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GLASS CEILING OR SLIPPERY FLOOR? GENDER AND PROMOTIONS IN IT FIRMS

ABSTRACT

The shaky ascent of women up the organizational ladder is a critical factor that contributes to the lack of women in IT. In this study, we examine the effect of gender on the likelihood of employee promotions. We also examine whether women get an equal lift in promotion likelihood from performance improvements as men. We analyze archival promotions, demographic, human capital, and administrative data for 7004 employees from 2002-2007 for multiple levels of promotions. We develop robust econometric models that consider employee heterogeneity to identify the differential effect of gender and performance on promotions. We find that contrary to expectations, women are more likely to be promoted, on average. However, looking deeper into the heterogeneous main effects using hierarchical Bayesian modeling reveals more nuanced insights. We find that, *ceteris paribus*, they realize less benefit from performance gains than men, less benefit from tenure within the focal firm, but more benefit from training than men. This is suggestive of covert rather than overt discrimination against women who have to rely on passive approaches, such as signaling via training, to restore parity in promotions. We find that the effect of gender and performance varies with the level of employee promotion; although not as much as men, women benefit more from performance gains at higher organizational levels. Our findings suggest several actionable managerial insights that can potentially make IT firms more inclusive and attractive to women.

Key words: Gender, Women in IT, IT Human Capital, Performance, Training, Promotions, IT Services Industry

INTRODUCTION AND BACKGROUND

“Wanted: More women in technology” (Sprague 2015)

The motivation of this study is the observation that women make up 57% of the US labor market (DoL Report 2015b), yet they only make up 23.1% of computer and information technology (IT) occupations (DoL Report 2015a). These inequitable trends echo across global IT firms (McGregor 2014, Woetzel et al. 2015);¹ recent reports even suggest that the number of women in IT jobs has been dropping significantly (Sherman 2015). While gender inequalities in labor market participation are large and globally persistent (ILO Report 2014), the glaring underrepresentation of women in the IT industry makes the glass ceiling seem particularly pertinent to technology firms (Ahuja 2002, Vara 2014, MacMilan 2012).

Gender equality is desirable not just from humanitarian but also from economic perspectives.² Reducing gender disparity by recruiting and retaining more women employees, especially for the IT industry where women are severely underrepresented, positively affects top line growth (McKinsey Report 2015). Despite the obvious benefits of gender parity, several social and structural barriers impede women in advancing their careers within the IT industry (Ahuja 2002). In particular, the lack of female role models and/or mentors in managerial ranks has emerged as one of the critical factors endemic to IT organizations. More women are earning STEM degrees, yet many do not opt for IT as a career because they do not find women rising to the top echelons of IT firms or even having successful careers in IT (Mundy 2017). Thus, the lack of women in leadership positions affects not only the inflow of women into IT but also their career growth prospects (Ahuja 2002). The conspicuous dearth of women in technology and leadership roles has been decried in both academic literature (e.g., Trauth et al., 2009) and popular press (Mundy 2017, Vara 2014). Yet, little systematic research has focused on identifying how women rise in IT organizations. In this study, we examine how *gender affects the likelihood of promotions in the context of the IT industry*.

¹ A diversity report released by Google in 2014 indicates that only 30% of its employees are women; in technical jobs, the search giant employs only 17% women (McGregor 2014).

² A recent OECD report finds that parity between men and women in labor markets in developed countries is expected to increase their GDP by 12 percent by 2030 (OECD Report 2012). Gender disparity is even more acute in Asia, and particularly so in India. If India and China matched the gender parity existent in Singapore, the incremental gains in GDP are to the tune of \$ 3.2 trillion (Woetzel et al. 2015).

Prior literature suggests that promotions are non-wage incentives aimed at identifying and retaining *high-ability* employees (Lazear and Rosen 1981). Firms typically reward good performance with promotions (e.g. Gibbons and Waldman 1999a, Prendergast 1993, DeVaro 2006a, Melero 2010), such that, promotions mimic tournaments in an organization's internal labor market (DeVaro 2006a, b, Lazear 1992). If promotions are arguably driven by employee performance, does the lack of women in higher echelons of IT firms indicate that they are less effective than men? While this strand of research has examined the role of performance on promotions, it is only now that a systematic examination of the interplay between gender and performance on promotions has begun. This examination is especially important to the IT industry in which tasks such as programming, analysis and design, testing, and project management are seen as "masculine" tasks (Chan and Wang 2017, Trauth et al. 2004, 2010) and women as the archetypal outgroup (Ahuja 2002, Mundy 2017, Trauth et al. 2005, Vara 2014). Thus, to understand the pertinent mechanisms affecting promotions, *we further examine whether men and women gain similarly from performance improvements in determining promotions*. To date, firms have incorporated egalitarian policies that ostensibly prevent discriminatory practices, yet women in IT continue to be visibly absent, and especially so as we move up the organizational ladder. Our research aims to comprehensively identify the role and extent of prejudicial ascriptive biases in the IT work environment that preclude successful careers for women in IT.

Extant research has sought to understand differential labor market outcomes between men and women in hiring, promotions, and wage differences. In particular, research on gender-based discrimination has extensively focused on hiring decisions and wage inequality (Booth 2009, Booth et al. 2003), real or perceived gender differences in competitiveness (Buser et al. 2014, Croson and Gneezy 2009), or organizational constraints (Ahuja 2002, Ibarra 1997, Ibarra and Andrews 2015, Trauth et al. 2009), yet discrimination in promotion decisions remains under researched (DeVaro et al. 2007, Sheridan et al. 1997). The current literature that assesses how employee gender and performance affect promotion remains tenuous when it comes to empirical validation (Sheridan et al. 1997); furthermore, it is unclear whether these findings directly translate to the IT industry where women constitute less than 25% of the IT workforce and rarely rise to influential managerial positions, and may be perceived as violating the traditional gender roles by pursuing

masculine careers (Chan and Wang 2017, Trauth et al. 2004, 2010), thereby meriting a closer examination. Finally, prior literature may also be constrained by methodological concerns intrinsic to this problem. Factors such as employee motivation and innate capability (Cappelli 2004), or gender based self-selection into jobs (Gneezy et al. 2003) may possibly confound the results. Together, these may hinder a more thorough understanding of how gender, together with performance, affects promotions of women in IT.

We address this gap in the literature by analyzing detailed, archival promotions, demographic, and human capital data for 7,004 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 individual level dataset and a hierarchical Bayesian modeling approach that models heterogeneity of the main effects, we are not only able to parse out the effect of pertinent factors such as performance, human capital investments, work experience, and organizational roles, but also how they affect the likelihood of promotions for women versus men.

Surprisingly, at least on the surface, we find women are more likely to be promoted. We also find that past performance has a positive impact on the likelihood of promotions but that there are differential returns to performance improvements for men and women: women employees are penalized for higher performance. Compared to men, all else being equal, women are also less likely to benefit from experience within the organization. This is suggestive of the fact that they are more likely to be taken for granted. They are, however, more likely to benefit from training, consistent with the literature that suggests that women are less likely to have time to nurture influential mentor networks and instead use training as a signaling mechanism, enhancing promotion likelihood. Together, our results reveal a nuanced effect of gender, performance, experience, formal training, and their interactions on employee promotions.

We contribute to the growing body of research on gender issues in IT organizations. In particular, using revealed preference based individual level administrative data on promotions at multiple levels, our finding on the negative interaction between gender and performance or gender and experience points to the more covert forms of discrimination against women in IT, complementing previous studies that relied on self-reported, survey data (e.g., Hersch and Viscusi 1996, Melero 2010). In not paying attention to such

nuanced sources of bias against women in IT, egalitarian HR policies seeking to stem discriminatory practices may bear little fruit. Our findings also emphasize the palliative effect of mechanisms such as training on women's promotability, which help women credibly signal their worth to senior management when they may be less inclined to lean-in and directly ask for promotions that they feel are due to them.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

Gender, Performance, and Promotions

Conventional wisdom suggests that in a meritocratic organization, *ceteris paribus*, an increase in employees' performance should increase the likelihood of their promotion, irrespective of their gender. Nevertheless, the social science and management literature presents mixed evidence with respect to gender, performance, and promotions. For instance, some of this research proposes that once differences between motivation and capability are accounted for, women are found to be 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. In contrast, there is also overwhelming evidence that women are penalized more in terms of career growth and that men are more likely to be promoted compared to women (Darity Jr. and Mason 1998, Ellingrud et al. 2015, Ibarra et al. 2010), especially in jobs with "masculine" attributes such as those in IT (e.g., Darity Jr. and Mason 1998, Gneezy et al. 2003, Ibarra et al. 2010).

Although the broader social sciences and management research finds the effect of gender on promotions to be ambiguous and therefore an open empirical question, our focus on women in IT paints a less rosy picture: these women, in taking on job profiles that have traditionally been considered masculine, may not be as likely as men to succeed in such careers (Chan and Wang 2017, Trauth et al. 2004, 2010), reflecting taste based, ascriptive discrimination in performance evaluations (Crandall and Eshleman 2003, Heilman 2001, Lyness and Heilman 2006, Nieva and Gutek 1980, Wallston and O'Leary 1981)³ and

³ Research has also shown that any performance shortfall on part of men may often be explained away as occurring because of adverse work conditions (such as a tough client, risky technology, more competition); however, women

promotions (Becker 1971, Darity Jr. and Mason 1998). Extant research suggests that *perception* of their performance and socio-structural factors impede women's career in IT organizations.

In meritocratic organizations, since performance is the single most important factor in promotion decisions, we argue that the link between gender and performance-based promotions in the IT industry is subtler. While absolute performance is desirable, it is only the *relative* evaluation of performance that leads to promotion for knowledge workers such as those in the IT sector (Rosen 1986, MacCromy et al. 2014). Therefore, factors such as preconceived notions of performance or capability (Landau 1995), gender-role orientation (Judge and Livingston 2008), and gender-biased evaluations (Heilman 2001, Nieva and Gutek 1980) may adversely affect relative performance assessment for women in IT and therefore lower the likelihood of their promotions.

In particular, IT tasks such as programming, analysis and design, testing, and project management are seen as “masculine” tasks (Chan and Wang 2017, Trauth et al. 2004, 2010). In a male dominated industry such as IT, women are the quintessential out-group (Ahuja 2002, Mundy 2017, Trauth et al. 2005, Vara 2014). Women in IT are, therefore, more likely to be perceived as violating the traditional gender roles (Baron et al. 1991, Baron and Bielby 1980, Eagly and Karau 2002, Heilman and Eagly 2008) such that differences in economic outcomes like promotions for men versus women cannot be attributed to intrinsic gender differences, if any.

We contend that such gender-role orientation (Judge and Livingston 2008, Unger 1976) for women in IT may engender prejudicial behavior on part of the supervisors (Choi et al. 2014, Crandall and Eshleman 2003, Verniers and Vala 2018). Furthermore, organizations that claim to be meritocratic may also suffer from the *paradox of meritocracy* (Castilla and Benard 2010) that ironically result in lower promotion likelihoods for women in IT. Castilla and Benard (2010) suggest that such structural biases may arise because claiming to be a meritocratic organization could merely be a symbolic gesture adopted for gaining legitimacy (Meyer and Rowan 1977) but not actually implemented (Edelman 1992). It could also be that senior managers in such

are more likely to be subjected to harsher criticism and blamed for their inadequate capabilities resulting in performance shortfalls rather than any unfavorable work environment (Park and Westphal 2013).

“meritocratic” organizations may paradoxically believe themselves to be unbiased and thus having moral credentials (Choi et al. 2014, Monin and Miller 2001) or being personally objective and therefore unbiased (Castilla and Benard 2010, Uhlmann and Cohen 2007). In such a scenario, they are less likely to closely examine their own motivation and biases, and feel justified in expressing their ingrained prejudices (Choi et al. 2014, Crandall and Eshleman 2003) in lowering women’s chances of promotions in IT organizations. Given these prejudicial biases as well as the existing socio-cultural and structural barriers, we expect women to be at a disadvantage when advancing their careers in the IT industry. We posit:

H1: *Ceteris paribus, women are less likely to be promoted than men.*

The impact of both performance and gender on the likelihood of promotions is clearly understood, it is less clear whether men and women derive commensurate benefits from performance gains. We now elucidate the more nuanced narrative of whether women are penalized or rewarded for better performance, compared to men. Milgrom and Oster (1987) examine promotions through the lens of discrimination in labor markets and propose the invisibility hypothesis. In a typical organizational context, although there is uncertainty about the productivity of new employees, it gets resolved over time as firms learn more about these employees’ abilities and productivity. However, it is likely that this uncertainty persists in the external labor market. Because more productive employees are promoted earlier, one way in which other firms can gauge the productivity of an IT employee is through promotions (DeVaro and Waldman 2012, Waldman 1984). Milgrom and Oster (1987) extend this argument to suggest that the normative employee is more visible in that his ability is publicly known, whereas the out-group employee is invisible as her ability is not known ex-ante. Therefore, women being the IT minority, are perceived to be lacking IT capabilities or simply deemed incompetent (Weinberger 2006). This invisibility could arise because of prejudice, more because of such misconceptions rather than antagonism for women, or the consistent presence of old boys club in IT firms that deems the productivity of male IT employees to be more visible (Morgan et al. 2004). Milgrom and Oster (1987) propose when a high ability invisible employee is promoted, the external labor market more accurately perceives her ability, and she becomes more desirable to other firms, making it difficult to retain her without raising her wages. Even for organizations with merit centric policies of promotion and evaluation, this is not a salubrious situation. As a

result, to deter poaching and to prevent wage hikes, the dominant strategy for the current employer would be to not promote women (the invisible employee) of high ability.

Research on discrimination against out-groups presents an alternate explanation for why women are unlikely to realize gains similar to men from performance evaluations in being promoted: *compensatory stereotype* (Carton and Rosette 2011, Igbaria and Baroudi 1995). This theory suggests that managers engage in goal-based stereotyping by rationalizing that women (but not men) fail because of negative attributes and succeed because of positive attributes other than capabilities (i.e., compensatory stereotypes). Consider the previous discussion that women in IT are not expected to be as successful as men in executing masculine tasks such as programing and analysis. When they are unsuccessful in these tasks, managers explain it to be because they are after all, women in IT and therefore could not be expected to be accomplish such masculine tasks. However, when women in IT *are successful* and perform well at their tasks, it violates these managers' gender-role expectations. In such a case, occupational minorities such as women in IT are thought to have compensatory attributes that may explain high performance. Managers may be less likely to attribute the female employee's performance to their domain expertise, or technical and analytical capabilities (capabilities that are typically valuable in an IT employee), but instead, attribute it luck or other external factors such their people skills, their ability to work with various stakeholders, or their "warmth" (Carton and Rosette 2011, Igbaria and Baroudi 1995, Yzerbyt et al. 2005). To sum, differences in what the performance is attributed to: ability and skills for men versus luck and external factors for women is likely to affect women's promotability. We thus posit that:

H2: Women and men experience differential outcomes from performance improvements in lifting promotion likelihood, such that compared to men, women gain less from performance improvements.

RESEARCH SETTING AND EMPIRICAL ANALYSIS

Research Setting

To evaluate our hypotheses, we conducted an extensive, in-depth field study at a leading IT services vendor headquartered in Bangalore, India. We collaborated and connected with the senior management at the company to enable this research. We held interviews with managers responsible for human resources (HR)

practices such as promotions as well as employees' learning and development in order to 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 gender ratio of women versus men within the firm is similar to many global IT firms, around 23:77 (DoL Report 2015a, Woetzel et al. 2015); this ratio persists to date. 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.⁴ We detail their roles and expectations in Appendix's section A.1:

The focal firm follows industry best practices to objectively evaluate adequate performance. To that end, the firm ensures that it has a meticulous performance evaluation process in place. Our interviews revealed that the firm was particularly sensitive to innate gender biases within IT industry and Indian society. To help with as unbiased a review as possible, the firm uses a "360 degree feedback" system to measure the employee performance annually instead of relying just on a supervisor provided rating. The employee performance evaluation considers how well an employee accomplished specific project oriented tasks, performance consistency, complexity of the work environment, and adherence to firm values. 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

⁴ From this study's perspective, these are the formative rungs and it is important to examine concomitant biases at these early career stages when these can potentially be fixed; these biases may exacerbate or confounded at later career stages (Gneezy et al. 2003).

(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 employees' annual raises.

Data and Measurement

We collected detailed archival data on 7004 employees for the years 2002-2007; these employees were randomly selected from the SE/PA/PM employee categories and represent an adequate sample from about 70,000 total firm employees. We were able to get access to data on an employee's current and previous role (e.g., SE or PA or PM), annual performance ratings, and other pertinent attributes such as the employee's gender, work experience in years (both at the focal company and the total work experience), time in current role, and complete training records. We describe these data below, Table 1 provides the summary statistics for our data for the overall sample as well as for the male and female subsamples.

Promotion: We were able to impute whether and when an employee has been promoted by comparing their last and current role. We code the promotion variable as 1 if we observe the employee being promoted in a particular year, and 0 otherwise. We observe two levels of promotions: software engineer (SE) to programmer analyst (PA), and programmer analyst to project manager (PM). In our sample, we observe each employee being promoted at most once. In our dataset, we observe 24.77% employees being promoted; 26.26% were promoted from SE to PA, and 21.43% were promoted from PA to PM.

Female: The variable *Female* is the dummy variable indicating the employee's gender. This variable is coded as 1 if the employee is female and 0 otherwise. Table 1 shows that there are around 23.4% women in our sample.

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 where employee exceeds expectations, and 4 the lowest where the employee did not meet expectations. Because of the meticulous and comprehensive nature of the evaluation, we assume that these ratings truly capture relative employee performance (Bapna et al. 2013). 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 $-1 \times \text{Employee Rating}$) in our analysis

(Langer et al. 2014). As Table 1 shows, the average performance rating is -1.776. The average performance rating for women is -1.845, and the average performance rating for men is -1.755.⁵

Experience: Prior literature suggests that performance, promotions, and experience are correlated (Joseph et al. 2015). 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*); the average experience is 6.14 years and the average firm experience is 4.31 years. This varies across men and women: men have an average work experience of 6.26 years compared to 5.76 for women, and have an average firm specific experience of 4.33 years compared to 4.22 for women.

PriorTraining: 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. To compute the training variable, we sum the total number of courses taken by an employee prior to promotion, normalized by the course duration. We find that 27.48% of employees took some training. We examine whether women or men take more training. The t-statistic is -0.112, with 47506 degrees of freedom; the corresponding p-value is 0.911, showing that women and men take statistically the same amount of training.⁶

Subsamples: Because we want to isolate the relationship between gender and promotions, we use the detailed demographic data to construct sub-samples for our analyses using gender. These subsamples allow us to validate both the hypotheses and are useful in analyzing the nuanced relationship between gender, performance, and promotions.

⁵ The t-statistic assuming equal variances is 8.569 with 27630 degrees of freedom, yielding a p-value < 0.0001, indicating that men's ratings are slightly better than those of women.

⁶ A probit model estimating the propensity to take training shows the coefficient for *Female* is insignificant, thus there are no differences between women and men in their propensity to take training. The results for this regression are available from authors upon request.

Table 1 describes our variables and provides the summary statistics. The correlation matrix between the dependent and explanatory variables is provided in Table 2. We standardized the relevant variables prior to our analysis to ease interpretation as well as to assuage any collinearity concerns (Aiken and West 1991).

<<Insert tables 1 and 2 about here>>

Methodology

The descriptive statistics provided in table 1 suggest that there is considerable heterogeneity in our sample.⁷ Employee performance as well as experience attributes differ across gender, across laterals and direct hires, and across roles. For instance, consider the inherent hierarchy in the organization, where a policy of merit-based promotions portends that competition gets tougher going forward, therefore an employee's current role may moderate the effect of performance on promotion decisions. Likewise, direct hires, in comparison to lateral hires, may manifest specific human capital that is more desirable to senior management, this may in turn moderate the effect of performance and hence on promotion likelihood (Becker 2003, Slaughter et al. 2007). Any examination of the drivers of promotions that does not take into account such intrinsic differences in employees would yield biased coefficient estimates (Gonul and Srinivasan 1993, Venkatesan et al. 2007). These in turn would lead to senior management making inferior promotion decisions and implementing suboptimal policies (Allenby and Rossi 1998). Accordingly, we model heterogeneity explicitly in our analysis using a hierarchical Bayesian modeling approach.

Our dependent variable is binary; we estimate the following binary logit model to confirm our hypotheses. The primary explanatory variables that inform our model in estimating the likelihood of employees' promotions are their performance and gender; allowing us to validate H1. In addition, we include firm and total experience as pertinent factors:

$$GotPromotion_{i,t} = \beta_{0i} + \beta_{1i} \cdot PerfRating_{i,(t-1)} + \beta_{2i} \cdot Female_i + \beta_{3i} \cdot FirmExp_{i,t} + \beta_{4i} \cdot TotalExp_{i,t} + \varepsilon_{i,t}, \quad (1)$$

⁷ For the sake of brevity, we only report the descriptive statistics for overall sample and across men v. women in Table 1. We are happy to provide these statistics for different subsamples, such as across direct v. laterals, or across different roles on request.

where $GotPromotion_{i,t} = 1$ if $GotPromotion_{i,t}^* > 0$; $GotPromotion_{i,t} = 0$ otherwise. Thus, the likelihood of promotions can be shown to be

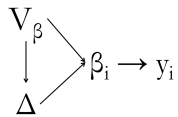
$$\Pr(GotPromotion_{i,t} = 1) = \frac{\exp [x'_i \cdot \beta_i]}{1 + \exp [x'_i \cdot \beta_i]} \quad (2)$$

In the above equations 1 and 2, ' i ' is each employee and ' t ' is the year. $GotPromotion_{i,t}$ is 1 if an employee ' i ' is promoted in year t , and 0 otherwise, $Female$ is a dummy variable indicating whether the employee is female ($Female=1$) or male ($Female=0$). Because promotions depend on how the employee has performed in the previous year, we use $PerfRating_{i,(t-1)}$, the lagged variable capturing employee performance for the year $(t-1)$. Finally, variables $FirmExp_{i,t}$ and $TotalExp_{i,t}$ are the firm level experience and total experience of the employee ' i ' at time ' t .' We assume the error terms $\varepsilon_{i,t}$ to be standard Type I extreme value distribution. In the 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 (both time-invariant and time-varying) in the panel model, such as an employee's capability, inherent drive, and task specificity within a project (Bapna et al. 2013). We use the simplified notation $\beta'_i = [\beta_{0i} \beta_{1i} \beta_{2i} \beta_{3i} \beta_{4i}]$ such that β'_i denotes all the coefficients in our model that affect the likelihood of an employee's promotion.

We assume that the employees within the firm vary along the following attributes: whether they were hired directly or were a lateral hire, training they took prior to promotion, and where they were in the organizational hierarchy (whether a software engineer, an analyst, or a project manager). To understand the nuances of this heterogeneity on the model parameters, we estimate a continuous employee heterogeneity model in which we allow the coefficients to be employee specific, as shown in equation 3:

$$\beta_i = \delta_0 + \delta_1 \cdot dDirectHire_i + \delta_2 \cdot PriorTraining_i + \delta_3 \cdot LastRole_i + v_i, \quad (3)$$

where $v_i \sim iid N(0, V_\beta)$ The hierarchical relationship shown in equations 1-3 indicates that β'_i can be thought of as a function of the three observable employee attributes and allows us to examine the effect of heterogeneity on our model parameters. Denoting $\Delta = [\delta_0 \delta_1 \delta_2 \delta_3]$, this hierarchical relationship is:



Thus, β'_i becomes a function of the three observable employee attributes and allows us to examine the effect of heterogeneity on our model parameters; the variables δ_1 , δ_2 , and δ_3 in Δ specify how *DirectHire_i*, *PriorTraining_i*, and *LastRole_i* affect the parameters specified in equations 1 and 2. As an example to illustrate this, β_{1i} measures the effect of performance on promotions for employee ‘i.’ Furthermore, the effect of *DirectHire_i* on β_{1i} denotes the **differential** impact of past performance rating on the likelihood of promotion for direct v. lateral hires. Thus, if $\beta_{1i} < 0$ and $\delta_1 < 0$, a lower performance rating lowers the likelihood of promotions, and this effect is greater for direct hires as compared to laterals.

In equation 3, the random variable v_i is the unobservable error component of the employer heterogeneity, which we assume to be distributed normally with mean 0 and variance covariance matrix V_β . The model specification in equations 1-3 is quite appealing as it allows us to estimate individual level coefficients that in turn allow us to evaluate the precise effect of various employee attributes on promotions. That is, the hierarchical specification allows us to understand the moderation effect of direct hires, organizational roles, and prior training on performance, gender, and experience in a more nuanced manner. We use the hierarchical Bayesian inference process to help with the computation intensity typical with such models (Rossi et al. 2005).⁸ In particular, we use standard techniques used in estimating Bayesian inference models: we set diffuse priors for the model parameters, and then apply Markov Chain Monte Carlo (MCMC) methods using a Gibbs sampler for data augmentation. Specifically, this semi-parametric approach involves draws from the Inverse-Wishart distribution in the Gibbs Sampler. We run the MCMC simulation for 50,000 draws, and only use the last 30,000, discarding the first 20,000 as burn-in. This exercise follows the guidelines about the convergence of the posterior distribution; figure 1 illustrates the likelihood convergence. In addition to this, we deploy the standard practice of using a thinning parameter of 20 – that is we retain every 20th draw of the posterior distribution – this helps to reduce the associated storage and computational burden

⁸ Estimation using Bayesian inference techniques can be more parsimonious in its data requirements as the estimation procedure is able to partially pool data across observations and thus present more information that can help estimate the individual-specific parameters (Allenby and Rossi 1998, Rossi et al. 2005). Allenby and Rossi (1998) offer more discussion on the appeal and constraints of Bayesian inference.

for the simulation. The mean rejection rate for the Metropolis-Hasting (MH) algorithm is 0.79; the desired rejection rate is 0.6–0.9.

Subsample Analysis: In addition to examining the effect of employee attributes on our sample, we are interested in understanding if the effect of the model coefficients varies between men and women, and whether men and women have differential returns to performance improvements in increasing promotion likelihood. Therefore, to validate H2, we analyze equations 1-3 for different subsamples constructed based on employee gender, omitting the variable *Female_i* in equations 1 and 2 from the subsample analysis.

Results and Discussion

Table 3 reports the population level parameter estimates $(\bar{\beta}_0 \bar{\beta}_1 \bar{\beta}_2 \bar{\beta}_3 \bar{\beta}_4)$ for equations 1 and 2. Contrary to our expectations, the positive coefficient for *Female* ($\bar{\beta}_2 = 0.209, p < 0.01$) indicates that women are, on average, more likely to be promoted. While this result may seem counter-intuitive to our hypothesis, several alternate explanations emerge when we take a deeper perspective: First, consider the widely recognized wage differential between men and women (Babcock and Laschever 2003, HBR Spotlight 2013, Leibbrandt and List 2015). 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 organizational 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. Third, it is also possible that these women are being promoted to a glass cliff, anchoring projects destined to fail (Bruckmüller et al. 2014, Cook and Glass 2014). Fourth, policies and processes implemented at the organizational level that increase transparency and accountability from managers potentially reduced overt biases against women in IT (Castilla 2008, Lerner and Tetlock 1999, Uhlmann and Cohen 2007). Together, these may explain why women are more likely to be promoted and why H1 is not supported. As expected, the coefficient for past year performance is positive and significant; this result is consistent for the overall sample ($\bar{\beta}_1 = 1.312, p < 0.01$) as well as the male ($\bar{\beta}_1 = 1.483, p < 0.01$) and female ($\bar{\beta}_1 = 1.243$,

$p < 0.01$) subsamples. H2 argued that women are likely the invisible employees whose performance is unknown compared to the norm, therefore firms have an incentive to not promote high performing women to prevent their poaching. Consistent with extant literature (Igbaria and Baroudi 1995), the effect of performance on promotion likelihood is smaller for women, supporting H2. Thus, a major nuance of our findings is that while on average there seems to be no overt discrimination in promoting women, *ceteris paribus*, the returns to a marginal improvement in performance are lower for women. This is troubling evidence of potentially covert discrimination, that looks at similar performance differently based on gender. Note all variables are standardized and thus comparing of coefficients representing the identical marginal effects, across the gender models is valid, and the difference is statistically significant.

Our estimates also indicate an interesting effect of experience on promotions. Firm level experience is positively associated with the likelihood of promotion ($\bar{\beta}_3 = 0.773$, $p < 0.01$). Again, this effect is smaller for women ($\bar{\beta}_{3M} = 0.856$, $p < 0.01$; $\bar{\beta}_{3F} = 0.223$, $p < 0.01$), suggesting that spending too long in the same role signals missed prior opportunities for promotions for women compared to men. Thus, while firm level experience is likely to increase promotion likelihood, it may weaken the case for future promotions for women. Using the lens of covert discrimination, the more time women spend within the focal firm, the more they are taken for granted and higher is their hurdle to promotion. In contrast, experience outside of the focal firm, which is associated with market power and outside options, enhances promotion opportunities, as the total experience is positively related to promotion ($\bar{\beta}_4 = 0.931$, $p < 0.01$); we find that women benefit more from total experience compared to men ($\bar{\beta}_{4M} = 0.762$, $p < 0.01$; $\bar{\beta}_{4F} = 2.081$, $p < 0.01$), as they are less taken for granted.

<<Insert table 3 about here >>

Tables 4A, 4B, and 4C report the estimation results of the posterior distribution of the hierarchical regression coefficients in the equation 3 for the a) overall sample, b) male subsample, and c) female subsample. These estimates offer several interesting insights. First, the heterogeneity variables are all positively associated with β_1 , the coefficient measuring the effect of performance gains on promotion likelihood. The reader is advised to read across row 1 of Table 4A – 4C to interpret this. We find that intrinsically, performance is positively associated with promotion likelihood: δ_0 is positive and significant for all three analyses. Further, the

hierarchical Bayesian model capturing individual level heterogeneity reveals that direct hires benefit more from performance gains, prior training is complementary to performance and to women, and those higher up in the organizational hierarchy reap more from performance improvements.

Some of these results speak to the specific human capital that direct hires garner in an organization; for the same total work experience, direct hires would have been longer in the focal organization, and more in tune with the organizational goals, and their performance accomplishments are more likely to be perceived as more valuable to the firm (Becker 2003, Slaughter et al. 2007), leading to the complementary relationship between direct hires and performance. Further, the complementary relationship between training and performance Becker (1962) suggests that it is likely that employees with superior performance 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 (Spence 1973). The positive coefficients (Δ) in table 4A for performance validate the theoretical predictions of DeVaro and Waldman (2012) and can provide precise predictions about the linkage between performance and promotions at the individual and cohort level for firms.

Tables 4B and 4C show how these coefficients differ across men and women. Women intrinsically benefit less from performance gains, especially when they are direct hires ($\delta_{1M} = 0.171$, $p < 0.01$; $\delta_{1F} = 0.104$, $p < 0.01$) This is again suggestive of the fact that in absence of market power and outside options that go along with laterals, women within the company's hiring and promotion ladder are more likely to be taken for granted. This is further reflected in the fact that compared to men, they seem to benefit less from performance gains at higher levels ($\delta_{3M} = 0.572$, $p < 0.01$; $\delta_{3F} = 0.405$, $p < 0.01$), suggesting the bar gets disproportionately higher with time and tenure for women. There is no clear ex-ante theoretical rationale for this. Nonetheless, it is interesting to note that even though women do not realize benefits similar to men from performance gains, they seem to get more relative benefits from better performance at higher organizational levels. An increase of one unit in performance for a women increases the promotion probability from 0.390 to 0.637 (an increase of 63.3%, compared to 146.53% for men) at the software engineer level, but from 0.017 to 0.066 (an increase of 290.65%, compared to 475.23% for men) at the

programmer analyst level. We reasoned that the effect of performance improvement on promotion likelihood is lower for women to prevent poaching of the invisible minority (Milgrom and Oster 1987), but our results suggest that this effect varies within the organizational hierarchy. While the desire to prevent poaching is still a factor, the fit of women's supposed compensatory attributes such as people and communication skills and warmth with the more managerial role of PM manifests in our findings that high performing women are penalized less when being promoted to PM than when being promoted to PA (Carton and Rosette 2011, Yzerbyt et al. 2005).

Second, the effect of the heterogeneity variables on β_2 is considerably varied, although the intrinsic effect (δ_1) positive for the overall sample, as also evidenced by $\overline{\beta_2}$. Women who are direct hires gain less than laterals ($\delta_1 = -0.003$, $p < 0.01$); however they gain more from training ($\delta_2 = 0.088$, $p < 0.01$). Interestingly, selecting into training, a more passive-aggressive form of signaling the desire to improve, learn, and be ready to lead is shown to be beneficial to women. As the analysis indicates, they benefit more from training ($\delta_{2M} = 0.167$, $p < 0.01$; $\delta_{2F} = 0.249$, $p < 0.01$). This effect is augmented in the finding that training enhances the effect of firm and total experience for women *more* than men. As an example, consider the effect of a one unit increase in training in the promotion probability for a direct-hire software engineer with average performance. For a woman in this position, the promotion probability is increased by 8.53% compared to a 6.73% increase for a man in this same position. At a higher organizational level (programmer analyst seeking to be a project manager), a unit increase in training increases the probability of promotion by 14.51% for the female employee compared to 8.14% for a male employee. This is consistent with the literature that suggests that women face more time constraints due to family and other obligations (Ahuja 2002, Bianchi et al. 2012, Kamp Dush et al. 2018). They are less likely to have time to nurture peer networks that 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. Consistent with the logic presented above, our results also suggest that training enhances the effect of firm and total experience for women more than men, and that this effect gets stronger as women rise up the value chain, indicating the strength of this credible signal in getting promotions.

<<Insert tables 4A, 4B, and 4C about here >>

Robustness Checks and Endogeneity:

Although the employees in our sample were randomly selected, in considering *alternate* specifications, we need to account for potential endogeneity in our model before we ascribe a causal linkage between these variables and the likelihood of promotions. The proposed Bayesian inference model is semi-parametric and hence not as restrictive as classical inference models in its assumptions of exogeneity, but any alternate specification requires instrumental variables to account for endogenous performance or human capital variables.⁹ To do so, we use the following Arellano–Bover/Blundell–Bond (AB-BB) dynamic panel model (Arellano and Bover 1995, Blundell and Bond 1998), using robust standard errors:

$$GotPromotion_{i,t} = \beta_0 + \beta_1 \cdot GotPromotion_{i,(t-1)} + \beta_2 \cdot PerfRating_{i,(t-1)} + \beta_3 \cdot Training_{i,(t-1)} + \varepsilon_{i,t} \quad (4)$$

In addition to the lagged dependent variable ($GotPromotion_{i,t}$), we use past performance and past training as explanatory variables (Bapna et al. 2013). The structure of the dynamic panel model is such that we can construct instruments using lagged values of our dependent variable, wherein these instruments have been shown to be uncorrelated with the error term. Note that this model is unable to account for any time invariant variable such as “*Female*.” We estimate the model specified in equation 4 for the overall sample and then separately for the two subsamples for men and women.

<<Insert table 5 about here >>

Table 5 presents the results from the dynamic panel specification. Overall, this model suggests that past promotion, past performance, and past training investments are positively related to promotion likelihood. Examining columns 2 and 3, we find that past promotion is positive and significant for only men, while the performance gains are significantly higher for men compared to women. Both these results support our

⁹ For instance, while gender is exogenous, there is a possibility that performance is endogenous; employee motivation and innate drive could influence employee performance. Further, the firm’s commitment to provide incentives such as promotions and fair evaluations may attract high performance individuals (Cappelli 2004). Classical econometric models mandate that we account for this endogeneity, else we may overestimate the marginal effect of performance on the likelihood of promotions. In other words, a naïve probability model would measure the marginal effect not of the performance, but rather the combined effect of performance improvement and being identified as an employee who improves the marginal performance.

previous findings and suggest covert discrimination against women. We also find that women derive better bang for the buck from training investments.

In summary, our overall results indicate that women in IT may not face overt discrimination in promotion.¹⁰ Indeed, on average, they are more likely to get promoted than men, *ceteris paribus*. Our current analysis is limited in its data to be able to pin down the exact mechanism for this. The literature points out that pay differentials could account for some of this; for the same job, women are a cheaper resource for profit maximizing firms (Albanesi et al. 2015, Castilla and Benard 2010). Alternatively, it could be linked to issues of superior soft skills (Blau and Kahn 2000, Bruckmüller et al. 2014). While future research is needed to tease this aspect out, we do have striking evidence of heterogeneity in the gender effect.

Our findings here are suggestive of covert discrimination (Swim et al. 1995) due to the differential returns from performance gains, where in as reasoned by the invisibility hypothesis, the high performing women are less likely to be promoted (Milgrom and Oster 1987). Put differently, all else being equal, women performing at the same level as men, are less likely to get promoted. Further, all else being equal, women with longer tenure in the company are less likely to be promoted. This is strong evidence that are they are taken for granted, as the effect flips to a positive sign for women hired from the outside.

These covert prejudicial tactics against women are somewhat mitigated by them, arguably in a passive aggressive fashion, by taking training. Training has a strong positive effect, all else being equal, for women seeking an alternative, less-in-your-face-vehicle to climb the promotion ladder. Thus, we argue that human capital investments such as training (Acemoglu 1997) may help women provide credible signals to circumvent structural impediments in tech firms (Gibbons and Waldman 1999b). Moreover, these signals are relatively more amenable to be used by women, who may be less inclined to lean-in and directly ask for promotions that they feel are due to them (Ahuja 2002, Ibarra 1992). Our results suggest that training serves as signaling

¹⁰ We provide additional robustness checks in the appendix table A.1. We further highlight the importance of considering employee level heterogeneity in modeling promotion decisions in the appendix. Appendix Table A.2 compares the model fitting statistics for these models, that is, the proposed model in equations 1-3 with alternate specifications; our proposed model fares better than these competing models, indicating that accounting for employee heterogeneity is critical for policy and management decisions.

mechanism that helps women circumvent the traditional biases and notions to establish their credentials as capable and driven IT employees. 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.

CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

The dearth of women in IT, well documented by both academia and industry, has been attributed in part to the lack of women in the higher echelons of organizational ladder, which not only affects the immediate career prospects of women in IT but also dissuades women who want to be part of IT labor markets (Ahuja 2002). While performance has long been understood to be the primary factor affecting promotions, the paucity of granular data has led to only an imperfect understanding of the interplay between gender and performance as they affect promotions for women in IT. In this study, we investigate the factors affecting women's rise in IT organizations. Our primary focus is on examining the role of gender on promotions in IT firms, but we also examine whether men and women experience differential or commensurate returns from performance gains in augmenting promotion likelihood.

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 processes geared towards fair promotion, training, and evaluation for its employees. We gained access to detailed, archival, administrative data on promotions, demographics, performance, and training for 7,004 employees from 2002–2007. This comprehensive dataset affords us the opportunity to examine not only the effect of gender but also performance for different levels of promotions, from software engineer to programmer analyst to project manager and for laterals versus direct hires. Our findings reveal that gender is a strong predictor of the likelihood of promotions. Contrary to our expectations, we find that women are more likely to be promoted than men. We offer several 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 be 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. Such a promotion strategy may also reflect glass cliffs, such that women are promoted to be part of failing projects (Cook and Glass 2014). Finally, it is possible that equitable organizational policies result in more transparency and accountability from managers and reduce blatant biases against women (Castilla 2008, Lerner and Tetlock 1999). Together, these factors may explain why women are more likely to be promoted. We also argued that gains from performance improvements in increasing promotion likelihood are lower for women. We find that women may be penalized for better performance in that their promotion likelihood increases with performance at a lesser rate compared to men. Considering that women are an occupational minority in the IT industry, it is likely that their competence is not known except to their employer, therefore, the firm has an incentive to not promote women with high performance and keep them “hidden” from competing firms (Milgrom and Oster 1987). It is also possible that senior management may attribute their performance less to ability than to luck, and hence women do not gain as much from performance improvements (e.g. Carton and Rosette 2011). Further, we find that women 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 promotability and/or signaling (Becker 1962, 2003, Stiglitz 1975). This allows them to circumvent any social and structural biases that may have otherwise prevented their climb up the corporate ladder, leading to promotions.

We believe that the strength, robustness, consistency, and validity of our findings stem from a) using detailed employee data for gender, performance, experience, and training for multiple levels of promotions that provides an adequate backdrop to examine the more intricate predictions of theories from economics and social sciences, and b) employing robust empirical specifications that address the heterogeneous differences between employees. The validity of our results is reflected in their consistency across different

specifications, including those that account for endogenous constructs such as motivation and drive that affect performance.

Our study contributes to the extant literature on IT labor markets in several important ways. First, we contribute to research on promotions and tournaments by positioning gender as an important determinant of promotions for women in IT. Ours is one of the first studies to unequivocally establish the economic significance of performance, outside experience, and training for women in IT seeking promotions. In sum, our study draws from and contributes to the labor economics and social sciences literature to provide a more nuanced but complete picture of the linkages between gender, relative employee performance, human capital investments, 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). Prior literature suggests that women lack influential mentor network (e.g., Ibarra 1993), leading to differences in how women are evaluated and promoted within an organization. Our primary managerial implication is that training helps women with low performance by thwarting any structural biases that may have otherwise inhibited them, especially at higher levels of promotion, underscoring the importance of training as a credible signal of ability and value. Although many IT organizations have diligently pursued unbiased evaluation and promotion practices, it is likely that subtle biases persist. 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. Further, we find that training and performance are complementary, such that training can help employees with high performance rise faster in the organizational hierarchy, this is especially . Therefore, managers can nurture the high performing employees and provide them resources to excel even more. Further, prior research suggests that fair evaluations and training are exemplary human resource practices that affect firm performance positively (Delaney and Huselid 1996). Our study suggests that adoption of processes and policies that limit individual manager's discretion (Elvira and Graham 2002), promote transparency and accountability (Castilla 2008, Lerner and Tetlock 1999), and even adequate managerial incentives (Sherf et al. 2018) that go beyond symbolic gestures will also help reduce biases against women in IT. 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; managers understand that they will be held accountable for biases but will also enjoy suitable rewards in being more equitable and fairer. Finally, we note that although focused on IT labor markets, the findings of this research are generalizable to women in other male-dominated industries, such as those in STEM.

Limitations and Future Research

Like all research, this study has limitations and provides opportunities for further research. We rely on critical data around three representative positions in the IT services work ladder from a single firm. It is possible that the results may not generalize to other firms or to other positions such as that of data analyst or data scientists. 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. While the growth in this sector portends wider appreciation and applicability of our findings and implications (Bartel et al. 2014), we caution the readers that our results may not generalize to firms that do not yet have process-oriented HR practices that inhibit overt gender biases. Additionally, we are hampered by not having access to wage data, which could offer a more comprehensive insight into biases against women in IT. 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. It would be interesting to understand how gender, performance, experience, and training dynamics change as one examines the higher echelons of the corporate ladder (Powell and Butterfield 1994). We hope that future work can utilize wage and promotions data to develop newer insights. For instance, future research could examine discrimination against women in IT taking into account societal and country level norms. Future research can further examine how factors such as peer and mentor networks impact employee promotions.

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TABLES AND FIGURES

Table 1: Data Dictionary and Summary Statistics

Variable Name	Variable Description	Mean (SD)		
		Overall	M	F
Promotion (t)	Variable indicating whether promotion occurred in year t or not	0.163 (0.369)	0.163 (0.369)	0.162 (0.368)
Female	Dummy variable indicating employee’s gender (1: Female; 0: Male)	0.234 (0.424)		
PerfRating	The relative performance rating of the employee, this ranges from 1 (excellent) to 4 (poor). To ease interpretation, we use -1*PerfRating.	1.776 (0.734)	1.755 (0.734)	1.845 (0.730)
TotalExp	An employee’s total IT work experience in years.	6.145 (2.273)	6.263 (2.351)	5.757 (1.946)
FirmExp	An employee’s work experience at the focal firm in years.	4.307 (2.132)	4.333 (2.163)	4.224 (2.026)

Variable Name	Variable Description	Mean (SD)		
		Overall	M	F
PriorTraining	The total number of training courses taken by an employee prior to promotion, normalized by course duration.	0.669 (1.003)	0.652 (0.993)	0.726 (1.104)
DirectHire	Dummy variable indicating whether an employee is a direct (from college) or lateral hire (1: Direct; 0: Lateral)	0.442 (0.497)	0.432 (0.495)	0.477 (0.499)
LastRole	Dummy indicating the last role: whether software engineer (SE), or programmer analyst (PA), or project manager (PM); coded as SE=0, PA=1, PM=2	1.278 (0.448)	1.306 (0.461)	1.189 (0.391)

Table 2: Correlation Matrix

	1	2	3	4	5	6	7
1 Promotion (t)							
2 Female	-0.0015						
3 PriorPerfRating	0.0543*	0.0515*					
4 TotalExp	0.0057	-0.0942*	0.2462*				
5 FirmExp	0.0202*	-0.0217*	0.1173*	0.2738*			
6 PriorTraining	0.0068	0.0311*	-0.0957*	-0.2783*	0.0583*		
7 DirectHire	0.0066	0.0386*	-0.1097*	-0.3828*	0.3595*	0.2944*	
8 LastRole	0.0016	-0.1108*	0.0923*	0.7259*	0.3215*	-0.0469*	-0.1614*

Note: * indicates correlations significant at 5% level.

Table 3: Likelihood of Promotion: Population Level Estimates

	Coefficient(SE) Overall	Coefficient(SE) Male	Coefficient(SE) Female
Past Year Performance	1.3123** (0.0034)	1.4834** (0.0036)	1.2434** (0.0092)
Female	0.209** (0.0013)		
Firm Experience	0.7727** (0.0068)	0.8564** (0.0077)	0.2233** (0.0204)
Experience	0.9310** (0.0105)	0.7619** (0.0108)	2.0807** (0.0404)
Intercept	-1.9352** (0.0129)	-2.002** (0.014)	-1.3216** (0.0374)

Notes: Standard errors are in parentheses. +Significant at 10%; *significant at 5%; **significant at 1%.

Table 4A: Likelihood of Promotion: Heterogeneity Estimates for the Overall Sample

	Intercept	Direct Hire	Prior Training	Last Role
Past Year Performance	0.5374** (0.001)	0.1473** (0.0005)	0.1854** (0.0003)	0.4395** (0.0007)
Female	0.2665** (0.0015)	-0.003** (0.001)	0.0881** (0.0004)	-0.0957** (0.0011)
Firm Experience	1.8002** (0.0012)	-0.2519** (0.0014)	0.3821** (0.0004)	-0.9293** (0.0007)
Experience	-1.6526** (0.0015)	1.0566** (0.0016)	0.3647** (0.0005)	1.3952** (0.0009)

	Intercept	Direct Hire	Prior Training	Last Role
Intercept	1.1744** (0.0009)	-0.1172** (0.001)	0.0586** (0.0003)	-2.4184** (0.0007)

Notes: Standard errors are in parentheses. +Significant at 10%; *significant at 5%; **significant at 1%.

Table 4B: Likelihood of Promotion: Heterogeneity Estimates for the Male Subsample

	Intercept	Direct Hire	Prior Training	Last Role
Past Year Performance	0.5539** (0.0013)	0.1705** (0.0008)	0.1666** (0.0004)	0.5717** (0.0009)
Firm Experience	1.8848** (0.0018)	-0.0806** (0.0026)	0.3381** (0.0006)	-0.9462** (0.0011)
Experience	-1.5989** (0.0021)	0.7692** (0.0034)	0.3742** (0.0006)	1.3116** (0.0013)
Intercept	1.0032** (0.0017)	-0.2622** (0.0017)	0.0802** (0.0005)	-2.247** (0.0014)

Notes: Standard errors are in parentheses. +Significant at 10%; *significant at 5%; **significant at 1%.

Table 4C: Likelihood of Promotion: Heterogeneity Estimates for the Female Subsample

	Intercept	Direct Hire	Prior Training	LastRole
Past Year Performance	0.5008** (0.0047)	0.104** (0.0027)	0.2487** (0.0014)	0.4046** (0.0034)
Firm Experience	1.6568** (0.0072)	-1.2186** (0.0061)	0.5518 (0.002)	-1.0355** (0.0043)
Experience	-2.1628** (0.0082)	2.6526** (0.0075)	0.4839** (0.0024)	2.0435** (0.005)
Intercept	2.5344** (0.006)	0.633** (0.0033)	0.138** (0.0014)	-3.6142** (0.0061)

Notes: Standard errors are in parentheses. +Significant at 10%; *significant at 5%; **significant at 1%.

Table 5: Robustness Checks: Dynamic Panel Model

	Overall	Males	Females
Promotion (t-1)	0.0897** (0.0274)	0.1142** (0.032)	0.0094 (0.0525)
Past Year Performance	0.4395** (0.0157)	0.4608** (0.0187)	0.3576** (0.0278)
Past Year Training	0.0578** (0.0109)	0.038** (0.0129)	0.129** (0.0197)
Intercept	0.2792** (0.0077)	0.2524** (0.2524)	0.3559** (0.0133)

Notes: 1. Standard errors are in parentheses. +Significant at 10%; *significant at 5%; **significant at 1%. 2. Post estimation Sargan test of overidentifying restrictions failed to reject the null hypothesis (H0) that overidentifying restrictions are valid, with Prob > chi2 = 0.228 (overall sample), 0.155 (male subsample), and 0.834 (female subsample) respectively.

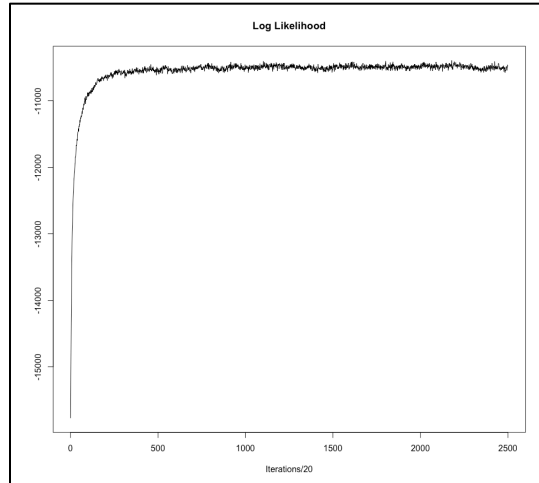


Figure 1: Values of the log-likelihood of the hierarchical Bayesian model evaluated at posterior draws of individual coefficient estimates show convergence; every 20th draw retained for analysis

APPENDIX

A.1: JOB ROLE DESCRIPTIONS – SOFTWARE ENGINEERS, PROGRAMMER ANALYST, PROJECT MANAGER

The entry-level position in the organization is that of a **software engineer (SE)**. 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, debug, and test the software. They would also need to understand the processes and frameworks that the organization uses to ensure quality and timeliness of the software to be delivered.

The next step on the organizational ladder is that of a **programmer analyst (PA)**. PAs take on more analytical and design responsibilities pertinent to software projects that go beyond coding. They interact with the clients to determine business requirements, analyze these requirements, and help with software design, architecture, and development. They may supervise programmers with code reviews and provide expert technical help when needed. They assist PMs in project scoping and 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 necessary for a successful project implementation and support. A typical PA would have 3 to 8 years of work experience.

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 that the proposal, estimation, and scope for a project is completed, build the project team, schedule assignments, monitor, review, and report project status, as well as manage project risks. To do these tasks, PMs need to interact with multiple stakeholders, such as the project team, clients, and senior managers. To ensure efficacious project delivery, PMs not only need to employ communication, project management, and leadership skills but also be versed in project-related technologies and business domains (Langer et al. 2014). A typical PM would have 8 to 15 years of work experience.

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, the firm has been assessed at level 5 for the people CMM (pCMM), ensuring that firm is committed to its human capital with fair policies that manage employee performance as a key aspect of its growth strategy.¹ 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 in-depth performance evaluations, appropriate employee incentives such as promotions and human capital alignment with the firm's strategic goals through provision of on-the-job training (Curtis et al. 2009).²

A.2: ADDITIONAL TABLES

In addition to the hierarchical Bayesian Model and the dynamic panel model described in the empirical section, to further demonstrate the robustness of our analysis, we estimate baseline logit and probit models for panel data. To account for endogenous variables such as performance, we use instrument variables; specifically we use the average rating of other employees in the same role as an instrument; this variable is related to employee performance but unlikely to affect promotion likelihood (Hausman and Taylor 1981). Table A.1 presents the estimations results from these models. Columns I and III show the results for panel regressions for naïve logit and naïve probit specifications; columns II and IV show the results for a GMM (IV) specification for an endogenous logit model (Foster 1997) and pooled model specification with clustered standard errors for an endogenous probit model (Papke and Wooldridge 2008) respectively.³ These results are qualitatively similar to those presented in tables 3 and 4 and indicate that as expected, performance is positively related to the likelihood of promotion. Similar to the results from the HB specification, we find that

¹ The CMMI institute provides more insight into the pCMM model at <https://cmmiinstitute.com/pm>.

² The focal 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. The firm has a dedicated education and research department to provide in-depth training to its employees. Training resources are made available to all its employees regardless of gender, age, or organizational level. In order to encourage their employees to take training as and when needed, the firm ensures that most, if not all, these resources are online.

³ More details on the estimation of these models are available from the authors on request.

women are more likely to be promoted. Likewise, we note that in line with the results from the HB model, the interaction coefficient between performance and the indicator *Female* variable is negative and significant in the two IV models, suggesting that women are less likely to derive commensurate benefits from performance gains in getting a promotion. To sum, the consistency and robustness of the results from these alternate specifications validate the hierarchical Bayesian model.

As noted in footnote 9 of the paper, we provide a comparison of the model fitting statistics for these models, that is, the proposed model in equations 1-3 with alternate specifications in Table A.2. Our proposed model fares better than other competing models, indicating that accounting for employee heterogeneity is critical for policy and management decisions.

Table A.1: Additional Robustness Checks

	I	II	III	IV
Past Year Performance	1.1745** (0.0244)	1.2754** (0.0244)	0.6667** (0.0134)	1.2998** (0.0140)
Female	0.1865** (0.0474)	0.0895** (0.0274)	0.1067** (0.0262)	0.0542** (0.0172)
Firm Experience	0.5156** (0.0279)	0.4125** (0.0279)	0.2987** (0.0155)	0.0525** (0.0187)
Experience	0.6125** (0.0317)	0.6137** (0.0317)	0.3605** (0.0170)	0.4422** (0.0256)
Female X Past Year Performance	0.0342 (0.0483)	-0.4192** (0.0483)	0.0252 (0.0270)	-0.8143** (0.0295)
Female X Firm Experience	-0.0015 (0.0628)	-0.1115* (0.0519)	-0.0106 (0.0355)	-0.1451** (0.0259)
Female X Experience	0.0670 (0.0669)	0.0710 (0.0629)	0.0536 (0.0374)	0.1483** (0.0290)
Last Role = Software Engineer	-1.4847** (0.0506)	-1.8453** (0.0205)	-0.8580** (0.0285)	-0.5565** (0.0372)
Intercept	-1.3302** (0.0256)	-0.8302** (0.0256)	-0.7821** (0.0141)	-0.5343** (0.0201)

Notes: 1. Column I: Panel Logit; model II: IV Logit (GMM); model III: Panel Probit; model IV: IV Probit. 2. Standard errors are in parentheses. +Significant at 10%; *significant at 5%; **significant at 1%.

Table A.2: Model Comparison

	Panel Logit	IV Logit	Panel Probit	IV Probit	Proposed Model
Log Likelihood	-11833.37	-45448.98	-11814.75	-42496.18	-10493.29
AIC	23686.73	90939.96	23649.50	85012.36	21028.58
BIC	23768.22	91111.09	23730.99	85093.85	21199.71