that of a programmer analyst (PA). PAs take on a more complex role in software projects. They interact with the users to determine client requirements, analyze these requirements, and help with software design and development. They may supervise programmers with code reviews and provide expert technical help when needed. They also assist in effort estimation. PAs may also assist with the project’s knowledge management and provide transition support, as the project moves from implementation to production. They'd thus need to be cognizant not only with technology but also domain and other functional knowledge.

Project Managers (PMs) constitute the next rung in the organizational hierarchy. Their tasks are much broader in scope. They are the key decision makers responsible for successful delivery and implementation of software projects. They participate and ensure proposal, estimation, and scope for a project is completed; build the project team, schedule assignments, monitor, review, and report project status, manage project risks. Therefore, they need to interact with multiple stakeholders, such as the project team, the clients, and senior managers. To accomplish these goals, they not only need to employ communication, project management, and leadership skills but also be versed in project-related technology or domain (Langer et al. 2014).
The promotion policies of the firm follow industry best practices to objectively reward adequate performance. To that end, the firm ensures that it has a meticulous performance evaluation process in place. Instead of relying on a supervisor provided rating, it uses a “360 degree feedback” system to measure the employee performance annually. This elaborate metric incorporates feedback from multiple stakeholders that an employee transacts with, such as team members, peers, subordinates, and supervisors, thereby providing a comprehensive performance evaluation (see also Bapna et al. 2013). To provide adequate incentive for its employees to improve their performance, the firm uses this performance metric to inform an employee’s annual raises.

**Data and measurement:** We collected data on 7918 employees for the years 2002-2007. Our data include the promotions data (time in current position, current and previous designations, etc.), performance rating, demographic details, work experience in years (both at the focal company and the total work experience), and complete training data. We describe these data below.

**Promotion:** We observe two levels of promotions: software engineer (SE) to programmer analyst (PA), and programmer analyst to project manager (PM). In our sample, each employee is promoted at most once.

**Employee Performance Rating:** Each year, the performance evaluation process scores each employee relative to others to yield a relative performance rating. This rating is on a scale from 1 to 4, with 1 indicating the highest performance level and 4 the lowest. Because of the meticulous and comprehensive nature of the evaluation, we assume that these ratings capture the relative employee performance. Furthermore, because a rating of 1 is better than a rating of 4, any increase in this rating indicates a decrease in employee performance. In order to interpret the coefficients with ease, we use PerfRating (computed as -1*Employee Rating) in our analysis (see Langer et al. 2014).
In addition, promotions are perceived as tournaments in the extant literature (see DeVaro 2006a). Therefore, relative performance of peers becomes important in determining the likelihood of promotions. We compute the \textit{AvgRatingRole} as the average employee rating for a particular role (software engineer, programmer analyst, or project manager) in a year to proxy the peer group’s performance.

\textit{Training Variables:} Our data include detailed information on the courses that each employee took. These data included the course name and a short description, the year the course was taken, etc. These course were labeled by their type, whether they contained with content related to domain, technology, behavioral, firm level processes, or to project management methodologies. While we can compute the total training that an employee took, it was more difficult to characterize the general or specific training. We follow Bapna et al. (2013)’s multipronged approach for this. That is, we draw upon extant literature for the initial categorization (Slaughter et al. 2007). Thus, we postulate that 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 like Java) impart skills that are of use not only within the firm but also outside the focal firm. Hence, we categorized these training courses as general. On the other hand, process and project management courses contained content that was specific to the focal firm. For instance, the process or project management courses imparted information about the usage of internal process frameworks or firm calibrated project estimation guidelines. We then approached senior managers to validate this categorization. Finally, we asked a panel of five experts for help. These five experts not only had requisite experience within the Indian IT services industry, but also had college level degrees in computer science or engineering. To maintain parlance with human capital literature, we instructed our experts on the definitions of general and specific training (Becker 1962). The experts were asked to rate each course based on its description on a scale of 1 (specific training) to 7
(general training). To ensure adequate familiarity, we used a pilot instrument. After the experts had rated the different courses in the dataset, we computed the inter-rater reliability using Cohen’s kappa (Cohen 1960). A high value of Cohen’s kappa (0.8 or above) suggests that the experts are in agreement with one another (Kvalseth, 1989), our tests revealed the Cohen’s kappa exceeded 0.8, therefore our experts agreed on the categorization of various courses into general or specific training. Following Bapna et al. (2013), we averaged the ratings across the experts to arrive at a final rating for the course; we categorized courses that were rated 4 or above as general and those rated below 4 as specific.

Table 1 provides some examples of different types of courses. To compute the training variable, we sum the number of courses taken by an employee in a year (total or general and specific), normalized by the course duration.

<< Insert table 1 about here >>

Controls: In addition to promotion, performance, and training, we control for employee’s demographic attributes. In particular, prior literature suggests that performance, promotions, and experience are correlated (e.g., Joseph et al. 2009). Furthermore, it is possible that the employees who have been longer with the firm are considered more valuable (Slaughter et al. 2007). Hence, we control for an employee’s total (TotalExp) and firm level experience (FirmExp).

Subsamples: Because we have the detailed demographic data, we can construct sub-samples for our analyses using gender and the level of promotion. We divide the data into two subsamples for men and women. We further divide these into the level of promotions. These subsamples are useful in analyzing the nuanced relationship between gender, training, and promotions.
Table 2 describes our variables and provides the summary statistics. The correlation matrix between the dependent and explanatory variables is provided in Table 3. Finally, we note that the use of interaction variables may exacerbate collinearity issues in our model. Therefore, we standardized the relevant variables prior to our analysis to ease interpretation as well as to assuage the collinearity concerns (Aiken and West 1991).

We articulate 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

Prior literature suggests that employees’ human capital investments and their performance affect the likelihood of their promotions; therefore we use these variables as the primary explanatory variables that inform our model. Although the employees in our data were randomly selected, we need to ensure that we account for potential endogeneity in our model before we ascribe a causal linkage between these variables and the likelihood of promotions.

Weiss (1995) proposes that employees who take training may be very different from those don’t. As Bapna et al. (2013) discuss, “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 (p. 643).” For instance, employee motivation and innate drive could influence their decision to take training. These same factors may also account for their performance improvements as well as their promotion likelihood. It could also be that an employee takes training to signal their ability to senior managers. Further, the firm’s commitment to provide
training may attract high performance individuals (Cappelli 2002). Therefore, both training and performance may be endogenous in that they may be correlated with the unobservable error term. If we do not account for this endogeneity, we may overestimate the marginal effect of both training and performance. In other words, a naïve model would measure the marginal effect not of the training (or performance), but rather the combined effect of training (or performance improvement) and being identified as an employee who takes that additional training (or improves the marginal performance).

To evaluate our hypotheses, we estimate the following model for an employee ‘i’ in year ‘t’. To identify the model that overcomes the aforementioned challenges, we specify the following Arellano–Bover/Blundell–Bond (AB-BB) dynamic panel model (Arellano and Bover 1995, Blundell and Bond 1998), using robust standard errors. The structure of the dynamic panel model is such that we can construct instruments using lagged values of our dependent variable, GotPromotion_{i,t}; wherein these instruments have been shown to be uncorrelated with the error term (see Bapna et al. 2013).

\[
\text{GotPromotion}_{i,t} = \beta_0 + \beta_1 \cdot \text{PerfRating}_{i,(t-1)} + \beta_2 \cdot \text{TotalTrng}_{i,(t-1)} + \beta_3 \cdot \text{AvgRoleRating}_{i,(t-1)} + \varepsilon_{it},
\]  

(1)

where GotPromotion_{i,t} is 1 if an employee ‘i’ is promoted in year ‘t’, and 0 otherwise, PerfRating_{i,(t-1)} and TotalTrng_{i,(t-1)} are the lagged variables capturing employee performance and training respectively for the year (t-1), AvgRoleRating_{i,(t-1)} is the average employee rating for that particular role (SE/PA/PM) in the previous year (t-1), and \( \varepsilon_{it} \) is the normally distributed error term. In the

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1 While Maddala (1983) criticizes the use of linear probability models (LPM) when examining dichotomous dependent variables, Ai and Norton (2003) advocate the use of LPMs for such models when these models include interactions of explanatory variables. Furthermore, Chatla and Shmueli (2013) show that if the dependent variable is naturally binary, as in our case, LPMs perform similar to probit and logit models in terms of classification as well as coefficient estimates. Our panel data regressions for linear, probit, and logit models show qualitatively similar coefficient estimates; results are available from authors upon request.
above model, $PerfRating_{i,(t-1)}$ is in particular useful because it encapsulates the effect of prior performance on the likelihood of promotion and hence subsumes some of the unobservable factors in the panel model.

An analysis of total performance and training in Equation 1 allows us to validate H1 and H2. We use the following specification to examine H3, where the variable $PerfRating_{i,(t-1)}*TotalTrng_{i,(t-1)}$ presents the interaction between performance rating and total training.

$$
\text{GotPromotion}_{it} = \beta_0 + \beta_1 . PerfRating_{i,(t-1)} + \beta_2 . TotalTrng_{i,(t-1)} + \beta_3 . AvgRoleRating_{i,(t-1)} + \beta_4 . PerfRating_{i,(t-1)} * TotalTrng_{i,(t-1)} + \epsilon_{it},
$$

(2)

Furthermore, to validate H4, we analyze the model in equation (1) for general as well as specific training (see Bapna et al. 2013).

**Subsample Analysis:** In addition to examining the effect of training on our sample, we are interested in understanding if the effect of the model coefficients varies between men and women, and between promotion from the first level to the second level (SE->PA), and from the second level to the third level (PA-> PM). Therefore, we analyze equation 1 for different subsamples constructed based on gender and for different levels of promotion.

**Robustness Checks:** While the dynamic panel model as specified in equation 1 helps with the endogeneity inherent in our problem, it is unable to provide any information on the effect of time-invariant covariates such as gender, or such variables such as experience, which offer no variation across the sample. As a robustness check, we estimate a Hausman Taylor (HT) specification (Hausman and Taylor 1981). In the HT model, individual means of the strictly exogenous regressors are used as instruments for the time invariant regressors, because the latter may be correlated with individual effects (see Baltagi 2001). In the HT specification, we also examine the
As shown in tables 4-6, we find that training has a positive impact on promotion. As expected, employee performance also positively impacts promotion. In addition, the results indicate...

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1 As further robustness checks, we analyzed our data using a logit (fixed effects) and a probit (random effects) model for panel data. The results are similar to the dynamic panel model. In addition, we examined a modified version of the Verbeek and Nijman’s extension of the Heckman model (Verbeek and Nijman 1996), wherein the sample selection panel model is estimated using random effects and the outcome panel model is estimated using fixed effects. While this method seems intuitive, as Bapna et al. (2013) point out, the model variables between the selection and the outcome equations may lack any exclusion criteria, such that the model is identified only due to the non-linearity of the inverse mills ratio. The dynamic panel AB-BB model that we use provides a more elegant approach to address the endogeneity concerns in our model (Arellano and Bond 1991).
competitiveness in promotions where higher the overall performance of cohorts, lower is the likelihood of getting promotion. Thus, we find support for H1 and H2. More interestingly, we find that training and performance interact positively, thus training is even more helpful for those employees whose performance is higher. This complementary relationship validates the theoretical predictions of DeVaro and Waldman (2012).

To understand the gender effects, we chose the subsample approach with male and female employees. The results for each group are consistent with the overall results, however there are several interesting size effects that vary between the groups. The positive effect of training is significantly large for women. This result suggests that women benefit disproportionately from training for promotion purposes. However, performance effects on promotion are similar across genders. HT results also suggest that women are more likely to be promoted. While this result may seem counter-intuitive to prior literature, we offer two alternate explanations for these findings: First, consider the widely recognized wage differential between men and women (Babcock and Laschever 2003, HBR 2010, 2013, Leibbrandt and List 2014). Booth et al. (2003) explain that women are more likely to be promoted because they are a “lower cost option” compared to men for the task that needs to be performed at the higher level. Second, in more recent research examining gender, trust, and helpfulness, women are found to be more helpful and trustworthy compared to men (see Orbell et al. 1994, Buchan et al. 2008). Hence, as employees move to more responsible roles that require increased interactions with various stakeholders (PA compared to SE, and PM compared to PA), it is likely that women are perceived to be a better fit. Together, these may explain why women are more likely to be promoted.

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3 It may be possible that women take more training and hence give more credible signals to management, earning faster promotions than men. However, our analysis shows that there are no statistical differences between men and women in their propensity to take training; the results are available from authors upon request.
Further, based on the HT specification, the estimates suggest that experience has an interesting impact on promotions. Firm level experience lowers the likelihood of promotion, suggesting that spending too long in the same role signals missed prior opportunities for promotions. This further weakens the case for future promotions. However, experience outside of the focal firm enhances promotion opportunities, as the total experience is positively related to promotion.

We next examine the results from our analysis for different levels of promotion. The first one entails promotion from a software engineer to programmer analyst – a more technical and lower level promotion than the second more advanced promotion from programmer analyst to a project manager, a role with more managerial responsibilities. Interestingly, training has a much stronger, positive impact for the lower-level promotions than for higher-level promotions. Additionally, the impact of employees’ performance on the likelihood of their promotion is markedly smaller at the higher level of promotion. This result suggests that significantly superior performance is needed to garner promotion as one climbs up the career ladder. Similar to the overall results, we find that excessive experience in the same role at the same firm is deleterious at the lower levels but does not matter in gaining promotion at higher levels. We also find that the effect of competition diminishes at the higher-level promotion. It is likely that factors other than pure performance based matrix increasingly come into play for promotion consideration at higher levels.

Analyzing the two levels of promotion along the gender lines reveals that the gender effects manifest prominently at higher-level promotions. Training effects are significantly higher for women. This is consistent with the literature that suggests that women face more time constraints due to family and other obligations. They are less likely to have time to nurture peer networks, which may enhance the likelihood of promotions. Therefore, women employees identify training as a structured approach to advance in their careers as opposed to ad-hoc personal interconnections.
Examining General vs Specific Training:

As shown in tables 7-9, when we break down the effects of type of training – specific versus general – we find that general training has a beneficial impact on promotion while specific training is not significant. This findings hold even when we consider gender differences. We believe that specific human capital is better garnered through informal channels rather than formal, firm provided training. Although at odds with Slaughter et al. (2007), this result is highly consistent with performance effects of training recently reported in the literature (Bapna et al. 2013).

The nuances of this overall insight become apparent when analyzing the impact of specific training at different levels of promotion. For the lower level promotion where the candidates have little experience and knowledge of the firm, specific training does seem to imbibe and offer benefits in chances of promotion. But at higher levels, where employees have been in the firm for a longer period of time, spending time and effort with formal specific training offers no benefits.

Interestingly, the subsample analysis shows that at lower levels, specific training is beneficial for men but is insignificant for women. The average age at the lower level of promotions is around 23, which roughly corresponds to the age when women professionals in India may be looking at marriage. This may entail a move to another geography, making it less likely that women will invest in or benefit from specific training. In contrast, Indian men rarely face such locational constraints, and hence any specific training investments they make positively affects their promotion likelihood (see Lewis 1986, Lazear and Rosen 1990, and Booth and Zoega 1999 for when women call it quits and their disincentive to invest in firm specific skills).
In summary, our overall results indicate that while training is an important predictor of promotions, there are subtler differences when it comes to men versus women, and from lower to higher levels of promotions. As we conclude in the next section, our findings have important implications for senior managers as they balance the gender bias and reward employees for performance improvements and skills acquisition via promotions.

5. CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

The need for investing in human capital is well understood by academia as well industry, especially in the context of knowledge workers such as those in the IT sector. Prior literature has identified the causal link between these investments, in the form of employer provided training, and employee performance for IT professionals (Bapna et al. 2013). However, what is less understood is the effect of these investments on how these IT professionals navigate organizational ladders via promotions, perhaps due to paucity of granular data. In this study, we investigate the effect of human capital investments on the likelihood of promotions.

Our study utilizes a unique setting in which to examine this research question – a leading IT services provider headquartered in India. At the time of the study, the firm employed close to 70,000 employees and made significant investments in formal training for its employees. We gained access to detailed, archival data on promotions, performance, training, and demographics for 7,918 employees from 2002–2007. This comprehensive dataset affords us the opportunity to examine not only the effect of total training, but also the effect of different types of training (general vs. specific) on promotions. In addition to answering our primary research question, we can also investigate how performance, gender, and their interactions with training affect employee promotions.

Our findings reveal that training as well performance are strong predictors of the likelihood of promotions. More interestingly, we find that women are more likely to be promoted than men, and
benefit disproportionately more from training. While our study does not delineate why it may be so, it is possible that women may be more opportunistic when it comes to enrolling for courses that ensure faster promotions, or they may imbibe knowledge more effectively and are more adept at translating knowledge gains into performance improvements and/or signaling, leading to promotions. Furthermore, while our results may seem counter-intuitive to prior literature, we offer two alternate explanations for the pure gender effect revealed in our findings. First, considering the wage differential between men and women, we posit that women are more likely to be promoted because they are a “lower cost option” compared to men for the task that needs to be performed at the higher level of organizational ladder. Second, recent studies suggest that women might more helpful and trustworthy compared to men. Hence, as employees move to more responsible roles that require increased social interactions with various stakeholders, it is likely that women are perceived to be a better fit. Together, these factors may explain why women are more likely to be promoted. We also find that contrary to extant literature, general training is more important for climbing the corporate ladder, while specific training is not.

We believe that the strength, robustness, consistency, and validity of our findings stem from a) using employee level data for training, performance, and multiple levels of promotions provides an adequate backdrop to examine the more intricate predictions of the human capital theory, and b) employing the dynamic panel model that addresses some of the identification issues that are inherent to the research problem, to wit, self-selection into training and constructs such as motivation and drive that affect both training and performance.

This study contributes to the extant literature several ways. First, we contribute to the human capital literature by being one of the first studies to unequivocally establish the economic significance of training on promotions. While extant literature has utilized theoretical models to predict the impact of training on promotions (e.g. Lazear and Rosen 1981, Becker 2003,
Prendergast 1993), our research setting and data enabled us to validate the theoretical predictions of these models in the context of a knowledge industry like IT services, where training is essential to the firm’s production function. We are able to parse out not only the impact of total training but also the differential impact of general and specific training for multiple levels of promotions, further extending the extant human capital literature (Lazear and Rosen 1990, Gibbons and Waldman 2006). In particular, we are able to shed light on how general training can be helpful for promotions (Prasad and Tran 2012 q). Second, we contribute to the literature on labor economics, which acknowledges the prevailing gender based discrimination in IT organizations, but does not focus on how human capital investments affect these dynamics within an organization (e.g., Ibarra et al. 2010), nor does it reflect on the interaction between performance and training (DeVaro and Waldman 2012). We show that the effect of gender on promotions is subtler than previously believed, in that women are more likely to be promoted and benefit more from human capital investments, especially when being considered for managerial roles. Our final finding speaks to the value high performing employees derive from training, in that training and performance are complementary. Finally, we contribute to the literature on tournaments (DeVaro 2006 a), where in we provide the link between human capital investments, relative employee performance, and promotions in the context of knowledge workers.

Our findings also have important implications for senior executives as they manage their human capital (Luftman et al. 2009). Our primary managerial implication is that investments in training, even after controlling for performance, can help employees rise in the organizational hierarchy. Prior research suggests that such human resource practices affect firm performance positively (Delaney and Huselid). In essence, such practices create a virtuous cycle; employees witness the value to investing in training to foster their growth within the organization, thereby improving their own and consequently the firm’s performance. Prior literature also suggests that
women lack influential mentor network (e.g., Ibarra 1993), leading to differences in how women are promoted within an organization. Senior managers can instill best practices such that women use training as a way to ameliorate any gender issues and climb the organizational ladder faster. Finally, we find that training is complementary to employee performance. Therefore, managers can nurture the high performing employees and provide them resources to excel even more.

**Limitations and Future Research**

Like all research, this study has limitations and provides opportunities for further research. We rely on critical data from a single firm, and it is possible that the results may not generalize to other firms. However, this firm has exemplary HR practices and resembles not only the other top 5 competitors within India but also global IT giants such as IBM and Accenture who operate captive centers in India and garner close to 80% of the Indian IT services market share. The growth this sector portends wider appreciation and applicability of our findings and implications (Bartel et al. 2014). That said, we are also hampered by not having access to wage data. We hope that future work can utilize wage and promotions data to develop newer insights. Future research can further examine how factors such as peer and mentor networks impact employee promotions.

Finally, we note that our data analysis is limited to lower levels of promotions. Therefore, our findings may not take into account the risk-loving and competitive behavior sought in executive and CXO positions (Gneezy et al. 2003), where many of the gender issues surface. However, as Gayle et al. (2012) imply, such differences may occur only because many women quit at later stages. Therefore, it would be interesting to understand how gender, training, and performance dynamics change as one examines higher echelons of the corporate ladder.
REFERENCES


APPENDIX

Table 1: Examples of Training Courses Offered

<table>
<thead>
<tr>
<th>Training Type</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>General</td>
<td>• J2EE Analysis and Design</td>
</tr>
<tr>
<td></td>
<td>• Overview of Derivatives</td>
</tr>
<tr>
<td></td>
<td>• Business Communication</td>
</tr>
<tr>
<td>Specific</td>
<td>• ITL Quality Foundation Course – Frameworks and Processes</td>
</tr>
<tr>
<td></td>
<td>• Introduction to ITL PM Elite Processes</td>
</tr>
</tbody>
</table>

Table 2: Data Dictionary and Summary Statistics

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Variable Description</th>
<th>Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Promotion (t)</td>
<td>Variable indicating whether promotion occurred in year t or not</td>
<td>0.163 (0.369)</td>
</tr>
<tr>
<td>PerfRating</td>
<td>The relative performance rating of the employee, this ranges from 1 (excellent) to 4 (poor). To ease interpretation, we use -1*PerfRating (See Langer et al. 2014).</td>
<td>1.637 (0.705)</td>
</tr>
<tr>
<td>AvgRatingRole</td>
<td>The average rating for a particular role (software engineer, programmer analyst, or project manager) in a given year. To ease interpretation, we use -1*AvgRatingRole (See Langer et al. 2014).</td>
<td>1.937 (0.367)</td>
</tr>
<tr>
<td>TotalTrng</td>
<td>The total number of training courses taken by an employee in a year, normalized by course duration.</td>
<td>0.599 (1.103)</td>
</tr>
<tr>
<td>GeneralTrng</td>
<td>The total number of general training courses taken by an employee in a year, normalized by course duration. These courses add to the general skills set of an employee and include technical training courses and domain training courses.</td>
<td>0.522 (0.979)</td>
</tr>
<tr>
<td>SpecificTrng</td>
<td>The total number of general training courses taken by an employee in a year, normalized by course duration. These courses add to the specific skills set of an employee and include project management courses, soft skills courses and process courses.</td>
<td>0.077 (0.292)</td>
</tr>
<tr>
<td>TotalExp</td>
<td>An employee's total IT work experience in years.</td>
<td>6.145 (2.273)</td>
</tr>
<tr>
<td>FirmExp</td>
<td>An employee's work experience at ITV in years.</td>
<td>4.307 (2.132)</td>
</tr>
<tr>
<td>dGender</td>
<td>Dummy variable indicating employee's gender (1: Male; 0: Female)</td>
<td>0.766 (0.424)</td>
</tr>
</tbody>
</table>

Table 3: Correlation Matrix

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Promotion</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PerfRating (t-1)</td>
<td>0.4355*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Please note that in the following tables, column I reports the results of the AB-BB model for overall sample; column II that of AB-BB model for female subsample; column III that of AB-BB model for male subsample; and column IV that of the Hausman Taylor specification for overall sample. For all tables, standard errors are in parentheses; + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 4: Effect of Total Training on Promotion

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance Rating (t-1)</td>
<td>0.3108*** (0.0064)</td>
<td>0.3098*** (0.0135)</td>
<td>0.3119*** (0.0071)</td>
<td>0.2838*** (0.0041)</td>
</tr>
<tr>
<td>Total Trng (t-1)</td>
<td>0.0890*** (0.0103)</td>
<td>0.1185*** (0.0183)</td>
<td>0.0743*** (0.0117)</td>
<td>0.0493*** (0.0089)</td>
</tr>
<tr>
<td>Average Role Rating (t-1)</td>
<td>-0.0248*** (0.0075)</td>
<td>-0.0144 (0.0139)</td>
<td>-0.0276** (0.0088)</td>
<td>-0.0460*** (0.0060)</td>
</tr>
<tr>
<td>Performance Rating (t-1)*Total Trng (t-1)</td>
<td>0.2299*** (0.0074)</td>
<td>0.2034*** (0.0137)</td>
<td>0.2382*** (0.0087)</td>
<td>0.0797*** (0.0042)</td>
</tr>
<tr>
<td>Gender = Male</td>
<td></td>
<td></td>
<td>-0.0600*** (0.0086)</td>
<td></td>
</tr>
<tr>
<td>Gender = Male*Total Trng (t-1)</td>
<td></td>
<td></td>
<td>-0.0223* (0.0094)</td>
<td></td>
</tr>
<tr>
<td>Firm Exp</td>
<td></td>
<td></td>
<td>-0.0598*** (0.0070)</td>
<td></td>
</tr>
<tr>
<td>Total Exp</td>
<td></td>
<td></td>
<td>0.0556*** (0.0071)</td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Effect of Total Training on Promotion from SE to PA

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance Rating (t-1)</td>
<td>0.3905*** (0.0094)</td>
<td>0.3705*** (0.0159)</td>
<td>0.3955*** (0.0115)</td>
<td>0.3321*** (0.0059)</td>
</tr>
<tr>
<td>Total Trng (t-1)</td>
<td>0.0570*** (0.0107)</td>
<td>0.0879*** (0.0202)</td>
<td>0.0450*** (0.0128)</td>
<td>0.0417*** (0.0114)</td>
</tr>
</tbody>
</table>
### Table 6: Effect of Total Training on Promotion from PA to PM

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Role Rating (t-1)</td>
<td>-0.0246* (0.0114)</td>
<td>-0.0062* (0.0199)</td>
<td>-0.0292* (0.0137)</td>
<td>-0.0066 (0.0083)</td>
</tr>
<tr>
<td>Performance Rating (t-1)*Total Trng (t-1)</td>
<td>0.1726*** (0.0087)</td>
<td>0.1651*** (0.0156)</td>
<td>0.1773*** (0.0108)</td>
<td>0.0570*** (0.0055)</td>
</tr>
<tr>
<td>Gender = Male</td>
<td></td>
<td></td>
<td></td>
<td>-0.0480*** (0.0091)</td>
</tr>
<tr>
<td>Gender = Male*Total Trng (t-1)</td>
<td></td>
<td></td>
<td></td>
<td>-0.0099 (0.0119)</td>
</tr>
<tr>
<td>Firm Exp</td>
<td></td>
<td></td>
<td></td>
<td>-0.1234*** (0.0136)</td>
</tr>
<tr>
<td>Total Exp</td>
<td></td>
<td></td>
<td></td>
<td>0.1334*** (0.0150)</td>
</tr>
</tbody>
</table>

### Table 7: Effect of General and Specific Training on Promotion

<table>
<thead>
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<th></th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance Rating (t-1)</td>
<td>0.3009*** (0.0085)</td>
<td>0.3228*** (0.0164)</td>
<td>0.2884*** (0.0096)</td>
<td>0.2719*** (0.0041)</td>
</tr>
<tr>
<td>General Trng (t-1)</td>
<td>0.0699*** (0.0108)</td>
<td>0.0694*** (0.0150)</td>
<td>0.0587*** (0.0123)</td>
<td>0.0656*** (0.0087)</td>
</tr>
<tr>
<td>Specific Trng (t-1)</td>
<td>0.0128 (0.0112)</td>
<td>-0.0142 (0.0183)</td>
<td>0.0225 (0.0146)</td>
<td>-0.0088 (0.0106)</td>
</tr>
<tr>
<td>Average Role Rating (t-1)</td>
<td>-0.0213* (0.0105)</td>
<td>-0.0060 (0.0123)</td>
<td>-0.0131 (0.0120)</td>
<td>-0.0357*** (0.0060)</td>
</tr>
<tr>
<td>Gender = Male</td>
<td>I</td>
<td>II</td>
<td>III</td>
<td>IV</td>
</tr>
<tr>
<td>--------------</td>
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<td>-----</td>
<td>----</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.0548***</td>
<td>(0.0085)</td>
</tr>
<tr>
<td>Gender = Male*General Trng (t-1)</td>
<td></td>
<td></td>
<td>-0.0154+</td>
<td>(0.0092)</td>
</tr>
<tr>
<td>Gender = Male*Specific Trng (t-1)</td>
<td></td>
<td></td>
<td>0.0203+</td>
<td>(0.0118)</td>
</tr>
<tr>
<td>Firm Exp</td>
<td></td>
<td></td>
<td>-0.0671***</td>
<td>(0.0068)</td>
</tr>
<tr>
<td>Total Exp</td>
<td></td>
<td></td>
<td>-0.0548***</td>
<td>(0.0085)</td>
</tr>
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</table>

**Table 8: Effect of General and Specific Training on Promotion from SE to PA**

<table>
<thead>
<tr>
<th>Performance Rating (t-1)</th>
<th>I (0.0102)</th>
<th>II (0.0160)</th>
<th>III (0.0127)</th>
<th>IV (0.0059)</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Trng (t-1)</td>
<td>0.0942***</td>
<td>0.1017***</td>
<td>0.0892***</td>
<td>0.0596***</td>
</tr>
<tr>
<td>Specific Trng (t-1)</td>
<td>0.0375*</td>
<td>-0.0105</td>
<td>0.0654**</td>
<td>-0.0281+</td>
</tr>
<tr>
<td>Average Role Rating (t-1)</td>
<td>-0.1080***</td>
<td>-0.0880***</td>
<td>-0.1093***</td>
<td>-0.0156+</td>
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<tr>
<td>Gender = Male</td>
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<td>-0.0379***</td>
<td>(0.0096)</td>
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<tr>
<td>Gender = Male*General Trng (t-1)</td>
<td></td>
<td></td>
<td>-0.0127</td>
<td>(0.0115)</td>
</tr>
<tr>
<td>Gender = Male*Specific Trng (t-1)</td>
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<td>0.0559**</td>
<td>(0.0176)</td>
</tr>
<tr>
<td>Firm Exp</td>
<td></td>
<td></td>
<td>-0.1288***</td>
<td>(0.0137)</td>
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<tr>
<td>Total Exp</td>
<td></td>
<td></td>
<td>0.1270***</td>
<td>(0.0150)</td>
</tr>
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</table>

**Table 9: Effect of General and Specific Training on Promotion from PA to PM**

<table>
<thead>
<tr>
<th>Performance Rating (t-1)</th>
<th>I (0.0096)</th>
<th>II (0.0256)</th>
<th>III (0.0103)</th>
<th>IV (0.0052)</th>
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<tr>
<td>General Trng (t-1)</td>
<td>0.0561***</td>
<td>0.1730***</td>
<td>0.0401**</td>
<td>0.0684***</td>
</tr>
<tr>
<td>Specific Trng (t-1)</td>
<td>0.0062</td>
<td>-0.0243</td>
<td>0.0094</td>
<td>-0.0067</td>
</tr>
</tbody>
</table>

Page 36 of 38
<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Role Rating (t-1)</td>
<td>-0.0541*** (0.0125)</td>
<td>-0.0353 (0.0309)</td>
<td>-0.0607*** (0.0149)</td>
<td>-0.0555*** (0.0127)</td>
</tr>
<tr>
<td>Gender = Male</td>
<td></td>
<td></td>
<td>-0.0611** (0.0205)</td>
<td></td>
</tr>
<tr>
<td>Gender = Male*General Trng (t-1)</td>
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<td></td>
<td>-0.0500** (0.0159)</td>
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<tr>
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<td>-0.0029 (0.0148)</td>
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</tr>
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<td>Firm Exp</td>
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<td>-0.0003 (0.0091)</td>
<td></td>
</tr>
<tr>
<td>Total Exp</td>
<td></td>
<td></td>
<td></td>
<td>0.2132*** (0.0132)</td>
</tr>
</tbody>
</table>