Return Migration and Gender Inequality in the Indian Technology Industry

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Abstract

This paper examines gender inequality in the job mobility of Indian return migrants. Prior research suggests that foreign human capital gives returnees labor market advantages after moving home, but little work has examined whether men and women benefit equally from these payoffs. This remains an open question given the large body of work demonstrating gender inequality in hiring and promotions in corporate settings, and these dynamics are even more salient in contexts like India with considerable gender inequality in the workplace.

I analyze a novel dataset of 1,591 time-varying cross-country employment histories from LinkedIn using logistic regression and survival analysis. I find that men are hired and promoted at higher rates than women, and subjective factors like gender carry more weight than objective factors like educational attainment. At the same time, a U.S. degree is associated with a boost in job mobility for women returnees, suggesting foreign educational credentials might mitigate some gender inequality.

The paper offers novel insights into the gender dynamics of return migration. The paper recasts our understanding of the power of foreign degrees in contexts with high levels of gender inequality.

Return migration is a crucial dimension of international migration that has long been understudied due to data constraints, and gender has often been overlooked in research on skilled migration. I analyze LinkedIn employment histories as digital data source to address these data limitations. I leverage the rich spatio-temporal information in these data to expand prior work on return migration to migrant career trajectories.

Introduction

Return migration is an essential but often overlooked dimension of international migration. Of the 280 million migrants living abroad, as many as half will move home within five years (Abel and Cohen 2019; Azose and Raferty 2019). Many people move to another country to work for a specified period of time before returning to their country of origin. In the United States, the H-1B skilled work visa program sponsors migrants for six years in sectors like technology and engineering, and many migrants return home when their visa expires (Jacobs 2019).

While return migration has become a more substantial dimension of the international migration system, there is much to learn about the outcomes of return migrants after moving home. In particular, the labor market re-incorporation is not well-understood. Return migrants bring foreign human capital, in the form of labor market experience, educational credentials, knowledge and expertise, back to their home markets.

Prior research suggests that foreign degrees and work experience give returnees labor market advantages after moving home, but little work has examined whether men and women benefit equally from these payoffs. This remains an open question, given the large body of prior work demonstrating gender inequality in hiring and promotions in corporate settings, and gender inequality in returns to education and human capital gains. These dynamics may be even more salient in contexts like India with considerable gender inequality in the workplace, especially in the technology sector, where gender inequality is well-documented (Burgess and Borgida 1999; Ridgeway 2006 ; Banerjee 2010; Williams, Muller and Kilanski 2012).

To address longstanding data constraints limiting research on return migration, I analyze LinkedIn employment histories as a novel data source to explore these dynamics. These data

offer rich spatio-temporal information that allow for dynamic analysis of return migration, and give detailed insights into career trajectories and gender, two major limitations to other data sources. I analyze a dataset of 1,591 time-varying cross-country employment histories from LinkedIn using logistic regression and survival analysis. The data examine Indian-origin migrants who worked in the United States before moving back to India to work in the technology sector.

This chapter offers novel insights into the gender dynamics of return migration. I find that men are hired and promoted at higher rates than women, and subjective factors like gender carry more weight than objective factors like educational attainment. At the same time, a U.S. degree is associated with a boost in job mobility for women returnees, suggesting foreign educational credentials might mitigate some of the gender inequality observed.

This chapter adds a gender perspective to prior research on the returns to foreign human capital for return migrants. It recasts our understanding of the power of foreign degrees in contexts with high levels of gender inequality, and reconsiders the long-term payoffs of foreign and domestic labor market experience.

Background and Literature Review

Migration Policy Context and the U.S.-India Case

U.S.-Indian migration is one of the largest migration flows in the world, and skilled migration is a central component of this migration stream (IOM 2024). The United States is the largest destination for skilled migrants, hosting almost half of all global migrants with a tertiary degree, and Indians comprise three quarters of migrants on U.S. skilled work visas (Kerr et al. 2016; Costa 2020; IOM 2022). Indian migration has increased significantly since the 1990s,

from a “trickle to a torrent,” driven by the expansion of the H-1B program (Chakravorty, Kapur and Singh 2016, 50). The H-1B is an employment-based temporary visa lasting six years granted to college-educated migrants in specialty occupations (see US Department of Labor for details). Employers sponsor the visa, meaning the legal status of an H-1B worker is tied to their employer and can constrain job mobility (Wang 2021; Costa and Hira 2023; Gupta 2023).

Because the visa is temporary and pathways to permanent residence are constrained, many migrants return home when their visa expires (Jacobs 2022). While it is possible to transition from an H-1B visa to lawful permanent resident (LPR) status, the processing time for Indian nationals can be up to 15 years due to nationality quotas in the visa system (Rissing and Castilla 2014). Thus, many Indian migrants return home rather than undergo this extended wait time, during which they experience suppressed wages and job mobility (Wang 2021; Gupta 2023). Further, India does not authorize dual citizenship and pathways to non-citizen permanent residence are limited, another reason some return to their country of citizenship (Jacobs 2019). In this study, over a quarter of all migrants in the technology sector returned to the Indian labor market.

Job Mobility in the Technology Industry

What determines the lengths of employment spells? Theories of job mobility generally assume that movement among jobs result from a combination of individual-level changes in human and social capital development and structural changes in the labor market such as labor supply and demand within certain industries, technological changes and governmental regulations (Kalleberg and Mouw 2018). Job sequences form the basis of a workers’ career, and inequality in employment duration, job sequences and patterns of mobility/immobility has major implications for understanding occupational attainment across the life-course.

Classic economic perspectives of job mobility theorize employment movement as a result of an employer-worker match that maximizes a worker's wages and returns to human capital (Rogerson, Shimer and Wright 2005). From this perspective, an employer change positively reflects worker quality and linear progress in human capital development (Lippman and McCall 1975). The speed and frequency of job changes reflects this skill growth, and thus higher levels of job mobility are related to higher levels of human capital development (Arthur and Rousseau 1996).

To assess sources of upward career trajectories across an individuals' labor market experience, occupational sociologists and labor economists examine internal and external moves as two key engines of wage growth, career development and status attainment (Kalleberg and Mouw 2018). Internal labor market perspectives focus on intraorganizational career ladders that provide mobility opportunities to workers within a company (DiPrete 1993). As employers and employees together invest in employee skill development that allows them to advance up the job ladder within a firm. In general, job stability and longer employer tenure is related to promotions and wage increases (Cobb-Clark and Dunlop 1999; Schmelzer and Ramos 2016).

However, in an increasingly dynamic labor market, interorganizational career ladders are gaining prominence and significance. Employers are more commonly making external hires, growing their talent pool through outside development rather than internal investments in employees (Cappelli 2008; Bidwell 2013; Lazear and Oyer 2004). In this model, employers grow the skill and knowledge base of their workforce through hiring workers with skillsets developed in other firms, with the goal of accruing knowledge and innovation (Tambe and Hitt 2013; Leung 2014). This is particularly pronounced in the technology sector, where "job hopping" between companies is seen as the primary mechanism for career growth.

These search-theoretic models interpret the achievement of a new employer-worker match as a reflection of increased human capital, assuming that workers make voluntary moves to maximize their returns to skill as reflect in their compensation (Topel & Ward 1992; Rogerson, Shimer and Wright 2005). Indeed, research shows that across-employer movement is a primary driver of wage growth (Bidwell 2011).

Job mobility patterns are influenced by labor market structure and organizational career ladders, which vary considerably across countries. The Indian economy has experienced significant growth in IT, business and finance (Das and Sagara 2017). However, few studies have examined job mobility within professional sectors of the Indian labor market (Pal and Kynch 2000; Sahoo and Neog 2017). This is especially important as sectors like information technology rapidly expand.

If the same dynamics extend to the tech sector of the Indian labor market, we should expect (H_1) higher levels of human capital in the form of labor market experience and educational credentials to be associated with higher levels of internal and external job mobility.

Gender inequality in job mobility

While there are clear socio-economic benefits to job mobility in the primary sector of the labor market, these trajectories are not equally accessible across groups; gender remains an important axis of stratification in the labor market. Women face discrimination in hiring, pay, promotions and management positions. As such, they continue to trail behind men in earnings and occupational status, and the promise of a college education still falls short in overcoming individuals' gender and nativity gap. On average, men hold more prestigious occupations and earn more than women, and the gender gap in earnings widens at higher levels of educational attainment (Padavic and Reskin 2002; England 2010; DiPrete and Buchmann 2013; Day 2019).

Common explanations for the gender gap in occupations and wages center on individual-level differences in human capital between men and women, organizational dynamics in the workplace, and discrimination in hiring and promotions (Reskin 1993; Padavic and Reskin 2002; Glick and Fiske 2007; England 2010; Bobbitt-Zeher 2011). Discrimination in hiring and promotions directly slows women's job mobility. Employers justify lower wages and lower positions for women in the workplace through gender-based assessments of skill and competence (Bobbitt-Zeher 2011). The effect of gender-based stereotypes is especially pronounced in sex-segregated contexts dominated by men; thus, the gender composition of the workplace matters as well (Burgess and Borgida 1999; Ridgeway 2006). And institutional factors such as workplace policies and team management strategies can advantage men over women (Reskin and Roos 1984; England and Ridgeway 2007; Kalev 2009). Some evidence suggests that dynamics are especially acute in male-dominated STEM fields, where the majority of skilled migrants are employed (Banerjee 2010; Williams, Muller and Kilanski 2012).

Given this, we should expect (H_2) men to have higher rates of job mobility than women, and (H_3) higher returns to educational attainment than women.

Transnational Labor Market Mobility and the Economic Reintegration of Return Migrants

Prior research has demonstrated the human capital advantages to job mobility and gender inequality in employment, but little is known about how these dynamics play out for the labor market outcomes of return migrants. Positive selectivity among women returnees might mitigate some of the gender inequality effects, or inefficiencies in foreign credential transferring could minimize the benefits of human capital developed abroad. Further, little is known about how job

mobility patterns between India and the U.S., which is an important question for skilled migrants moving between these labor markets.

How well do return migrants reincorporate into home economies? A limited but growing body of work indicates mixed results (Constant 2020). Some return migrants see earnings returns to human capital developed abroad (Stark 1991; Sanderson and Painter 2011). Highly skilled African migrants, for example, earn more at home after working in Europe (Castagnone et al. 2014). Return migrants experience a wage boost in middle-income origin countries like Hungary, where some saw a 40 percent increase (Co et al. 2000; De Vreyer et al. 2010). Much of this earnings premium can be attributed to skills developed abroad (Sanderson and Painter 2011). Some Indian firms consider migration experience to be a useful skill for working with international clients (Jacobs 2022). Further, return migrants are more likely to start a business after returning home, facilitated by the capital earned abroad (Martin and Radu 2012). Some countries like Italy and the Netherlands incentivize high-skilled return migration through tax exemptions, giving returnees additional economic benefits (Timm, Giuliodori and Muller 2022; Bassetto and Ippedico 2023). Returnees in Australia also report higher levels of social satisfaction after re-settling (Wu and Bernard 2024).

At the same time, other returnees struggle to reintegrate. Return migration does not necessarily mean higher earnings: in Albania, high-skilled returnees had no wage premium, and guestworkers leaving Germany saw little return on migration (Constant and Massey 2002; De Coulon and Piracha 2005). Some returnees struggle to translate foreign skills into home labor markets, or must catch up from the occupational downgrading, limited job mobility and lower earnings abroad (Zeng and Xie 2004; Caron and Ichou 2018; Lancee and Bol 2017; Wang 2021).

For example, Indian H-1B visa holders earning lower wages are more likely to emigrate from the U.S. and re-enter the Indian labor market with a lower base pay (Depew et al. 2017).

The selectivity of migrants and returnees plays an important role in understanding reintegration outcomes.[1] Success in home labor markets might result from a particularly successful group of returnees, while struggles might be associated with challenges from time abroad (Constant 2020). The selectivity of return migrants is a highly debated topic, but empirical findings are mixed whether return migrants are positively or negatively selected (de Haas et al. 2014).

New Economics of Labor Migration theories take migration to be a long-term strategy for economic mobility (Stark 1991; Massey et al. 1993). From this perspective, migration is an investment to develop human and financial capital that facilitates life-course events like homeownership, starting a business or marriage (Massey and Parrado 1998; Parrado 2004). Following NELM frameworks, return migrants have successfully achieved target goals in the destination country (Stark 1991). In contrast, neoclassical economic models argue that migrants move to the labor market that maximizes wages, and a return indicates employment failure (Sjaastad 1962; Borjas et al. 2019). Unemployed migrants, for example, are more likely to return home (Constant and Massey 2002).

Migration policies also influence the selectivity of return migrants by limiting visa availability, constraining long-term settlement and creating shocks in legal status (Hagan and Wassink 2020). Skilled migrants left the U.K. after they lost work authorization post-Brexit (Stawarz and Witte 2023). In the U.S., migrants on temporary visas leave when their visa expires

[1] Skilled Indian migrants in the United States are positively selected by educational attainment, class and caste due to socioeconomic stratification in India and migration policies that select for highly-educated migrants (Chakravorty et al. 2016; Czaika 2018).

and pathways to permanent status are timely and costly (Jacobs 2019). This can influence the selectivity of returnees who lack the social or financial capital to settle permanently, or who move home where they have relatively higher socioeconomic status (Stark and Taylor 1989; Rissing and Castilla 2014; Jacobs 2019).

This work presents a mixed portrait of return migrant outcomes, with a strong focus on earnings. As Hagan and Wassink (2020) note, most econometric studies rely on wages and self-employment as easily instrumentalized indicators to identify the causal relationship between migration and the labor market outcomes of return migrants. Yet little is known about other labor market outcomes, like career trajectories. Upward job mobility is associated with wage growth, skill development and occupational status attainment (Kalleberg and Mouw 2018). The speed and frequency of promotions reflect human capital growth and maximize returns to new skills (Rogerson, Shimer and Wright 2005).

At the same time, positive selectivity among skilled Indian immigrant women might alleviate some inequality in labor market outcomes like wages and career mobility. Indian migrant women have high levels of human capital that might position them for occupational success (Pessar 2003; Huh 2017). The general Indian migrant population is highly positively selected in terms of educational attainment and class due to significant stratification in the sending country. In addition, Indian migrant women are further selected due to high levels of gender inequality in the Indian educational system (Feliciano 2005; Chakravorty et al. 2016; Huh 2017). At the same time, a direct comparison of men and women migrants indicates that Indian migrant men have higher levels of education than Indian migrant women, and are thus more positively selected (Feliciano 2005).

This paper picks up on Donato and colleagues' (2006, 2017) calls to expand the research on gender and migration and bring an explicit gender analytical framework to migration studies. While scholars have begun to generate important findings employing these perspectives to research on constructions and narratives of gender for refugees and asylum seekers, gender differences in educational enrolment in the second generation and historical trends in the gender composition of migrants, little work has focused on the gender dynamics among skilled migrants (Kofman 2004; Doanto and Gabaccia 2015; De La Cruz 2017; Pullés and Brown 2017; Wang 2017). Mainstream accounts of skilled migration and the global economy often take a "gender-neutral" approach that overlooks the central role of gender inequality and power dynamics in shaping employment and labor migration processes and outcomes (Sassen 1998; Kofman 2004). This paper aims to fill this gap as we employ a gender perspective to understand the relational dynamics between highly educated immigrant men and women in the workplace. Further, this paper provides a longitudinal perspective on immigrant labor market outcomes, an area that is understudied due to scant data.

If prior work demonstrating the value of foreign human capital for return migrants holds, we should expect (H_4) U.S. degrees and U.S. labor market experience to be positively associated with job mobility in the Indian labor market. Combined with prior work demonstrating stronger human capital advantages for men than women, we should expect (H_5) these effects to be particularly pronounced for male returnees.

Data and Methods

This paper analyzes LinkedIn user profile data of return migrants working in the Indian technology sector. The study focuses on 1,591 Indians who completed their Bachelor's degree in

2009, worked in the United States for at least six months, and were working at a technology company in India at the time of data collection, 2019. I analyze job mobility patterns from labor market entry in 2009 through 2019, which provides insights into early career migrants in their first ten years in the labor market. These data are derived from a larger dataset of 7,177 skilled ever-migrants working in both the U.S. and India. This macro sample is used in the analysis to test for selectivity between returnees and migrants in the U.S. (More details about the characteristics of the macro-sample are available in Jacobs 2025.)

Beginning with the first job and ending with the most recent job reported in 2019, I created a time-varying employment-history data file of 5,147 total job spells. This contains all reported job spells for each person, beginning and end dates, spell duration, country of spell, job title, company, and whether the spell is censored. The independent covariates include a combination of time-varying and time-constant measures. Identifying information such as name, university, and company have been modified to minimize the risk of re-identification (Kim et al. 2022).

Measures

Employer change. The first outcome variable measures an employer change at each reported job spell, measured as a change in company.

Promotion. The second dependent variable measures a promotion at each reported job spell, measured as an upward change in job title (1=promotion; 0=no new job title, lateral change, downward change, or censored).

Job spell duration. I measure the duration of each job spell in months. Current employment spells are right-censored; 21 percent of job spells are current (and thus censored). From this

measure, I calculate the cumulative duration of labor market experience at each job spell. For ease of interpretation, I present the results in years.

Job location. I use the location information reported in each employment entry to code job country.

Job Industry. Using employer names, I code each job into one of four industries: technology, engineering, business, and "other." This analysis focuses on the technology sector.

Country of degree. I code school country (U.S., India, other) by using the university name reported for each degree, and match that with school location.

Highest degree at job spell. A time-varying variable that indicates Bachelor's, Master's or Doctorate at time of job (some migrants obtain additional degrees after time in the labor market). I construct dichotomous variables for having a Bachelors, Masters, or Doctorate and then combine Master's and Doctoral degrees into a single "advanced degree" variable. All individuals in the sample have at least a Bachelor's degree.

Top school. A dichotomous dummy variable "top school" (1 or 0) based on 2009 U.S. News and World Report rankings.

Gender. At time of data collection, LinkedIn profiles did not report gender. I infer gender through profile names, pictures and pronouns to construct a dichotomous variable "male." While this reinforces a gender binary and conflates gender identity and gender presentation, it helps assess how workplace perceptions of gender relate to employment mobility outcomes (Schilt 2011; Lockhart, King and Munsch 2023).

Previously had H-1B visa. I construct a dichotomous time-varying variable to indicate whether a migrant previously held an H-1B visa. Legal status is not systematically reported in LinkedIn profiles, so I infer H-1B status by leveraging elements of the visa design and information on

profile pages.[2] Many users volunteer H-1B visa status in their bios through phrases like "H-1B approved" or "green card holder," or are members of LinkedIn groups like "H-1B Visa Holders." Almost half of profiles in the sample (46%) provided visa status indicators. To infer H-1B status of the remaining profiles, I used a temporal threshold of nine years of continuous U.S. employment. This nine-year window captures the six-year duration of the H-1B visa plus three additional years of U.S. employment to account for visa processing time and delays, which are especially common for Indian nationals (Costa 2020). Some migrants transition to permanent legal status in a shorter window, meaning that this approach might include some lawful permanent residents (Jacobs 2019). I use a wide temporal threshold to capture any migrant who ever had an H-1B visa.[3]

Sample characteristics

Table 1 reports the descriptive characteristics of migrants in the sample at the most recent job spell. It shows that over two thirds of the sample are between 30-34 years old, and almost three in four are male. Seventy-nine percent currently or previously held an H-1B visa. Twenty-six percent hold a Bachelor's degree, 71 percent have a Master's degree and three percent hold a doctorate. Sixty-seven percent has a U.S. degree and 39 percent attended a top-ranked school.

[2] Demographic inference of sensitive characteristics like legal status raises important ethical considerations for the responsible use of these data. Researchers are establishing a set of ethical protocols and data management best practices, and this paper follows in these guidelines (Salganik2018; Cesare et al. 2018; Drouhot et al. 2023; Donato et al. 2025).

[3] This wide temporal threshold might overestimate job mobility by including those with LPR status (Wang 2021). I re-coded the data using a 5-year threshold and the results were consistent. I further checked the robustness of the results by analyzing the 46 percent of profiles that disclosed legal status and re-coded them using the 9-year temporal inference approach. I found that the inferential approach had 83 percent accuracy. Finally, I compare the characteristics of inferred H-1B holders with ground-truth data and find that the gender and educational attainment of migrants in the sample reflected the traits of the Indian H-1B population in the United States (Chakravorty et al. 2016).

The average length of a job spell was 1.63 years, and the average number of total reported jobs was 6.89, with an average of 5.25 employers and 1.94 promotions across the employment period.

LinkedIn as a data source

The sample draws from LinkedIn, which is a professional networking website with over 1 billion users in over 200 countries (LinkedIn About 2025). Employers and job seekers use the platform for recruitment and networking. Users post online resumes listing their work and education background.

Digital data sources like LinkedIn are an exciting new source of information for migration research (Kashyap 2021; Drouhot et al. 2023; Rampazzo, Rango and Weber 2023). These data offer access to hard-to-reach and highly mobile groups that are difficult to measure in conventional data sources and provide fresh insights into the mobility and integration of migrants (Alexander, Polimis and Zagheni 2019; Donato et al. 2025).

LinkedIn provides an unparalleled richness of information about skilled migrant mobility, and researchers are beginning to exploit its potential for analyzing migration dynamics and gender gaps among professionals (State et al. 2014; Breschi et al. 2020; Kashyap and Verkroost 2021; Author 2022; Perrotta et al. 2023; Heo et al. 2023). The temporal and spatial resolution is particularly valuable for studying cross-national migration patterns over time. These data provide detailed cross-country longitudinal information about educational attainment and employment transitions that are unavailable in U.S. or Indian administrative data. LinkedIn is especially useful to follow skilled labor migrants moving between India and the United States because these are the two leading countries with the most registered LinkedIn users (Breschi et al. 2020; Dixon 2023).

While digital data offer useful new insights into migration dynamics, there are limitations to consider with their use. These data were not designed for scientific research, and may have some bias between usership and the general population (Cesare et al. 2018). Building on a long tradition in demographic research using statistical techniques to address limitations with imperfect data (Kashyap 2021), Zagheni and Weber (2015) offer a framework for addressing bias in non-representative internet data. This approach calibrates online populations with official government estimates to adjust for systematic differences between social media users and the general population. I use these frameworks to test the extent of biases between the LinkedIn population and available "ground truth" data on skilled migrants from the U.S. Department of Homeland Security. I report the full results of this calibration in Jacobs 2025, which shows that the LinkedIn sample in this study largely reflects the population of H-1B migrants and is highly correlated with DHS data on key characteristics such as gender, educational attainment, and industry.

This calibration suggests there are not systematic biases, and LinkedIn is well-suited to study the population of interest: college-educated Indian-origin professionals in technology, engineering and business moving between India and the United States (Cruz 2021; Dixon 2023). LinkedIn is the industry standard for recruiters and job seekers in technology, engineering and business, which employs about 85 percent of H-1B workers (Dixon 2023). In both India and the United States, LinkedIn usership is concentrated among college-educated users aged 25-34, which also elegantly captures the population of interest in this study (Cruz 2021). The findings cannot be generalized beyond this group, but these data represent over a billion LinkedIn users and provides important insights into a politically and economically significant migration stream.

Another consideration when working with novel digital data sources is maintaining user privacy. Following the guidelines for ethical digital data use outlined by Salganik (2018), these data have been gathered, stored and analyzed to maintain privacy. Identifying information has been removed, and the data have been aggregated to a level that protects identities and minimizes risk of re-identification (Kim et al. 2022). This study was approved by University of Pennsylvania IRB and complies with ethical regulations. In line with other studies aiming to achieve a balance between maintaining privacy and replicability of findings, aggregated data will be made available upon request (Kim et al. 2022; Perrotta et al. 2023).

Empirical strategy and models

Logistic Regression

To examine the different factors related to external hires for men and women in the Indian technology sector, I conduct binary logistic regression analysis using Stata. The analysis in Table 3 models the determinants of employer change. Supplemental analysis in Panel B stratifies the model by gender, to measure the differential effects for men and women.

The model considers different factors related to gender, labor market experience, educational attainment, and legal status. It measures the effects of U.S. and Indian labor market experience, as well as level of degree, country of degree, and field of degree. To account for the selectivity of return migrants, I explore the association of whether a migrant attended a top-ranked school. Additionally, to account for constrained job mobility in the U.S. labor market associated with employer-sponsored work visas, it factors in prior legal status in the U.S. (Jacobs 2025).

Survival analysis

To model job mobility across a return migrant's tenure in the Indian labor market, I estimate the risk of promotion using discrete-time event history models (Yamaguchi 1991). These models consider how migrant gender, labor market, educational and legal status characteristics relate to the risk of experiencing a promotion event. Panel B stratifies the analysis by gender to see how specific effects carry different weight for men and women.

The event history models allow me to adjust for time dependency in the risk of a promotion event, and because individual migrants have different durations of employment. I use semi-parametric Cox regression models and estimate the partial likelihood of the hazard of a promotion event. Cox regression modeling best fits the data because it prioritizes the ordering of events and allows for episode-splitting to address time-dependent variables such as level of educational attainment (Allison 2010). To address issues with reverse causation, I lag time-varying explanatory variables by 12 months. I use the Efron method for ties to increase precision when the number of events is a substantial proportion of the number at risk at multiple time points (Allison 2010).

Because I am interested in the incidence of promotions across a migrant's tenure in the labor market, I model repeated events. I treat each successive job spell as a distinct observation, and pool all such intervals. Time (t) is measured in months. In the discrete-time model, the failure corresponds to the *promotion* definition of a move, i.e. first report of a higher position with the same employer. Formally, the Cox model is expressed as the hazard rate $h(t)$ and is estimated with time-lagged variables as:

$$h(t)=h_0(t)\times exp(\beta_1 x_1+ \beta_2 x_2+ \beta_3 x_3(t-1)...+ \beta_p x_p)$$

The baseline hazard provides information on the pattern of duration dependence but might be affected by unmeasured differences within individuals (Allison 2010). I run supplemental fixed-effects analysis to address potential unobserved heterogeneity within individuals. This allows me to control for all stable predictor variables while addressing the problem of dependence among repeated observations.

Results

I start the analysis by establishing the overall rate of return migration by gender. Figure 1 compares the rates of employment in India, long-term U.S. employment, and onward migration by gender from the macro-sample of current migrants and returnees. The figure shows that over a quarter of Indian-origin men and women working in the United States eventually return to India. Men returned to India at slightly higher rates than women: 30 percent of men and 22 percent of women returned to India for work temporarily or permanently. Conversely, in line with prior literature, the figure shows that women remained in the U.S. long-term at higher rates than men (70 percent and 58 percent respectively). Twelve percent of men and eight percent of women moved onward to another country like the United Kingdom, Canada, or Australia.

Next, I explore patterns of employment trajectories among return migrants in India. Figure 2 shows the number of employer changes in the Indian technology sector for men and women. It shows that men have more external hires than women. Sixty percent of men have three or more employer changes during the period of study. In contrast, 63 percent of women had two or fewer employer changes.

Figure 3 shows the survival curve of promotions in the Indian technology sector by gender

First, it indicates that in addition to more external hires, men also have more promotions than women. Ninety-four percent of men were promoted at least once during their tenure in the Indian labor market, compared to eighty five percent of women. The figure also shows that men experience faster rates of promotion than women in the Indian labor market. The figure indicates that by the end of the first year working in India, almost forty percent of men were promoted, while less than twenty percent of women experienced a promotion in the first year. This gap continues to grow in the second and third years: by the third year of employment in India, more than eighty percent of men were promoted, compared to about half of women. Women begin to converge with men in their promotion rates after about five years of employment, where the gender gap in employment rates closes to about ten percentage points, indicating that there is still some persistent inequality in promotions.

These outcomes might be related to positive selectivity among return migrants (Constant 2020).[4] To explore systematic differences between returnees and those who remained in the U.S., Table 2 compares the characteristics of migrants working in India and the U.S., stratified by gender. It shows that return migrants differ from migrants in the U.S. with respect to visa status, educational attainment and industry. Men and women returnees are similar with respect to labor market experience, but women have slightly higher educational attainment from more prestigious schools.

[4] Another dynamic that could influence the outcomes is incomplete employment reporting on LinkedIn profiles. As with any self-reported information, LinkedIn users might omit periods of unemployment or "irrelevant" job experience. This would bias the data towards upward job changes and inflate the observed outcomes. To test whether underreporting periods of un- or under-employment is biasing the results, I conducted supplemental analysis comparing the job spell duration between migrants with upward, lateral and downward job moves when re-entering the Indian labor market. In the analysis, there was no statistically significant difference in the job spell duration in the job immediately before migrating, which would capture potential overreporting of employment duration to cover a period of un- or under-employment. As a robustness check, I excluded 387 cases where the job spell was more than six months longer than average and did not find a significant difference in results.

Table 2 shows that return migrants were more advanced in their careers, having moved back to India after a job spell in the U.S. Men return migrants on average have 2.14 more years of labor market experience than migrants in the U.S.; women returnees have 2.17 more years of experience. Some of the differences between the groups are driven by longer time in the labor market and we would expect to see systematic differences. The table shows that there are statistically significant differences between migrants in the U.S. and returnees in the number of reported jobs, employers and promotions, which is a function of time in the labor market.

The table shows systematic educational differences between return migrants and those working in the U.S. Seventy-five percent of male return migrants and 79 percent of women return migrants hold advanced degrees, compared to 66 percent of male migrants and 68 percent of women migrants in the U.S. This means that the return migrant population has higher levels of education, especially among women.

In contrast, fewer return migrants have U.S. degrees. Whereas 78 percent of male migrants in the U.S. hold a U.S. degree, only 55 percent of men who return hold a degree from a U.S. university. These patterns hold for women as well: 81 percent of women migrants working in the U.S. have a U.S. degree, compared to 51 percent of women returnees.

Finally, I do not find a statistically significant difference among returnees of either gender with respect to university prestige. Forty-six percent of men returnees and 48 percent of women returnees attended top-ranked schools, compared to 51 percent of men in the U.S. and 52 percent of women. This indicates that return migrants are positively selected on level of educational attainment, especially for women, negatively selected on place of education, especially for men, and have no difference in school rank for either gender.

The table also examines the relationship between legal status and return. It shows that H-1B holders return to India at disproportionate rates. Whereas 71 percent of male migrants working in the U.S. hold or previously held an H-1B visa (and 68 percent of women), 79 percent of men returnees and 80 percent of women returnees are prior H-1B holders. As a six-year temporary work visa, the H-1B is a driver of emigration from the U.S. (Rissing and Castilla 2014; Author 2019).

Having established the prevalence of return migration, patterns of job mobility for return migrants in India, and some selectivity of return migrants, I now analyze factors related to job mobility for return migrants in the Indian labor market. I use binary logistic regression to understand the determinants related to external hires in the Indian technology sector, bearing in mind the selectivity of returnees established above.

I report the results in Table 3. Panel A shows the full analysis and indicates that men have a higher likelihood of employer change compared to women. In addition, prior work and educational experience from the United States is positively associated with being promoted when first returning to the Indian labor market.

First, the table shows a positive effect of being male (β=0.119) on external hires. This supports the expectations of (H_2), that men would have higher rates of job mobility than women.

Next, I find that each additional year of labor market experience is associated with a slight increase in the likelihood of being promoted, and the effect is slightly stronger for U.S. labor market experience (β=0.004) compared to Indian labor market experience (β=0.002). This result provides partial evidence to the expectation of H_1, that more labor market experience would be associated with higher levels of job mobility. It supports the expectation of H_4, that foreign

human capital would carry particular value, by demonstrating the stronger effect of U.S. labor market experience compared to Indian labor market experience.

With regards to educational attainment, the results indicate that U.S. degrees and STEM degrees are associated with a higher likelihood of external hires, while advanced degrees have no effect. In addition, it shows that highly ranked schools have a positive association with job mobility. These results complicate the expectation of H_1, which suggested that higher levels of education in the form of advanced degrees should be associated with more mobility. Instead, it supports the expectation of H_4, that U.S. degrees would boost job mobility.

Finally, in line with prior work, I find that those previously on an H-1B visa have a higher likelihood of external hires.

To see how these factors carry different weight for men and women returnees, I stratify the analysis by gender in Panel B. I find that years of labor market experience boosts job mobility for men and women at similar levels.

The results indicate that the benefits of educational attainment vary by gender. While holding an advanced degree does not have a significant effect for either gender, the positive effect of a U.S. degree is more pronounced for women (β=0.076) than for men (β=0.065). The results also indicate that graduating from a top school also has a statistically significant effect for women (β=0.112), but not for men, suggesting that prestigious educational credentials have value for women in the Indian labor market. In contrast, STEM degrees carry more weight for men (β=0.030) compared to women (β=0.018). These results challenge our expectations of H_3, that men would have higher returns to education, and H_5, that foreign human capital benefits would be particularly pronounced for men. Instead, the results suggest that U.S. credentials carry more weight for women returnees.

The table also factors in prior legal status in the United States, to account for constrained job mobility in the U.S. labor market associated with employer-sponsored work visas (Jacobs 2025). The results show that both men and women who previously held H-1B visas while working in the U.S. are more likely to be promoted upon returning to the Indian labor market, with a slightly more positive effect for women (β=0.133) compared to men (β=0.123).

These results demonstrate gender inequality in external hires, and differential payoffs of educational attainment. To understand whether these dynamics persist within companies for internal promotions over a returnee's tenure in the Indian labor market, I use survival analysis to model the factors associated with the risk of promotion over time.

Using Cox regressions, I model the risk of promotion for men and women return migrants in the Indian labor market. Table 4 explores the labor market and educational factors associated with promotion and reports the hazard ratios. A value over one indicates a positive relationship. Panel A examines patterns across all return migrants and Panel B stratifies the analysis by men and women to see how effects vary by gender.

The results of Panel A indicate that being male increases the likelihood of being promoted (β=1.092), as does additional years of labor market experience. The effect of Indian labor market is particularly pronounced (β=1.198). These results support H_2, that men will have higher rates of job mobility than women, and H_1, that higher levels of labor market experience boosts job mobility.

Panel A further shows that the educational attainment and legal status variables are not statistically significant. These results complicate our hypothesized expectations. Here, we do not see the expected effect in H_1 that educational background would be positively associated with job mobility, nor do we see the expected positive effects in H_4 of U.S. degrees.

To examine how these effects operate differentially for men and women, I stratify the analysis by gender. The results in Panel B indicate that overall time in the Indian labor market is the strongest predictor of promotion for men, while educational credentials are central for increasing women's promotion risk.

For both men and women, additional years of Indian labor market experience is associated with a higher risk of promotion, especially for men (β=1.234). U.S. labor market experience has a small positive effect for women. This indicates that for men, Indian labor market experience is more relevant for internal hires, compared to the value of U.S. labor market experience for external hires. This suggests that additional time in a company carries particular weight for within-company mobility, where employees may develop stronger internal networks and company-specific skills. This finding supports the expectations of H1 that increased labor market experience is associated with mobility, and challenges the expectations of H_4, that foreign human capital would boost job mobility, and that these dynamics would be especially pronounced for men (H_5).

The results indicate that for women, educational credentials have a positive and significant effect on job mobility. Holding a U.S. degree has a strong positive effect (β=2.914) on women's promotion risk, as does graduating from a top-ranked school (β=2.674). Conversely, educational credentials do not have a significant effect for men. These results further challenge the expectations in H_5 that foreign degrees would have stronger benefits for men than women. Instead, these results indicate that other subjective factors, such as gender itself, are playing a bigger role in men's promotions within companies.

Discussion

This chapter offers novel insights into the gender dynamics of return migration in the Indian technology sector. Return migration is a central facet of international migration, but little is known about the labor market outcomes of returnees, especially with respect to gender inequality and the returns to foreign human capital in domestic markets.

Logistic regression and Cox regression analysis of 1,591 Indian migrant returnees reveals gender inequality in job mobility in the Indian technology sector. I find that men are hired and promoted at higher rates than women, and subjective factors like gender carry more weight than objective factors like educational attainment. At the same time, a U.S. degree is associated with a boost in job mobility for women returnees, suggesting foreign educational credentials might mitigate some of the gender inequality observed.

The results add nuance to prior research demonstrating the benefits of foreign human capital for return migrants (Stark, 1991; Co et al., 2000; De Vreyer et al., 2010; Sanderson and Painter, 2011; Jacobs, 2022a). The results indicate that these benefits are gendered, with U.S. degrees and years of U.S. labor market experience generating job mobility for women. For men, however, foreign degrees and labor market experience have less of an effect, and being male itself has a significant mobility-generating function for both hiring and promotions. The results suggest that for men, additional time within a company carries particular weight for internal hires, where more subjective factors like gendered interactions, internal networks and company-specific skills may carry additional weight in promotion decisions.

This complicates prior work indicating that men see higher returns to education than women (Padavic and Reskin 2002; England 2010; DiPrete and Buchmann 2013; Day 2019). In the context of returnees in the Indian technology sector, U.S. credentials may play a mitigating function against broader gender inequality in the workplace. This echoes the findings of Jacobs

and Kreisberg (2022), which demonstrates the value of a U.S. degree for women's job mobility in the U.S. labor market.

By adding a gender perspective to the research on skilled migration, the findings shed light into the challenges women face when returning to the Indian technology sector (Donato et al. 2006; Donato et al. 2017). It highlights opportunities that improve opportunities for all workers, such as policies that emphasize objective criteria like educational credentials in hiring and promotions. This would increase equality of opportunity and improve overall labor conditions in the Indian tech sector.

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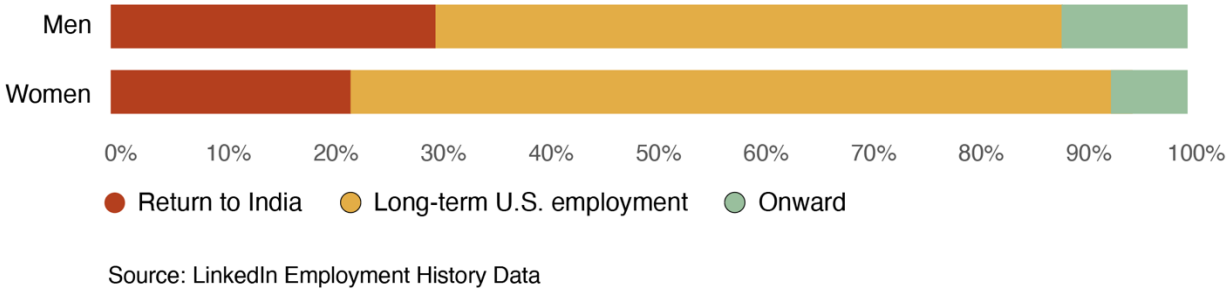
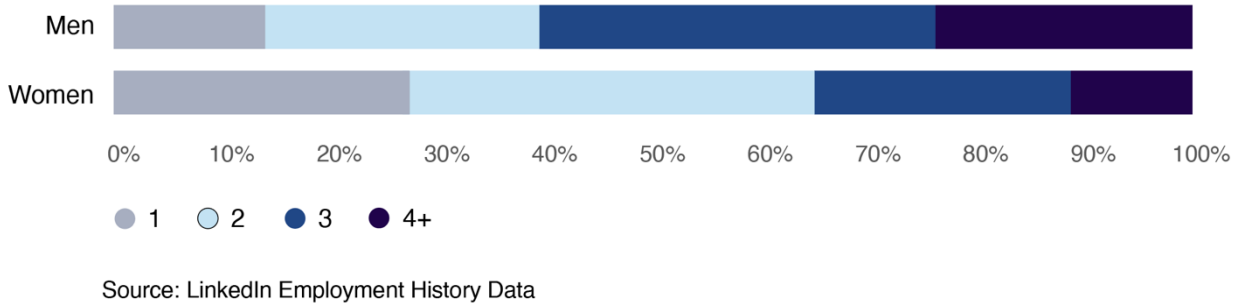
Figure 1. Migration Trajectories Between India and the United States, by Gender



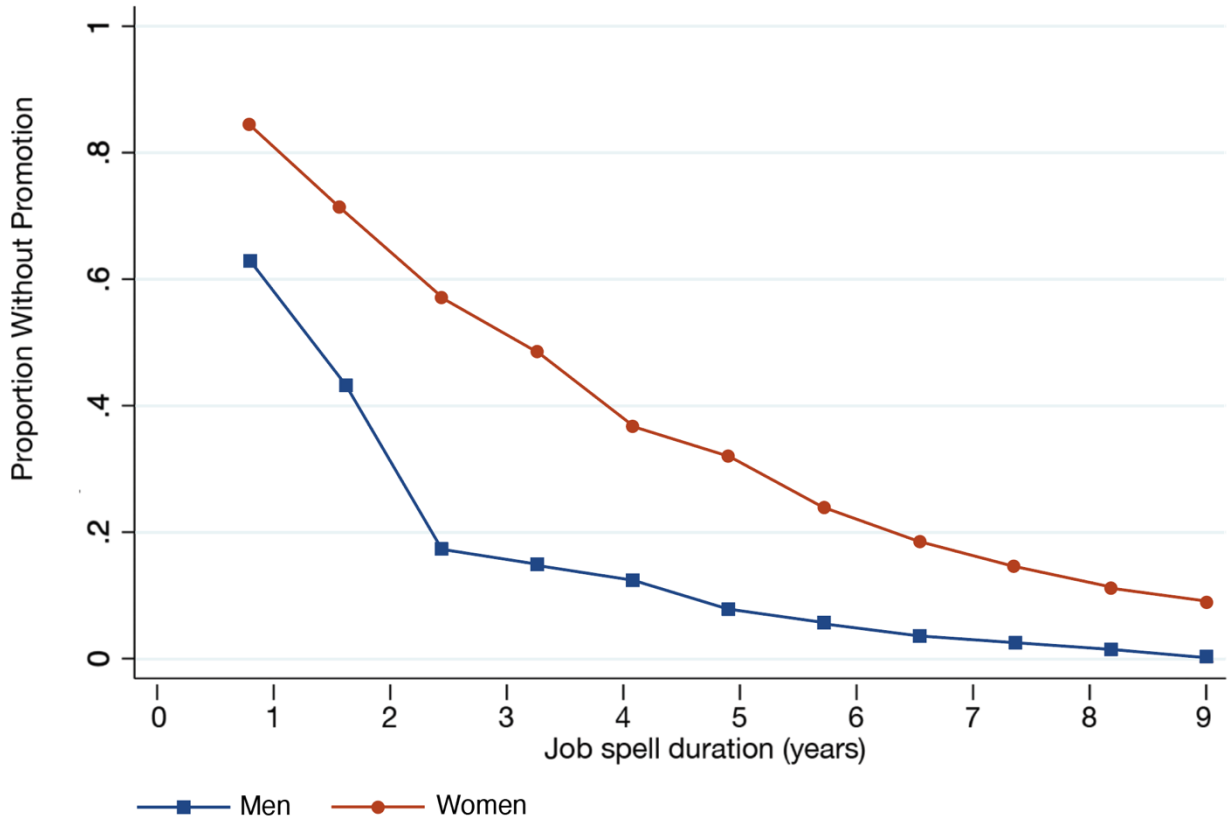
Source: LinkedIn Employment History Data

Figure 2. Number of Employer Changes in Indian Technology Sector, by Gender



Source: LinkedIn Employment History Data

Figure 3. Survival curve of promotions in the Indian technology sector by gender



Source: LinkedIn Employment History Data

Table 1. Descriptive statistics

	% of sample (N=1,591)
Age	
>25	1%
25-29	23%
30-34	69%
35-39	6%
40+	1%
Current or prior H-1B	79%
% Male	73%
Education	
Bachelor's	26%
Master's	71%
Doctorate	3%
STEM degree	84%
Any U.S. degree	67%
Top school	39%
Employment	
Average job spell length (years)	1.63
Number of reported jobs	6.89
Number of employers	5.25
Number of promotions	1.94

Source: LinkedIn Employment History Data

Table 2. Comparison of LinkedIn sample currently working in India and the U.S.

Panel A. Men

	Migrants in U.S. (N=2,777)		Return migrants in India (N=1,164)		
	Mean	SD	Mean	SD	Welch's t-test
Labor Market Experience at Most Recent Job					
Years of labor market experience	8.19	2.58	10.33	2.91	***
Number of reported jobs	4.89	1.19	6.08	1.52	***
Number of employers	3.84	1.99	5.93	1.84	***
Number of promotions	1.79	0.99	2.84	1.32	***
Median job spell length (years)	2.03	1.35	1.66	1.21	**
Educational Attainment at Most Recent Job					
Advanced degree	0.66	0.48	0.75	0.45	***
U.S. degree	0.78	0.51	0.55	0.49	***
Top school	0.51	0.48	0.46	0.42	
Legal Status					
H-1B visa (current or previous)	.71	.11	.79	.16	***

Panel B. Women

	Migrants in U.S. (N=1,027)		Return migrants in India (N=427)		
	Mean	SD	Mean	SD	Welch's t-test
Labor Market Experience at Most Recent Job					
Years of labor market experience	8.22	2.55	10.39	2.93	***
Number of reported jobs	4.91	1.20	6.11	1.50	***
Number of employers	3.88	2.00	5.87	1.84	***
Number of promotions	1.82	0.97	2.79	1.33	***
Median job spell length (years)	2.01	1.35	1.69	1.20	**
Educational Attainment at Most Recent Job					
Advanced degree	0.68	0.48	0.79	0.45	***
U.S. degree	0.81	0.51	0.51	0.49	***
Top school	0.52	0.48	0.48	0.42	
Legal Status					
H-1B visa (current or previous)	.68	.13	.80	.17	***

Source: LinkedIn Employment History Data
Note: Binary variables range in value from 0 to 1, with the mean representing the proportion of the sample coded as "1"

*** $p \leq 0.001$, **$p \leq 0.01$, * $p \leq 0.05$

Table 3.
Panel A. Logistic Regression Analysis of Determinants of Employer Change in Indian Technology Sector

	β	(SE)
Male	0.119**	(0.031)
Labor Market Experience		
Years of U.S. Labor Market Experience	0.004***	(0.002)
Years of Indian Labor Market Experience	0.002***	(0.001)
Educational attainment		
Advanced Degree	-0.005	(0.988)
U.S. Degree	0.071**	(0.044)
STEM Degree	0.029**	(0.026)
Top School	0.036*	(0.519)
Legal Status		
H-1B Visa (Prior)	0.075***	(0.032)
Constant	0.628***	(0.026)
R-squared	0.073	
N	1,591	

Panel B. Gender-stratified analysis

	Men		Women	
	β	(SE)	β	(SE)
Labor Market Experience				
Years of U.S. Labor Market Experience	0.003***	(0.001)	0.004***	(0.001)
Years of Indian Labor Market Experience	0.002***	(0.000)	0.002***	(0.000)
Educational attainment				
Advanced Degree	-0.001	(0.990)	-0.017	(0.037)
U.S. Degree	0.065**	(0.041)	0.076*	(0.042)
STEM Degree	0.030**	(0.024)	0.018*	(0.038)
Top School	0.031	(0.513)	0.112**	(0.087)
Legal Status				
H-1B Visa (Prior)	0.123***	(0.028)	0.133**	(0.048)
Constant	0.656***	(0.030)	0.657***	(0.051)
R-squared	0.041		0.055	
N	1,164		427	

*** $p \leq 0.001$, **$p \leq 0.01$, * $p \leq 0.05$

Source: LinkedIn Employment History Data

Table 4.
Panel A. Cox Regression Hazard Ratios of Promotion Risk in Indian Technology Sector

	β	(SE)
Male	1.092**	(0.162)
Labor Market Experience		
Years of U.S. Labor Market Experience	1.001*	(0.003)
Years of Indian Labor Market Experience	1.198***	(0.002)
Educational attainment		
Advanced Degree	0.955	(0.146)
U.S. Degree	0.926	(0.618)
STEM Degree	0.998	(0.020)
Top School	1.293	(0.422)
Legal Status		
H-1B Visa (Prior)	1.228	(0.209)
Observations	5,147	
Unique individuals	1,591	
Chi2	77.02	
LogL	-1269.55	

Panel B. Gender-stratified analysis

	Men		Women	
	β	(SE)	β	(SE)
Labor Market Experience				
Years of U.S. Labor Market Experience	0.996	(0.003)	1.003*	(0.005)
Years of Indian Labor Market Experience	1.234***	(0.005)	1.115***	(0.006)
Educational attainment				
Advanced Degree	0.894	(0.163)	1.325	(0.410)
U.S. Degree	0.701	(0.130)	2.914**	(1.047)
STEM Degree	0.987	(0.018)	1.219	(0.040)
Top School	0.728	(0.332)	2.674**	(1.218)
Legal Status				
H-1B Visa (Prior)	1.213	(0.243)	1.227	(0.532)
Observations	3,657		1,490	
Unique individuals	1,164		427	
Chi2	63.46		184.91	
LogL	-903.10		-2070.74	

*** $p \leq 0.001$, **$p \leq 0.01$, * $p \leq 0.05$

Source: LinkedIn Employment History Data