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How Migration Reshapes Education-Occupation (Mis-)match? A Study of the Indian Labor Market

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Abstract

The existing literature on education-occupation mismatch has uncovered the different ways an individual can face mismatch in his or her work, namely vertical and horizontal skill mismatch. Albeit the incidence of overeducation as an essential measure of vertical skill mismatch has emerged as a critical issue employment discourse across different countries world over, it would be essential to note its interaction with migration and gender, an under researched area. Therefore, the present study investigates the phenomenon of education-occupation mismatch among migrant and non-migrant workers in India, with a special focus on gender. Utilizing data from the Periodic Labor Force Survey (PLFS) 2020-21 and employing bivariate probit regression analysis we measure the likelihood of being overeducated. The variable overeducation is being constructed following the realized matching method, where we proxied the educational attainment by the number of years of formal schooling, and the required education is estimated using the mean and one standard deviation of educational levels within 3-digit occupational codes based on NCO-2004. Our analysis reveals critical insights into whether migration mitigates skill mismatch, accounting for worker heterogeneity. The results suggest that though migration in general helped mitigate overeducation, it increased the mismatch for female-migrants. Furthermore, individuals with vocational and technical education were found to reduce the likelihood of mismatch, compared to those with general education alone. It underscores the need for policies that align the supply of educated workforces with evolving labor market demand to minimize education-occupation mismatches and better harness the country's present phase of demographic dividend.

Keywords: *Migration, Overeducation, female migrants, education-employment mismatch, Indian labor market*

JEL Classification: J6, J24, J20

1. Introduction

"Educated workers enjoy at least three basic advantages over less educated workers in the labor market: higher wages, greater upward mobility in income and occupation, and greater employment stability" (Mincer, 1991). However, this benefit does not accrue to an individual if the supply of education qualification does not align with the requirement of a job, leading to education-occupation mismatch. The extant literature (Chowdury, 2014; Bahl & Sharma, 2021; 2023, Gooptu et al., 2023) have highlighted the issue of overeducation, where the educational qualification or the skill of an individual exceeds the requirements of the job, resulting in diminished expected returns from education. It not just leads to wage penalty, and inefficient use of human resources, but also the dissatisfaction that comes with it. The incidence of overeducation, has emerged as a critical issue in India's employment discourse. Albeit, the issue is discussed round the world, it would be interesting to note its interaction with migration and gender, an under researched area in academia.

Migration, both internal and international, is a powerful labor market adjustment mechanism. It allows individuals to relocate in search of better employment opportunities, better living standards, thereby facilitating structural transformation (Mundell, 1957; Heckscher & Ohlin, 1991; Srivastava, 2011). However, not all labor mobility guarantee employment commensurate with skills or education with urban India projected to host around 607 million people by 2030 and out of which migration is expected to contribute nearly 40 per cent to urban growth (United Nation, 2019). These dynamics is further altered once a gender lens is adopted to view the issues. While better occupation is put forward as the major nudge to migrate, the case may be very different for male and female. The PLFS 2020-21 reports that while male migration is largely driven by employment-related reasons, over 43per cent, while women migrate excessively due to marriage, nearly 87 per cent. This gendered nature of migration is far-reaching.

Women migrants are less likely to participate in the labor market and more prone to underutilization of education due to cultural norms, caregiving responsibilities, and informal employment arrangements (Srivastava, 2020). This raises concerns about both labor force participation and the quality of employment for migrant women. India's labor market is segmented across lines of gender, social groups, and geographical regions, leading to unequal access jobs, particularly formal jobs. While overall migration has risen modestly from 26.8per cent to 28.9 per cent in the last two decades (2001-2021), it has been not benefiting females'

migrants showing divergent trends (India employment report, 2024). Skill mismatch among migrants reflects the deeper demand-supply disjunction in India's labor market. On the supply side, factors like education inflation, low employability, and gendered social norms limit productive employment. On the demand side, mechanization, the shift to capital-intensive production, and declining labor demand in agriculture and household industries shrink employment opportunities especially for women (Lahoti & Swaminathan, 2013; Kapsos et al., 2014; Klasen, & Pieters, 2015; Afridi, Dinkelman, & Mahajan, 2018; Deshpande & Singh, 2021). These intersecting forces reinforce one another, leading to both low labor force participation and widespread overeducation among those employed.

Overeducation, when an individual possesses more education than required for their job, is not just a labor market anomaly; it reflects a misallocation of human capital. As Frank (1978) conceptualized, overqualified workers receive the same wages as exactly qualified workers, implying a wage penalty and no return on surplus education. Empirical studies (Rumberger, 1987) confirm that overeducation lowers job satisfaction, reduces returns to education, and leads to inefficient employment matching. In India, this problem is exacerbated by poor-quality education, lack of vocational training, and regional disparities in economic development. As Gooptu et al. (2023) and Bahl & Sharma (2023) argue, mismatches are particularly acute in manufacturing hubs and among male migrants who are more likely to experience the "bumping down" effect-where overeducated individuals crowd out those with lower but adequate qualifications. This cascade results in a deadweight loss of years invested in education and rising joblessness among even adequately qualified youth.

A distinctive contribution of this paper lies in its use of the latest unit-level migration data from PLFS 2020–21, to particularly track gender differences in the issue of overeducation among migrant and non-migrant workers in India. The data collection period overlaps with the COVID-19 pandemic, but to ensure analytical clarity, we explicitly account for pandemic-induced distortions by carefully netting out the effects of COVID-related and return migration from our sample. These adjustments allow us to examine structural patterns of mismatch that are not solely driven by temporary shocks.

The rest of the paper is organized into the following sections: section 2 outlines the related literature, followed by methodology section 3. Description of the database is provided in section 4, while the results of descriptive and empirical analyses have been provided in sections 5 and 6, respectively. Our last section 7 brings out the conclusion and policy implications.

2. Education-Occupation mismatch and related literature

Skill-occupation mismatch has emerged as a critical area of inquiry, attracting researchers globally and within India. This review synthesizes seminal studies, categorized into international and national (Indian) research, to trace the progression of understanding regarding education-occupation mismatch (EOM), overeducation, and undereducation.

2.1. International Evidence on Education–Occupation Mismatch and Migration

The phenomenon of education–occupation mismatch, particularly among migrants, has been widely explored across different global labor markets. One of the earlier theoretical foundations explaining overeducation is rooted in Thurow's Job Competition Model (1975), which posits that employers use education as a screening mechanism, often hiring the most educated candidates irrespective of job requirements. This results in the underutilization of human capital and contributes to overeducation. Building on this foundation, Velden and Allen (2001) examine how mismatches not only influence wages but also affect occupational choice, job satisfaction, and labor turnover. Their findings reveal that the wage penalty associated with overeducation is typically more substantial than the wage penalty for undereducation, underscoring the economic inefficiency of surplus schooling. Kalter & Kogan (2006) explores mismatch in a cross-country context, specifically analyzing how educational mismatch in the country-of-origin shapes migrants' mismatch outcomes in host countries like Australia. His study finds a strong path dependency: migrants who experienced mismatch before migrating is more likely to remain mismatched in the host labor market. In a related contribution, Chiswick and Miller (2009) highlight the role of pre-migration job experience in explaining mismatch patterns among immigrants. Their study shows that job experience in the home country significantly influences occupational placement abroad, especially among those with non-transferable or informal credentials. Klaveren and Tijdens (2011), using data from 13 European countries, argue that education mismatch is more prevalent among migrant workers than natives. Their study distinguishes between undereducation often tied to informal or experiential skills-and overeducation, which reflects a lack of suitable job opportunities matching formal qualifications. Supervisory roles and job-specific tasks requiring tacit skills also explain some forms of undereducation. A more recent contribution by Pivovarova and Powers (2022) examines the incidence and structure of education-job mismatch across immigrant generations in the United States using PIAAC data (2012-2014). Their findings suggest that first-generation immigrants are significantly more likely to be mismatched both

overeducated (27 per cent) and undereducated (39 per cent) compared to native-born workers (16 per cent and 24 per cent respectively). These results reaffirm the salience of human capital theory in explaining migrant mismatch, with race, language proficiency, and generational status acting as significant mediators.

2.2. Indian Evidence on Skill Mismatch and Migration

In the Indian context, the literature points to a complex interplay between structural constraints, labor migration, and employment mismatch. Sarkar (2019) studies male labor migrants from Bihar using NSSO 2007-08 data. His analysis highlights how migration flows from underdeveloped states (like Bihar) to economically advanced states (such as Maharashtra, Delhi, and Gujarat) do not necessarily result in better occupational outcomes. Many migrants end up in low-skilled employment due to mismatch, revealing the paradox of migrating for opportunity but encountering poor job alignment. Chowdhury (2014) identifies the simultaneous existence of employability gaps and skill shortages, which create allocative inefficiencies in India's labor market. He argues that the underutilization of educated women in particular reflects a severe disconnect between the supply of education and the demand for job-relevant skills, resulting in joblessness, productivity losses, and income disparities. A detailed empirical analysis by Bahl and Sharma (2021), using NSS 2011-12 data, estimates the wage penalty for overeducation in India at around 7 per cent. Their study finds no earnings reward for undereducation, and they emphasize that overeducated workers earn significantly less than their well-matched peers despite having higher levels of schooling. Expanding on this, Gooptu et al. (2023) analyze three rounds of PLFS data (2017-18 to 2019-20) and find widespread overeducation across Indian states, particularly in industrial hubs. The study warns of the "bumping down" effect, where more educated individuals occupy jobs meant for less educated workers, displacing the latter and exacerbating mismatch. Despite rising vocational training participation, the supply of skilled labor continues to outpace demand, reflecting ineffective coordination between the education and employment sectors. Bahl and Sharma (2023) further examine the heterogeneity of migrant experiences in relation to mismatch using PLFS data. Their analysis shows that internal migrants who secure employment before migrating earn higher returns to education-both required and surplus-than those who migrate and search afterward. They also find that females and higher-educated individuals face sharper wage penalties for educational deficits. Finally, Sengupta (2017) emphasizes the importance of investing in generic soft skills and modernizing India's vocational and technical training

ecosystem. He argues that bridging the skills gap requires alignment between training systems and labor market needs, particularly for women and youth.

The reviewed studies offer rich evidence that skill mismatch-particularly overeducation-remains a pressing challenge in both global and Indian labor markets. The evidence further underscores that migration, while often undertaken to secure better employment, does not uniformly alleviate mismatch-especially for women and marginalized groups in India. This necessitates integrated policy approaches that bridge supply and demand gaps while accounting for regional, social, and gender disparities in labor market participation.

3. Methodology

3.1 Methodology on Overeducation

The literature on Education-Occupation Mismatch has uncovered the diverse ways an individual can face mismatch in his or her work, namely vertical and horizontal skill mismatch. This paper focuses on vertical skill mismatch using over-education to define how an individual's education level far exceeds the requirement level of his or her job. The study focuses on only those with formal education, and education level is determined by the number of years spent on formal education, instead of general education level. This helps in eliminating any assumption of treating two people with same level of general education but different years of attainment as the same.

Literature on skill mismatch elucidates different methods to capture the element. Three of the most applied methods are Job-Analysis (JA), Workers' Self-Assessment (WA) and Realized Matching (RM). While the JA method consists of industry experts or employers defining the required skills for a particular occupation, it is more expensive and time-consuming to collect the data, and it has the potential risk of biasness. The WA method is equally time-consuming and has the risk of workers assessing their skills as adequate or even over-qualified for self-esteem. Studies by (Duncan & Hoffman ,1981; Hartog & Tsang,1987; Sicherman ,1991) have used the WA method for analysis. However, the question on educational requirement to 'get' a job opposed to the educational requirement to 'perform' a job, makes a difference. The respondents' perception is a crucial factor in this case (Hartog, 2000). For this paper, RM method proves to be compatible with the given data. The RM method defines the ranges within which a person is adequately educated, or over and under educated, using statistics like mean

and standard deviation. One notable example by Verdugo and Verdugo (1989) using standard deviation for analysis of over-education shows the importance of the tails in normal distribution, and how RM methods usually produce symmetry in these distributions.

The paper defines over-qualified or over-educated, under-educated and adequately educated on the following terms-

i. Over-Educated if Ei > Mean + S.D.
ii. Non-Over-Educated if Ei < Mean + S.D (which includes under-educated and adequately educated).

Here, Mean and Standard Deviation of the education levels of all the workers (aged 15 to 59) of each occupation is calculated, and the range of required education (Mean + S.D.) is thus derived for each occupation. Ei denotes the number of years of schooling of i^{th} individual.

The RM method can be used taking the central tendency measure as mode instead of mean. Although, mean is more affected by outliers in a distribution, the risk of a multi-modal distribution is more. Studies using mode as the preferred central tendency measure also have the requirement to ensure additional criterion, to minimize the errors of measurement. A strict criterion of, say, modal number of years of schooling shared by 60% can be undertaken but, if the incidence of over (or under) education be greater than 60%, the practicality of such a scenario is difficult to assert. The mode method is likely to generate exaggerated results depending on equilibrium outcomes in the market, even if there is no change in the job market or production technology.

Another methodology proposed by (Unni ,2016) is a screening test to sort out the proportion of over-educated people in a field of work. Albeit the focus of the paper was on tertiary education, and it was categorized into different levels of Higher Education- namely, graduate and non-graduates, and technical and non-technical education. Furthermore, different lines of occupations were then classified by their level of graduate-intensity. The screening took place by showcasing the share of graduates with non-technical educational degrees in non-graduate-intensity jobs, which was concluded as over-education in the respective field. However, even as the screening method is beneficial in this approach, it is concerned only with tertiary education and applicable in ruling out jobs where degree of education is either clearly or vaguely defined. However, this paper is inclusive of all fields of occupation (following 3-digit NCO 2004 code structure) and the RM method is applicable even in jobs that do not define a

required educational degree. The RM method has been applied in several contemporary studies as well (Kukreja ,2018; Bahl & Sharma, 2021,2023).

3.2 Econometric estimation

The present study investigates the phenomenon of overeducation among migrants and non-migrants in India, specifically examining how does how being a male and female impacts the incidence of overeducation. It is important to make a note that the relationship between our dependent variable 'overeducation' and our key explanatory variables 'migration' is not exogenous. There are several unobserved factors that have an impact on the variables like-motivation, family needs, migration network, determination, risk factors, and so on, making the two separate binary dependent outcomes to be determined jointly, with their error terms correlated. To address this issue, an instrumental variable technique has been used for the analysis. It helps in examining the causal effect of 'being a migrant or a non-migrant' on the 'likelihood of overeducation'.

Following is our binary response model for examining this causality:

$$\text{Overedu}_i^* = \alpha_0 + \alpha_1 \text{Mig}_i + \beta` X_i + u_i$$

Here, overeducation is a latent variable which is not observed directly.

$$\text{We observe: Overedu} * = \begin{cases} 1 \ , if \ \text{Overedu} > 0 \\ 0 \ , if \ \text{Overedu} \leq 0 \end{cases}$$

X_i is a vector of the control variables like age, sex, caste, religion, caste, and so on, and u_i is the error term capturing the unobserved factors affecting the likelihood of overeducation. But the error term u_i is correlated with the error term υ_i.

$$\text{Cov}\ (u_i, \upsilon_i) \neq 0 = \rho$$

If we ignore the potential endogeneity issue in equation (1), and run simple probit model our results will be misleading. Moreover, for the issue of estimating the impact of binary endogenous covariates on the binary response model, existing studies generally use the bivariate probit model or a seemingly unrelated bivariate probit model (Bairagya et al, 2021). In our study, the endogenous covariate is the migration variable. The following equation helps determine migration:

$$\text{Mig}_i^* = \gamma_0 + \gamma_1 Z_i + \lambda Y_i + \upsilon_i$$

Mig_i is a binary indicator (1=migrant and 0= non-migrant) and a latent variable.

$$\text{we observe: } \text{Mig} * = \begin{cases} 1 \ , if \ \text{Mig} \ > 0 \\ 0 \ , if \ \text{Mig} \ < 0 \end{cases}$$

The decision to be a migrant or non-migrant is regressed on (Z_i), $_{which}$ is instrument variable (lagged district-level migration rate from NSSO 2007-08), along with the exogenous variables denoted by its vector ($Y_{i.}$). The lagged migration rate affects the rate is used as an instrument variable for our study because two reasons (i) temporal relevance that it is a lagged variable and (ii) it helps mitigating endogeneity as it affects the rate of migration in the current year but not the likelihood of overeducation. Past migration rate signals the potential migrant of the presence of a network and that the destination is attractive. This is referred to as 'herd effect' in the literature (Calvo-Armengol and Zenou,2005).

4. Database

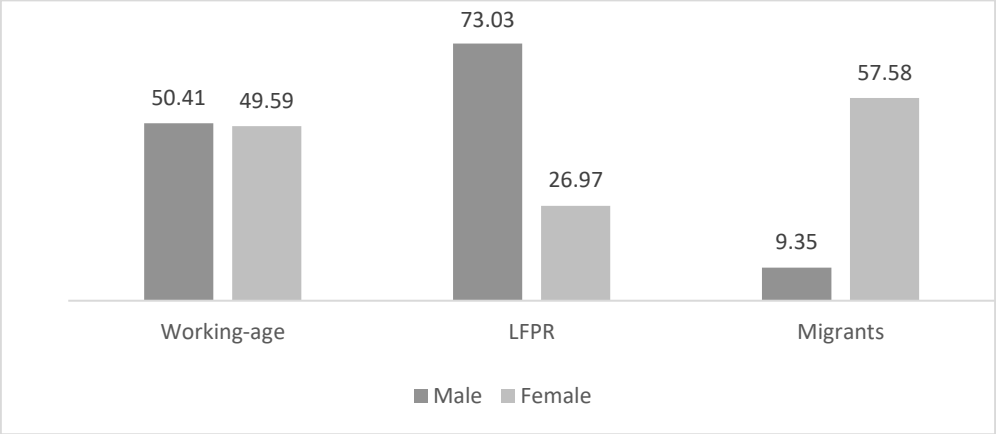
This study utilizes data from the Periodic Labor Force Survey (PLFS) conducted by the National Sample Survey Office (NSSO) for the period June 2020 to July 2021. The PLFS 2020-21 is a nationally representative survey covering the entire Indian Union, except for inaccessible villages in the Andaman and Nicobar Islands, and includes 100,344 households (55,389 rural and 44,955 urban) and 410,818 individuals. This dataset is selected as it provides the most comprehensive and recent unit-level information on migration, capturing demographic profiles, employment details, and both past and present occupational statuses of migrants. The total number of migrants is 113,998, but for our study we have considered only those who have not migrated directly in response to pandemic. The data collection period overlaps with the COVID-19 pandemic, but to ensure analytical clarity, we explicitly account for pandemic-induced distortions by carefully netting out the effects of COVID-related and return migration from our sample. These adjustments allow us to examine structural patterns of mismatch that are not solely driven by temporary shocks. So, after careful accounting, we could carefully, net out 14,998 migrants, and we proceed for our analysis with 99,000 migrants. We have studied mismatches only for the working population aged 15 to 59 years. The study employs the usual principal activity status, defined as the activity on which an individual spent the majority of their time during the 365 days preceding the survey date (PLFS, 2021). This definition ensures a robust assessment of labor market engagement, critical for analyzing education-occupation mismatch.

5. Descriptive Analysis for Overeducation

Figure 1 provides a compelling starting point for our discussion. It clearly brings out the stark gender gap in India, which registers high growth rates in the last two decades.

We note that the labor force participation rates of male (73 per cent) are nearly three times higher than females (27 per cent), despite both having an almost equal share of the working-age population. While existing literature are abundant that addresses supply- and demand-side explanation to this puzzling low female labor force participation, our study attempts to explore how migration intersects gender to shape such inequality. We take our discussion further in exploring the education-occupation mismatch among the migrants and non-migrants men and women workers in India.

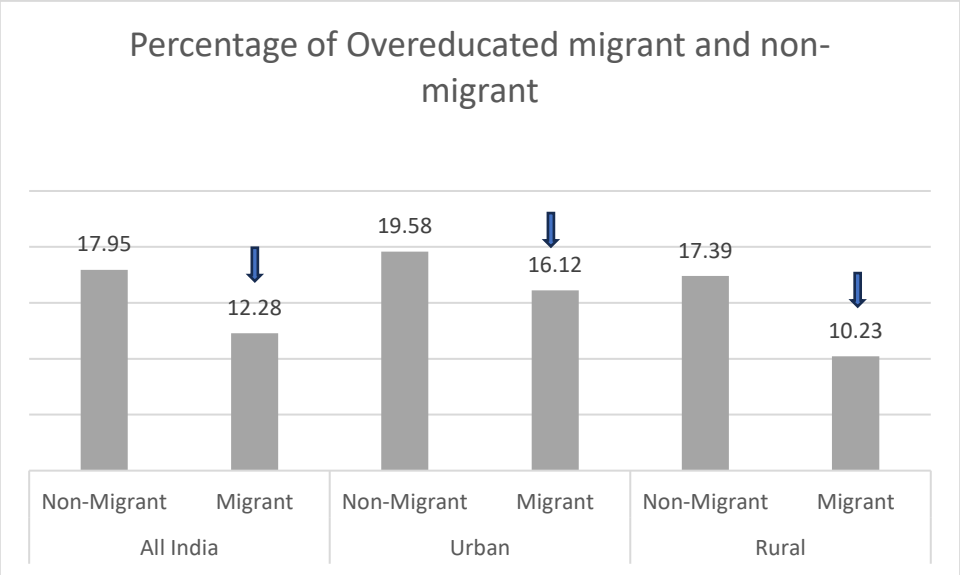
Figure 1: Labor force participation rate and migration by gender and working age (15-59 years)



Source: Author's computation using PLFS 2020-21
Note: Given the fact that data on the employment status of migrants are only based on their principal status, we calculated LFPR by considering the principal work status of working-age men and women.

Figure 2 reveals two key insights. First, it shows how the incidence of overeducation varies across sectors in India. Second, it compares overeducation rates between migrants and non-migrants. Notably, across all levels-rural, urban, and all-India-the rate of overeducation is consistently lower among migrants than non-migrants. This aligns well with the core hypothesis of the Harris-Todaro migration model, which puts forward that individuals migrate in pursuit of better employment opportunities. In this context, migration appears to function as a labor market equalizer, helping workers better match their skills to job requirements.

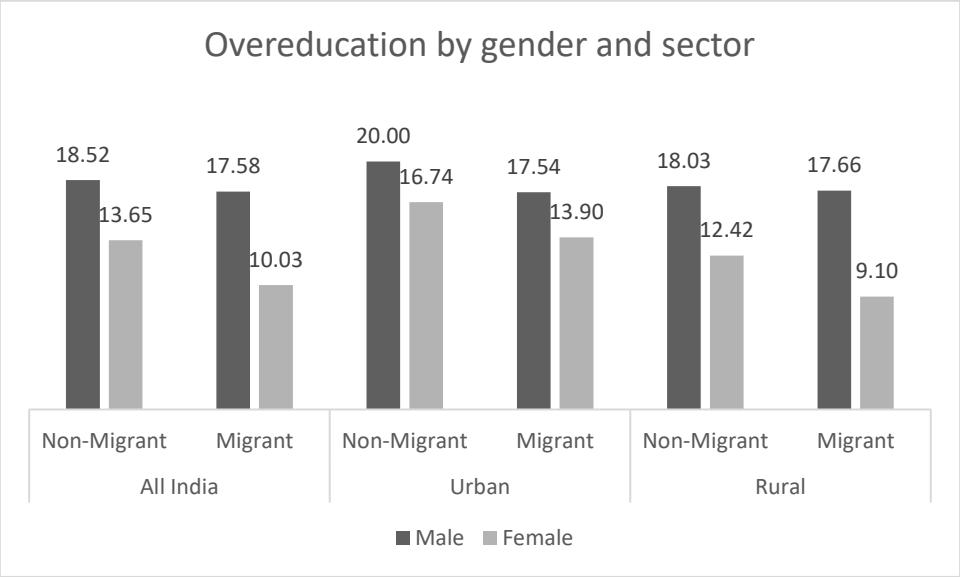
Figure 2: Education and Occupation (mis-)match for migrant and non-migrant workers in the working-age group (15-59 years): By Rural, Urban and All India.



Source: Author's computation based on PLFS 2020-2021

Migration and Overeducation: Through gender lens

Figure 3: Education and Occupation (mis-)match for migrant and non-migrant workers in the working-age group (15-59 years): By gender and sector



Source: Author's computation based on PLFS 2020-2021

Figure 3 presents the gender-wise and sector-wise breakdown of overeducation incidence among migrants and non-migrants. It is evident that migration reduces the incidence of

overeducation for both male and female. But when compared between males and females, a low overeducation is recorded among both female migrants and non-migrants. However, such low overeducation in case of female workers is not a correct indicator of better job matching for women. The results will differ once we control for the endogeneity issues under our empirical analysis.

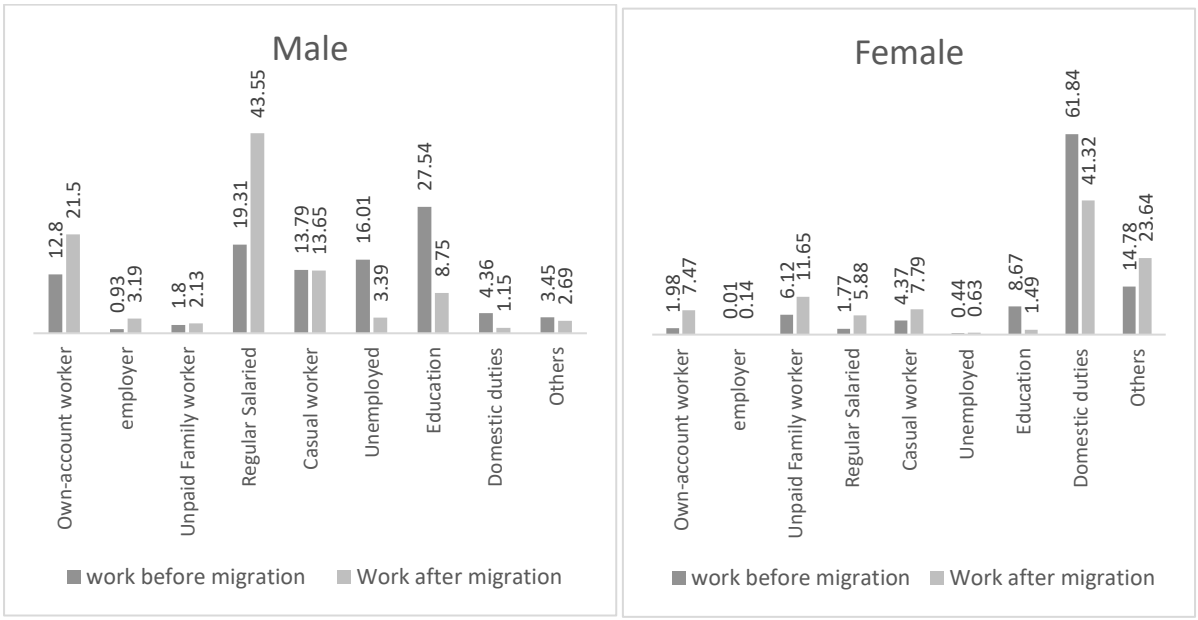
Employment status and migration

The PLFS 2020-21 data reveal distinct shifts in principal activity status before and after migration for male and female workers aged 15-59 years, highlighting gendered labor market dynamics in India. As per fig 4, for male migrants, there is a marked increase in regular salaried employment, own-account work, and employer roles post-migration, with notable reductions in education, unemployment, and domestic duties. Casual work remains stable. For female migrants, domestic duties and education decline significantly, while own-account work, unpaid family work, regular salaried employment, and casual work increase. A substantial proportion of women shift to "other" activities, potentially non-labor market roles, with a slight rise in unemployment. These trends suggest migration enhances labor market engagement, but males predominantly access formal roles, while females often transition to informal or non-market activities, reflecting marriage-driven migration constraints (PLFS, 2021; Chowdhury, 2014).

These shifts explain earlier EOM findings, where male migrants showed lower overeducation and higher adequate matching, driven by transitions to salaried roles that align with qualifications. Female migrants' higher undereducation, particularly in rural areas, corresponds to their shift to informal work, as marriage-driven migration limits skill-appropriate job access (Bahl & Sharma, 2023). Males benefit from formal employment, reducing overeducation, while females' informal roles increase undereducation, exacerbating economic disparities (Global Gender Gap Index, 2025). Migration acts as a partial equalizer for males, aligning with the Harris-Todaro (1970) framework, but its benefits are less pronounced for females due to non-employment-driven migration. This aligns with Sarkar (2019), who found that male migrants often secure urban jobs, albeit sometimes low-skilled, while women face constraints in accessing formal employment. The high pre-migration engagement in education for both genders and its decline post-migration suggest that many young migrants enter the labor market prematurely, contributing to mismatch. This underscores the need for enhanced vocational training, as advocated by Sengupta (2017), to align skills with market demands. The "bumping

down" effect, where overeducated workers displace less educated ones, further highlights economic inefficiencies (Gooptu et al., 2023).

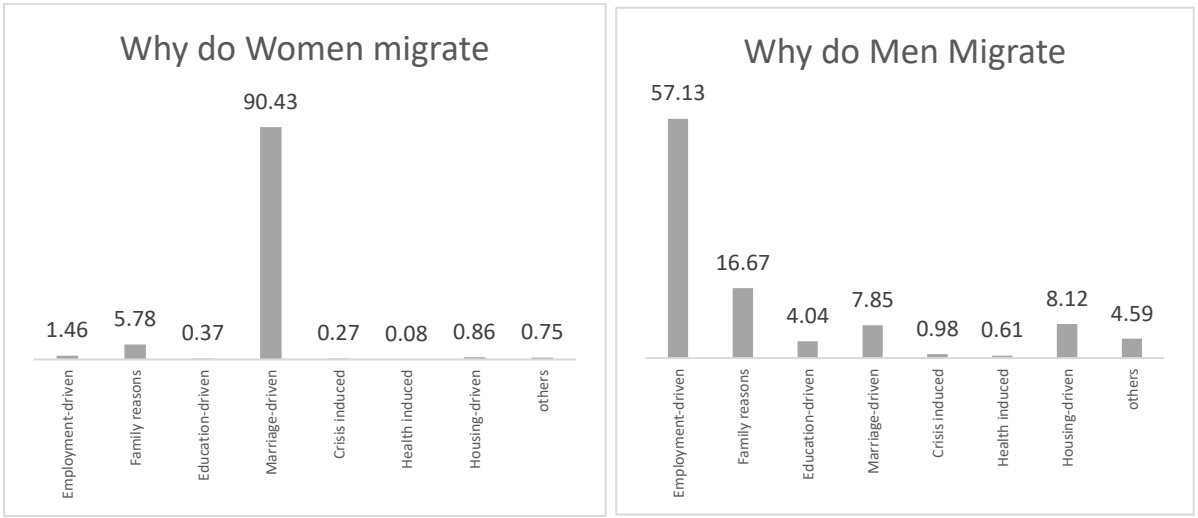
Fig 4: Descriptive Analysis of Principal Activity Status Before and After Migration for the age group (15-59 years)



Source: Author's computation based on PLFS 2020-2021

Reasons for Migration

Fig 5: Reasons for migration by gender for the age group (15-59 years)



Source: Author's computation based on PLFS 2020-2021

The figure 5, clearly illustrates that migration for men is predominantly employment-driven, while women migrate overwhelmingly due to marriage, with starkly contrasting implications for their labor market integration, and likelihood of skill mismatch. 57.13% of male migrants moved for employment-related reasons compared to only 1.46% of females. An overwhelming 90.43% of female migrants move due to marriage compared to only 7.85% of males. This reflects the patriarchal social structure in India, where women's mobility is largely tied to familial or spousal decisions, rather than individual employment aspirations. As documented by Deshingkar & Akter (2009) and the India Employment Report (2024), women are often secondary migrants with limited agency, migrating with or to join their husband post-marriage, which significantly reduces their probability of labor force participation. This form of migration rarely leads to meaningful employment outcomes and increases the likelihood of undereducation or occupational downgrading, due to constrained mobility, time poverty from domestic work, and weak access to job networks (Chowdhury, 2014; ILO, 2016). Education-motivated migration is negligible for both sexes, though slightly higher for males (4.04%) than females (0.37%). This reflects structural constraints on female educational mobility. Velden & Allen (2001) stress that undereducation often arises from such constrained access to educational pathways, especially for women from rural or conservative backgrounds. The gender gap in employment-driven migration is pivotal in explaining why women face lower labor force participation (LFPR) and higher undereducation. As highlighted by Verick (2018) and Srivastava & Bhaskar (2020), women who migrate due to marriage or caregiving often lack access to employment networks, and when they work, they settle for flexible, informal roles, despite possessing education that could justify formal jobs. This creates a pattern of educational underutilization (Chiswick & Miller, 2009) and long-term skill depreciation. This gendered migration logic reinforces occupational segregation, low female LFPR, and mismatches in skills and employment.

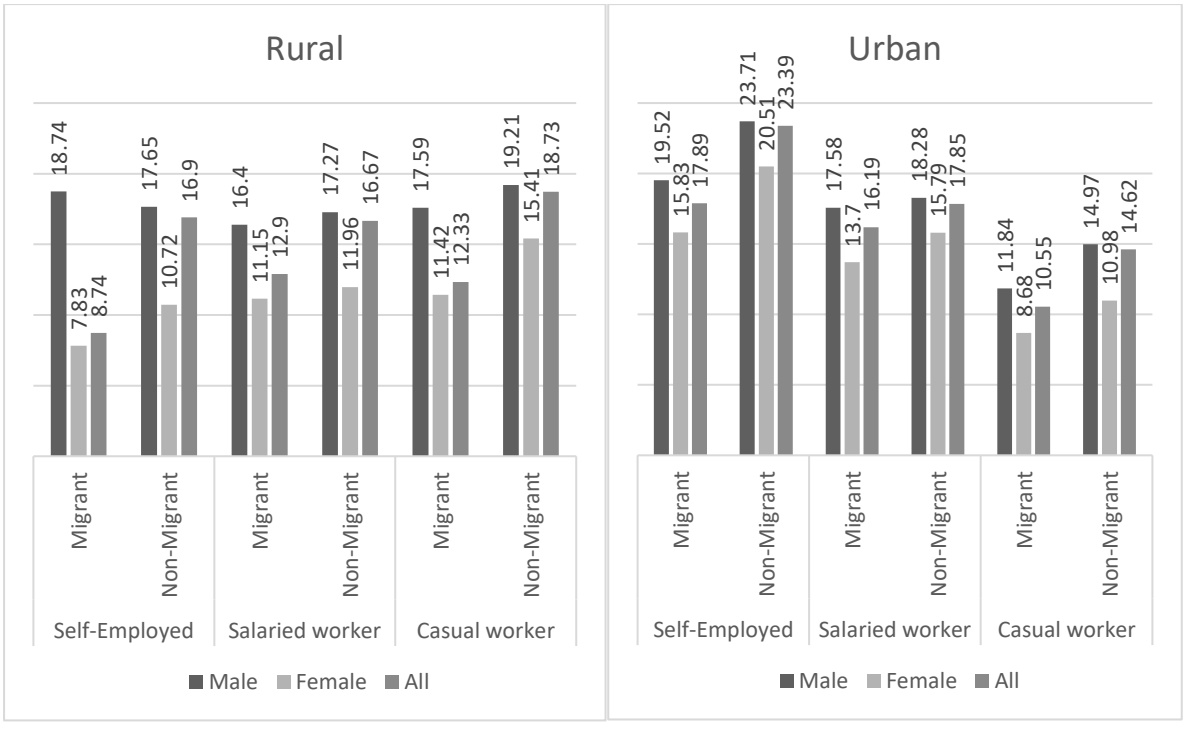
Migration and Overeducation: Across Self-employed, salaries workers and Casual workers

Figure 6 below presents a nuanced picture of overeducation segmented by employment status; self-employed, salaried, and casual across migrant and non-migrant workers in both rural and urban India. Several patterns emerge that reflect the structural segmentation of India’s labor market.

In rural areas, overeducation among non-migrant salaried and casual workers is markedly higher than that among migrants. This aligns with existing literature suggesting that non-migrant workers often lack mobility to optimize job-skill alignment, especially in less dynamic rural labor markets (Sarkar, 2019). Interestingly, migrant women in rural areas report lower overeducation across all employment types, particularly in casual and self-employment, suggesting that marriage-driven migration and informal nature of work may be associated with educational underutilization rather than surplus; a hypothesis supported by findings from PLFS 2020–21 and India Employment Report 2024.

In contrast, urban non-migrants-especially males, exhibit higher overeducation in self-employment and salaried categories, reflecting a saturation of educated workers in formal urban markets and increasing educational attainment outpacing demand for skilled jobs (Gooptu et al., 2023). For urban migrant women, the overeducation rate is lower across employment types, indicating a dual effect of migration constraints and occupational flexibility, women are likely selecting into roles that accommodate household responsibilities, even if misaligned with their qualifications (Chowdhury, 2014; Bahl & Sharma, 2023).

Fig 6: Reasons for migration by gender for the age group (15-59 years)



Source: Author's computation based on PLFS 2020-2021

Overall, casual work shows the highest overeducation among non-migrant women in both sectors, underscoring the structural barriers and informality faced by women in the labor market. Conversely, self-employment among migrants, both rural and urban, exhibits the least overeducation, suggesting that self-employment may act as an absorptive buffer, especially for educated migrants unable to secure formal jobs that match their skills.

These patterns reinforce the dual reality of India's labor market: while migration may serve as a mechanism for reducing overeducation among men, it often translates into educational underutilization or informal employment among women, due to gendered motivations for migration (primarily marriage) and a lack of supportive infrastructure for labor market inclusion (Srivastava & Bhaskar, 2020).

Migration and Overeducation: Heterogeneity across Caste

Caste remains a fundamental axis of labor market segmentation in India, shaping access to education, occupational outcomes, and the very experience of migration. Structural disadvantages faced by Scheduled Castes (SCs), Scheduled Tribes (STs), and Other Backward Classes (OBCs) contribute to persistent educational inequalities, occupational immobility, and skill mismatches (Deshpande,2011; Thorat & Newman, 2012). Hence, examining overeducation through the lens of caste and migration is critical to understanding labor market inefficiencies in a stratified society like India.

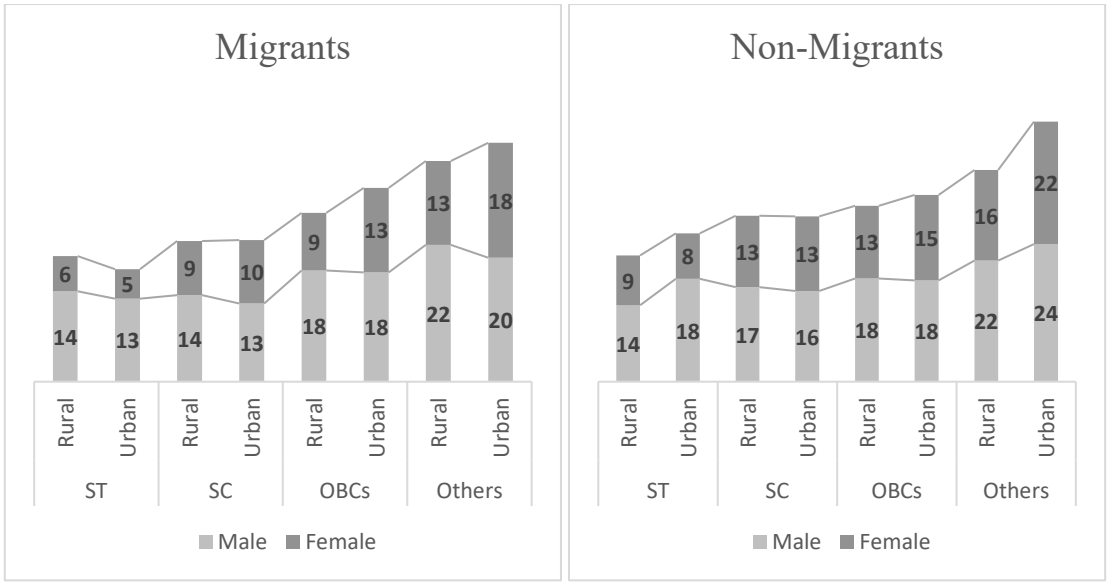
The data in fig 7, on overeducation among migrants and non-migrants by caste and gender offer compelling insights. Among migrants, male overeducation is consistently higher than that of females across all caste groups, with the widest gender gap observed in the 'Others' category in both rural and urban areas. This reflects that upper-caste men, despite their educational advantages and mobility, often accept jobs below their qualification levels, likely due to urban job saturation or high competition (Kannan & Raveendran, 2012). Interestingly, overeducation among ST and SC migrants is relatively low and stable across rural-urban while female rates remain modest, potentially pointing to limited participation in formal or skill-intensive sectors despite migration.

Among non-migrants, overeducation is significantly higher across caste groups compared to migrants. Urban ‘Others’ non-migrants exhibit the highest mismatch, suggesting that migration may help reduce overeducation- particularly for upper-caste individuals who possess greater

social capital and access to better job networks (Munshi & Rosenzweig, 2006). For OBC and SC women, however, overeducation levels remain similar regardless of migration status, reflecting limited occupational mobility and higher likelihood of informal, low-matching jobs. This points to both caste-based occupational segregation and the persistence of gendered care responsibilities that restrict women's job-seeking behavior and location flexibility (Neetha, 2014; IHD, 2020).

These findings reinforce the argument that migration, though potentially equalizing, does not automatically translate into better employment outcomes for all. Social capital, caste, gender, and location intersect to shape the effectiveness of migration as a labor market strategy. Thus, affirmative employment policies, such as targeted skilling, anti-discrimination enforcement, and job placement support, are necessary to bridge caste-based gaps in skill utilization (Jodhka & Newman, 2010). Furthermore, urban labor markets need to become more inclusive and responsive to the educational profiles of historically marginalized groups to prevent overeducation from becoming a structural norm.

Fig 7: Overeducation among male and female migrants and non-migrants by Caste, for the age group (15-59 years)



Source: Author's computation based on PLFS 2020-2021

6. Econometric Analysis

We have used both probit and bivariate probit regression analysis techniques for our study. We begin our estimation with a probit regression model, to see the association between overeducation and migration, with other control variables. We estimate four specifications to unpack the heterogeneity, including being a migrant, a female migrant, work-related migrants and work-related female migrants. Since the probit estimates are not directly interpretable, we follow a marginal effect estimation for all our specifications. The table below discusses the results of probit estimates.

Table1: Probit estimates for determining the likelihood of overeducation among working-age (15-59 years) migrants and non-migrants in India.

	Probit Estimates (Marginal Effect)			
	Specification-I	Specification-II	Specification-III	Specification-IV
Explanatory Variables:				
Migrants	-0.015 ***	-0.025 ***		
	(0.004)	(0.005)		
Female migrants		0.026 ***		
		(0.007)		
work-related migration			-0.018 ***	-0.014 ***
			(0.003)	(0.003)
work-related female migrants				-0.034 ***
				(0.007)
age	-0.005 ***	-0.005 ***	-0.005 ***	-0.005 ***
	(0.001)	(0.001)	(0.001)	(0.001)
age square	0.0003 ***	0.00004 ***	0.00004 ***	0.00004 ***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Household size	0.002 ***	0.002 ***	0.002 ***	0.002 ***
	(0.001)	(0.001)	(0.0004)	(0.0004)
female	-0.004	-0.026 ***	-0.021 ***	-0.019 ***
	(0.003)	(0.007)	(0.002)	(0.002)
ST	-0.014 ***	-0.013 ***	-0.014 ***	-0.014 ***
	(0.004)	(0.004)	(0.002)	(0.002)
SC	0.013 ***	0.013 ***	0.023 ***	0.024 ***
	(0.004)	(0.004)	(0.002)	(0.002)
Minorities	-0.005	-0.005	-0.018 ***	-0.018 ***
	(0.004)	(0.004)	(0.002)	(0.002)
Urban	-0.062 ***	-0.06 ***	-0.068 ***	-0.068 ***
	(0.003)	(0.003)	(0.002)	(0.002)
Married	0.021 ***	0.021 ***	0.018 ***	0.018 ***

	(0.004)	(0.004)	(0.002)	(0.002)
Divorced/widowed/separated	0.019 **	0.021 **	0.027 ***	0.027 ***
	(0.009)	(0.009)	(0.006)	(0.006)
Secondary education	0.313 ***	0.313 ***	0.316 ***	0.316 ***
	(0.009)	(0.009)	(0.005)	(0.005)
Higher secondary education	0.607 ***	0.607 ***	0.626 ***	0.627 ***
	(0.01)	(0.01)	(0.004)	(0.004)
Graduation & above	0.584 ***	0.585 ***	0.67 ***	0.671 ***
	(0.009)	(0.009)	(0.004)	(0.004)
Vocational Training	-0.009 ***	-0.009 ***	-0.009 ***	-0.009 ***
	(0.003)	(0.003)	(0.002)	(0.002)
Technical Education	-0.016 ***	-0.016 ***	-0.032 ***	-0.031 *
	(0.004)	(0.004)	(0.002)	(0.002)
Developed States	0.005	0.006	-0.01 *	-0.011 ***
	(0.009)	(0.009)	(0.005)	(0.005)
Developing states	0.026 ***	0.027 ***	0.018 ***	0.017 ***
	(0.003)	(0.003)	(0.002)	(0.002)
Observations	39,051	39,051	1,40,328	1,40,328

Source: Authors' estimation using Periodic Labor Force Survey (PLFS) data for 2020–20.

Note: Overeducation is our dependent variable.

Note: *** and * indicate 1 per cent and 10 per cent levels of statistical significance, respectively. Robust standard errors are reported in parentheses. The different specifications are used to check the robustness of the results of the regression model.

Table 1 clearly presents heterogeneity arising from gender and motive to migrate, again by gender, in the likelihood of overeducation. It is observed that migrants are less likely to be overeducated than non-migrants (reference category). The results are in line with migration theories, Lewis and Harris Todaro (1970), that states better employment and wages as the very purpose for migration. However, the results are very different for female migrants[1], that shows being a female increases the likelihood of overeducation. Other very interesting result is that, when we see by just by gender, for females, it is showing negative and significant coefficient. It indicates that compared to males (refence category), the incidence of overeducation is less among females.

Further, disaggregating by the work and non-work-related purpose (reference category), and by gender, our results indicate a negative and significant coefficient, meaning that when individuals migrate with a clear intent for work, their likelihood of finding a better-fit job is more, resulting in reduced overeducation. Interestingly, for female migrants who migrated for work-related reasons, the likelihood of overeducation is less. But, in our descriptive statistics, we have shown that around 90 per cent women migrate for marriage purpose while only 1.46

[1] Female migrants is our interaction variable. The reference category is female non-migrants, male migrants and male non-migrants.

for work-related reasons. It highlights an array of issues prevailing in the Indian society. Albeit, the economy has progressed in closing the gender gap at the educational level, the women are still disadvantaged in the society due to prevailing, social and cultural norms that limit their search for a better suited and high paid jobs. As a result, we see low female labor force participation in India.

The education variables also portray intriguing stories. The likelihood of overeducation is more among those with general education (elementary and below is our reference category) increasing from secondary, to higher secondary, to post graduation and above. However, it reduces for those with vocational training and technical education. This gives a clear prompt to the policy makers to make vocational and technical education more accessible and affordable. Other control variables also give consistent results across all four specifications. Under table 2, we have estimated the bivariate model with different specifications of variables. In the first specification we have considered all migrant and female migrants, while the second specification is followed by adding reason for migration, particularly the migration for work and female migrants who migrated for work.

Table 2: Determinants of the likelihood of overeducation among working-age (15-59 years) migrants and non-migrants in India using migration interacted with gender as our key explanatory variable.

	Bivariate Probit Estimates			
	Specification -I		Specification -I	
	Probit	Marginal Effect	Probit	Marginal Effect
Explanatory Variables:				
Migrants	-0.369 **	-0.045 **		
	(0.148)	(0.02)		
Female migrants	0.168 ***	0.021 ***		
	(0.061)	(0.007)		
work-related migration			-0.14 **	-0.001 *
			(0.062)	(0.001)
work-related female migrants			-0.268 ***	-0.002 ***
			(0.063)	(0.001)
age	-0.035 ***	-0.004 ***	-0.034 ***	-0.00021 ***
	(0.008)	(0.001)	(0.004)	(0.00005)
age square	0.0003 ***	0.00003 ***	0.0002***	0.0000012 *
	(0.00009)	(0.00001)	(0.00005)	(0.0000006)

Household size	0.013 **	0.001 **	0.011 ***	-0.001 ***
	(0.005)	(0.001)	(0.003)	(0.0002)
female	-0.117	-0.004	-0.126 ***	-0.007 ***
	(0.075)	(0.007)	(0.013)	(0.001)
ST	-0.11 ***	-0.014 ***	-0.095 ***	-0.001 ***
	(0.034)	(0.004)	(0.015)	(0.0002)
SC	0.095 ***	0.012 ***	0.141 ***	0.0004**
	(0.026)	(0.003)	(0.013)	(0.0002)
Minorities	-0.039	-0.005	-0.119 ***	-0.003 ***
	(0.028)	(0.003)	(0.013)	(0.0004)
Urban	-0.432 ***	-0.047 ***	-0.449 ***	0.003 ***
	(0.033)	(0.003)	(0.013)	(0.0005)
Married	0.175 ***	0.024 ***	0.115 ***	0.004 ***
	(0.037)	(0.005)	(0.016)	(0.0005)
Divorced/widowed/separated	0.126 **	0.013 *	0.151 ***	0.002 ***
	(0.057)	(0.007)	(0.034)	(0.0005)
Secondary education	1.27 ***	0.154 ***	1.233 ***	0.01 ***
	(0.032)	(0.006)	(0.015)	(0.001)
Higher education	2.034 ***	0.248 ***	2.061 ***	0.015 ***
	(0.034)	(0.009)	(0.016)	(0.001)
Graduation & above	2.132 ***	0.259 ***	2.301 ***	0.018 ***
	(0.036)	(0.01)	(0.016)	(0.002)
Vocational Training	-0.076 ***	-0.012 ***	-0.049 ***	0.001 ***
	(0.022)	(0.003)	(0.011)	(0.0002)
Technical Education	-0.143 ***	-0.02 ***	-0.222 ***	0.001 **
	(0.034)	(0.004)	(0.02)	(0.0002)
Developed States	0.058	0.012	-0.071 *	0.002 ***
	(0.065)	(0.008)	(0.038)	(0.001)
Developing states	0.19 ***	0.024 ***	0.108 ***	0.002 ***
	(0.02)	(0.003)	(0.011)	(0.0002)
Migration rate (2007-08)		0.00007 ***		0 .00013***
		(0.00002)		(0.000013)
Constant	-1.052 ***		-1.191 ***	
	(0.162)		(0.067)	
Observations	37,785	37,785	1,36,081	1,36,081
Wald Chi2	10300.05		37176.13	
Prob > chi2	0.000		0.000	
Log likelihood	-26229.8		-73366.2	
rho	0.121		0.024	
athrho	0.122		0.024	
	(0.0887)		(0.0335)	

Source: Authors' estimation using Periodic Labor Force Survey (PLFS) data for 2020–20.

Note: Overeducation is our dependent variable.

Note: *** and * indicate 1 per cent and 10 per cent levels of statistical significance, respectively. Robust standard errors are reported in parentheses. The different specifications are used to check the robustness of the results of the regression model.

The results (table 2) of the bivariate analysis reaffirm that overeducation reduces with migration. Under specification 1, one unit increase in migration reduces the probability of overeducation by 4.5 percentage points. However, the same is not true if the migrant is a female, where the incidence of overeducation increases by 2.1 percentage points. Interestingly, being a female is associated with low incidence of overeducation, compared to their male counterparts. Gazing it through migration reasons, it is learned that when migration is for work-related purpose, it leads to reduction in overeducation incidence. The relation with age depicts an inverted U-shape relationship, where initially with an increase in age overeducation rises, but after reaching a certain point, it starts to decline. The explanation for this could be both the prevailing demand- and supply-side issues of labor force participation in the market. Upto middle-age (late 30s), women have more burden of childcare, unpaid work and not enough work experience. This is the phase in women like when they enter, exit and re-enter the work market several times (Deshpande & Singh, 2021). But after a woman crosses middle-age and they are set free from childbearing responsibilities, they put in more effort to fit in least unfit jobs, reducing overeducation.

The larger size of the household puts enough financial burden on the individual, limiting their power to exercise choice in the work market, and this shows up in positive coefficient for overeducation. However, it is less for work-related female migrant. The social caste in India is also a prime deciding variable. Our results, reveal less overeducation among people from schedule tribe (ST), while more for Schedule caste (SC). The reason lies in the limited and low-skill jobs taken up by the ST, like barbers, cobbler, blacksmith (Agarwal.T,2016). Similar reasons may also follow for people in minorities religion. Overeducation less in urban compared to rural, but overeducation is positive and significant for work-related female migrant. Rural areas mainly engage female as unpaid helpers or engage in agricultural fields. But urban areas have more diverse and competitive jobs. Being married, widowed or separated again leads to more overeducation, compared to unmarried, because it demands more financial stability. As a result, there is limited job selection, compelling them to accept any available possible jobs. General education is not sufficient alone to reduce overeducation. However, when supplemented with technical or vocational training, it helps individuals minimize overeducation probability. But when it comes to developed and developing states, the values are positive and significant specifying lack of limited formal job opportunities, cannot absorb high influx of migrants. Subsequently, they end in informal or contractual jobs, meaning

underutilizing education. And finally, we found our instrument variable to be positive and significant.

7. Conclusion and Policy Implications

The paper analyzed the likelihood of overeducation among migrants and non-migrants, with special focus on the role played by gender. Both the descriptive and empirical estimation techniques have been used to study the incidence of overeducation. The first step in the estimation procedures was to create the overeducation variable, for which we used a realized matching method. We have defined overeducation as a case where the educational qualifications an individual possesses exceed the requirements of the job. Under realized matching method, we proxied the educational attainment with the number of years of formal schooling, thereafter, calculating the mean and standard deviation within 3-digit occupation code using National Classification of Occupation (NCO) 2004. If the difference of supply and the demand-side was greater than zero, we call it the classic case of overeducation. Others with a difference of less than or equal to zero were undereducated and adequately educated simultaneously. For our regression analysis we used bivariate probit regression technique, due to the case of endogeneity between our dependent variable 'overeducation' and our key explanatory variable 'migration'. And to correct this we employed lagged migration rate variable as our instrument.

The result of bivariate analysis reveals that while migration generally reduces the likelihood of overeducation, this effect varies across different groups, particularly, female migrants. The likelihood of overeducation was more when only female migrants were studied, depicting the socio-cultural barriers. Our descriptive statistics suggests that more than 50 per cent migrants are women, but among them 90 per cent migrate only for marriage-related reasons. This means women are bound with domestic responsibilities and might prefer to take up job, which is more flexible to help her balance both family and work. But among those who especially migrated for work, experience a reduced incidence of overeducation, depicting that the reason behind migration affects the motivation to job search.

An inverted U-shaped relationship between age and overeducation indicates that younger individuals face higher overeducation due to inexperience and life-cycle factors such as childcare responsibilities. This gap narrows as individuals grow older and better align their employment with their qualifications. Social and demographic characteristics such as household size, caste, marital status, and urban-rural location also influence overeducation

outcomes. Scheduled tribes (STs) and minorities had lower likelihood of overeducation, due to their occupational segregation into specific type of job, particularly low-skilled jobs for STs and reservation policy affecting both minorities and lower social group.

Further, the results suggest that vocational and technical training significantly lowers the probability of overeducation, indicating the value of skill-based training over general education alone. In developed and developing states, overeducation remains high due to the inability of formal sectors to absorb the growing supply of educated labor, especially migrants. Along with that there is also huge informal market structure. Finally, the positive and significant instrumental variable validates the robustness of the migration variable in influencing overeducation outcomes, reinforcing the causality.

Based on the above results from analysis, the policy suggestions focus on expanding more vocational and technical education. Bairagya et al (2021) stated that female's enrolment in the vocational training is limited and those already under training, either drop out or take up short duration training, which fails to translate into productive employment. Also, creating sufficient work arrangements for working mothers, develop re-entry programs for women workers, so that their exit and re-entry penalties could be reduced. Additionally, the job fairs would further help both women migrant and non-migrants to make informed decisions related to work opportunities. India claims to narrow the gender gaps at the education level, but the stark difference in the labor force participation still exits. Apart from the excessively discussed supply-side factors, it now time to wake up to the major role, job availability at the demand-side play. If overeducation persists, it not just results in wage penalty, unemployment, dissatisfaction, encourages feminized division of occupation in the society and also discourages the education of the future generation. Hence, prompt policy intervention is required, to deal with the issue of overeducation, keeping a close watch at how these policies could benefit both male and female, leveraging the demographic dividend of India. Our analysis results showed clear evidence of gender being a differentiator.

Funding Declaration

No funding was received to assist with the preparation of this manuscript. There is no potential conflict of interest involved in the paper.

APPENDIX:

Table A1: Description of the variables used in different regression analysis.

Variables	Descriptions
Dependent Variable:	
Overeducation	Overeducation= 1, if overeducated; Ref: non-overeducated (undereducated & adequately educated)
Endogenous Covariate:	
Migration	Migration =1, if the present place of enumeration differs from the last usual place of residence. Ref: Non-migrants
Other key explanatory variables:	
Female migrants	Interaction variable. Variable=1, when female=1 and migration=1. Ref: female non-migrants, male migrants, male non-migrants
Work-related migration	Variable=1, when the reason for migration is only work & work related. Ref: migration for reasons other than work
Work-related female migrants	Interaction variable. Variable =1, when work-related migration=1 and female=1
Instrument:	
Lagged migration rate from NSSO (2007-08)	We have used the district-level rate of migration from the years 2007-08 as our instrument. Since people migrate interdistrict, intradistrict, interstate, district level migration rate (percentage) was used.
Socio-economic and demographic characteristics:	
Age and squared age	Age of the person measured in years
Size of the household	Household-level information stating the size of the family
female	The variable is 1, when gender is female. Ref: male
SC and ST	SC and ST =1 if belongs to socially disadvantaged groups, Scheduled tribes and scheduled caste. Ref: Non-SC ST=0, i.e., general class (upper class) and Other backward caste (OBCs)
Minority	Minority=1 if person is non-Hindu. Ref: Hindu
Urban	Urban=1, if the person belongs to urban areas. Ref: Rural region
Married	Married=1, when the marital status is currently married. Ref: unmarried
Widowed/divorced/separated	Widowed/divorced/separated =1, if marital status is widow or separated. Ref: unmarried
Education Level- Elementary & below	Elementary & below=1, if the general education level is those with no education and those who completed elementary education.
Education Level- Secondary	Secondary education=1, if the person completed secondary education

Education Level-higher secondary education	Higher secondary education=1, if the person has completed education up to a higher secondary level.
Education Level- graduation & above	Graduation & above=1, if the person has completed graduation, post-graduation and qualified beyond it. We have chosen Elementary & below as our reference category.
Vocational training	Vocational training=1, if the person has completed either formal or informal vocational training or both. Ref: having no vocational training
Technical level education	Technical level education=1, if the person has technical education in any field. Ref: person with no technical training
Developed states & Developing states	Developed states=1 if the HDI score of the Indian states is above 0.80 and above in the year 2017-18. Developing states=1, if the HDI score of the Indian states is between 0.70 to 0.79. Ref: states with HDI score below 0.70.

Source: Author's computations using PLFS 2020-21.

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