Skill-based Wage Differentials Between Migrants and Non-migrants in the Indian labour market

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Highlights

- The study investigates skill-based wage disparities between migrant and non-migrant workers in Indian labour market.
- To address the selection bias arising from migration decisions and wage determination, the analysis applies an endogenous switching regression model
- Significant wage gaps are observed, with migrants earning more in medium- and high-skilled segments.
- While the conditional value suggests wage penalties for migrant workers in across skill level.
- For non-migrants, wage penalties are limited to the high-skilled category only.

Abstract

Skill plays a central role in determining wage earnings between migrant and non-migrant workers and contributes to persistent wage disparities even among workers with the same skill level. This study aims to examine skill-based wage disparities between migrants and non-migrants using the Periodic Labour Force Survey 2020–21 dataset. The study investigates how socio-economic and demographic characteristics influence both wages and migration decisions across high-, medium-, and low-skill groups. Additionally, to address potential selection bias in migration decisions and associated wage disparities, the analysis employs an endogenous switching regression model. The results reveal the persistence of social group-based discrimination within the labour market. Significant wage differentials are identified across skill categories. Observed mean wage for migrants indicates higher earnings relative to non-migrants in the high- and medium-skill groups. Additionally, unconditional estimates suggest an apparent wage advantage for

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migrants across all skill levels. In contrast, conditional (selection-corrected) results reveal a consistent wage penalty associated with migration across skill groups. Among non-migrants, wage penalties are limited to the high-skill category, with relative advantages detected in the medium- and low-skill groups. These findings highlight the persistent shortage of suitable employment opportunities and the ongoing skill mismatches in the Indian labour market. The study emphasises the importance of strengthening local employment generation, enhancing social security coverage, expanding market-oriented skills development, and promoting fair and inclusive labour market outcomes for all workers. This study supports Sustainable Development Goals 8 and 10 by addressing social protection and wage inequalities between migrant and non-migrant workers.

Keywords: Wage disparities, Skill level, Labour migration, Endogenous switching regression, Employment outcomes, India.

1. Introduction

Migration has emerged as one of the most significant engines of demographic and socio-economic transformations in developing countries. Internal migration substantially contributes to economic development through various mechanisms. It leads to a reduction of regional inequality and the facilitation of structural changes within economies (Mendola, 2012; Ray & Dutta, 2019). Following the economic reform of 1991 in India, there has been an acceleration of internal migration for employment and other economic opportunities (Hnatkovska & Lahiri, 2013; Bhagat, 2015). Employment-related migration plays a crucial role in enhancing productivity and incomes by reallocating labour to more efficient sectors and enabling workers to access better job prospects across regions and industries (Harris & Todaro, 1970). This reallocation of labour leads to more efficient resource utilization, promoting regional economic integration and economic modernization, which is crucial for developing countries (Roland-Holst, 1999). Additionally, labour migration plays a vital role in poverty reduction and economic growth, particularly in developing countries like India (Deshingkar & Akter, 2009). Despite these developmental benefits, migrants often experience multiple disadvantages, including wage discrimination, linguistic and socio-cultural barriers, and limited access to public services at destinations (Dustmann et al., 2013; Srivastava & Sutradhar, 2016; Chiswick, 2018). Wage differences between migrants and non-migrants occur due to several reasons, such as skill levels, education, job opportunities, bargaining power, and discriminatory practices within labour markets (Borjas, 1985; Cai & Zhang, 2025).

Wage disparities are a consequence of higher returns to skills and variations in skill level (Jovicic, 2016). Skill refers to a person's ability to perform their duties effectively, as associated with a specific job (Madan

& Mor, 2020). Skill has had its place in the labour market discourse since the era of Adam Smith (1776), and it is more appreciated in the human capital discourse (Mincer, 1974; Becker, 1975). Additionally, skills also play a crucial role in labour market disparities, as labour mobility reduces differences in regional unemployment rates, while the migration of high-skilled workers tends to reinforce these disparities (Granato et al., 2015). Workers earn different wages because jobs require different skills and tasks. Occupations that demand higher skills, involve more complex tasks, or carry greater risk generally offer higher wages (Liu & Grusky, 2013; Williams & Bol, 2018). The occupational hierarchy also affects wage differences between migrants and non-migrants (Khan, 2017). Wage differentials between migrants and non-migrants have been widely debated in labour economics, particularly in developing countries like India, where migration plays a crucial role in shaping labour market dynamics (Roland-Holst, 1999; Khan, 2016; Ray & Dutta, 2019; Cai & Zhang, 2025). Although several studies have examined wage differences between migrants and non-migrants, even after controlling for observable characteristics, these differences are generally interpreted as evidence of systematic disadvantage or discrimination against migrants (Wang et al., 2015; Pritchett & Hani, 2020; Bhatt et al., 2025). In the Indian context, Khan (2016, 2021) has also examined the wage differentials between migrants and non-migrants. The results indicate that migrants earn lower wages at the bottom of the wage distribution but surpass non-migrants at the higher end. Additionally, there is very limited research that has been conducted on how different skill levels contribute to these wage gaps in the Indian labour market (Madan & Mor, 2020; Motkuri, 2025). Most of the studies on skills and earnings focus on international migration. Previous literature primarily discusses brain drain, high-skill versus low-skill migration, and the differences in wages between migrants and native workers (Khadria, 2002; Yabuuchi & Chaudhuri, 2007; Behrens & Sato, 2011; Batista et al., 2025).

However, it is crucial to analyse how skill levels shape wages and wage differences between migrants and non-migrants within India's internal labour market and migration system. This is especially important because India has one of the largest internal migrant populations (Census, 2011). In this backdrop, this study focuses on occupation-based skills to explain why workers with similar skill levels can still have different wage outcomes in the regular salaried labour market. Occupation-based skills are pertinent because they play a central role in determining wages through the wide range of tasks involved in different occupations. Moreover, the returns to the same level of skill can differ depending on the type of employment. For example, earnings vary across regular salaried, casual labour, and self-employment. In this study, regular-salaried employment is used because it encompasses a wide range of skill levels and occupations, which more accurately reflects the market value of skills (Motkuri, 2025). While self-employed workers' earnings include profits and other factors, this makes it difficult to isolate the return to skill. Casual labourers are also not suitable as they are mostly concentrated in low-skill jobs and do not represent the full range of occupations. Hence, analysing the regular salaried workers allows for a more

reliable comparison of wage differences between migrants and non-migrants based on occupation-specific skill levels in India.

The rest of the article is structured as follows: Section 2 presents the literature review; Section 3 outlines the methodology; Section 4 discusses the empirical findings; and Section 5 concludes the study.

2. Review of Literature

Wage differentials between migrants and non-migrants have been the focus of extensive research across diverse economic contexts, with skill level emerging as a key explanatory factor. From a theoretical perspective, the internal and international migrants are often positively selected on skills, implying that individuals with higher education and qualifications are more likely to migrate and receive higher wage returns (Borjas, 1985; Stark, 1994; Fratesi & Riggi, 2007). The impacts of migration on the wage structure of host regions can be understood within a perfectly competitive labour market featuring skilled and unskilled workers. Migration changes the combination of skills in the labour market, thereby affecting wages in different ways. When more workers with similar skills enter in the labour market, wages for those competing groups tend to fall, while wages for complementary skill groups may rise, resulting in unequal wage effects rather than uniform changes across workers (Borjas, 1989, 1995).

Empirical studies in both developing and developed countries confirm that skill-based selection plays a significant role in shaping migrant wage advantages; however, these benefits are not always universal (Ruhose et al., 2015). Migrants tend to carry more human capital than non-migrants, and this skill composition produces higher average wages in receiving regions relative to sending regions. Because high-skilled workers are more likely to move towards regions with better wage structures and with richer fixed assets, whereas low-skilled workers are inclined to remain in underdeveloped areas. Consequently, migration can increase wage and income per capita gaps between origin and destination areas rather than equalize them (Fratesi & Riggi, 2007). Moreover, low-skilled workers are disproportionately exposed to larger and more volatile declines in both wages and employment compared to their high-skilled counterparts, thereby further intensifying the wage gap across skill levels (Hoynes, 1999). Higher occupational skill levels are associated with substantially higher wages, and these skill premiums increase with work experience. Differences in wages between skill levels also grow with work age/experience, indicating a strongly skill-based pay structure that amplifies wage differences regardless of migrant status (Motkuri, 2025). When high-skilled workers migrate, the relative supply of low-skilled workers left behind increases, leading to a decline in low-skill wages. While the scarcity of skilled labour drives up high-skill wages, this exacerbates the skill-related wage gaps between remaining high- and low-skilled non-migrants in the source regions (Uprety, 2020). Additionally, wage gaps between migrants and non-migrants are only

partly explained by observable skill differences, with labour-market institutions and within-skill wage dispersion playing a significant role (Freeman & Schettkat, 2001; Jovicic, 2016). Surprisingly, Devroye and Freeman (2001) establish that the relationship between the distribution of wages and the distribution of skills reveals that skill inequality explains only 7% of wage inequality. Within-skill-group inequality plays a larger role than inequality between skill groups in explaining wage inequality.

The impact of skilled labour migration on relative wage inequality is counterintuitive, highlighting key policy considerations for developing countries like India (Yabuuchi & Chaudhuri, 2007). Internal migrants in India have better living standards than non-migrants, although migrants face higher economic inequality than non-migrants (Kumar & Pradhan, 2025a). Additionally, internal migrants are relatively high-skilled and earn higher wages than non-migrant workers (Khan, 2016). Rural-to-rural and rural-to-urban migrants earn lower wages than comparable non-migrants, whereas urban-to-rural and urban-to-urban migrants earn higher wages than their non-migrant counterparts (Hnatkovska & Lahiri, 2013). Studies reveal that, low-skilled migrants are discriminated at the destination and paid lower wages than non-migrants in the urban informal sector (Duraisamy & Narasimhan, 1997). Additionally, wage differentials are observed between native and in-migrant workers, with discrimination and lack of integration into local society being significant factors in Kerala (Saalim & George, 2021). Khan (2016) analysed wage differences between migrants and non-migrants at both the mean and across the wage distribution. The study also examined the factors driving this wage gap and found that most of the wage gap is explained by variations in observable characteristics between the two groups. Likewise, migrants had significantly higher wages than non-migrant workers, and both rural and urban migrants experienced a wage advantage in urban labour markets (Khan, 2017, 2021). A recent study by Bhatt et al. (2025) indicates that internal migrants earn less than non-migrants in rural areas but have higher earnings in urban areas.

Despite the insights in the existing literature, systematic evidence on wage differentials between migrants and non-migrants within comparable skill groups remains insufficiently explored. Moreover, labour-market outcomes are strongly shaped by skill segmentation in India (Motkuri, 2025). An interest also lies in exploring occupation-based skill level wages, which have sparked discussions and debates around the industry and businesses globally. However, there is a dearth of studies from a skills perspective, especially in the Indian context. Therefore, this study aims to estimate the wage differences between migrants and non-migrants within the skill level among Indian regular salaried workers.

3. Data and Methodology

3.1 Data

This study utilized unit-level data from the Periodic Labour Force Survey conducted by the National Statistical Office during the period 2020-21. This national representative survey contains information on socio-economic and demographic characteristics of individuals and households, such as age, gender, marital status, caste, religion, education, place of living, as well as detailed information on industry and occupation of employment, unemployment and wage earning (by) of workers. *An individual is classified as a migrant*[2] *if his/her present place of enumeration is different from their last usual place of residence*[3]. The skill level of workers is determined by the nature of their occupation and the minimum required educational qualifications, as outlined in the National Classification of Occupations (NCO[4]). For analytical clarity, occupations have been grouped into three broad skill-level categories: high-skill, medium-skill, and low-skill, based on the three digits of the NCO code (see Table A1). Occupations such as legislators, senior officials and managers (code 111 to 130), professionals (code 211 to 246), and associate professionals (code 311 to 348) are classified as high skill, given their typically higher educational requirements. Occupations requiring secondary education (codes 411–834) are classified as medium-skilled. While elementary occupations (codes 911–933), which require primary education or informal skills, are classified as low-skilled (Ankita & Singh, 2025). Notably, these skill-level distinctions are not explicitly defined within the NCO framework but are derived for the purpose of this study.

The total sample size consists of 410,818 individuals. From this, 39,455 regular salaried employees with complete information were included in the analysis. Among them, 12,889 are migrants and 26,566 are non-migrants. By skill level, there are 4,669 migrants and 8,109 non-migrants in the high-skill group. In the medium-skill group, there are 5,993 migrants and 15,215 non-migrants, while the low-skill group includes 2,227 migrants and 3,242 non-migrants. The detailed procedure for sample selection is illustrated in Figure 1. The key variables used to explain wage differences between migrants and non-migrants are identified based on existing literature. Workforce status is determined using the Usual Principal Activity status, while wages are estimated using the Current Weekly Status. For regular salaried employees, wages are reported for the preceding month of the interview date. Additionally, the descriptions of the variables and their units of measurement are provided in Table A2 (Appendix). For simplicity, we have grouped occupations into three broad skill categories: high-skill, medium-skill, and low-skill (Table A1).

[2] Migration in India 2020-2021

[3] The usual place of residence is the village or town where a person has stayed continuously (or intends to stay) for at least 6 months.

[4] File-3.doc

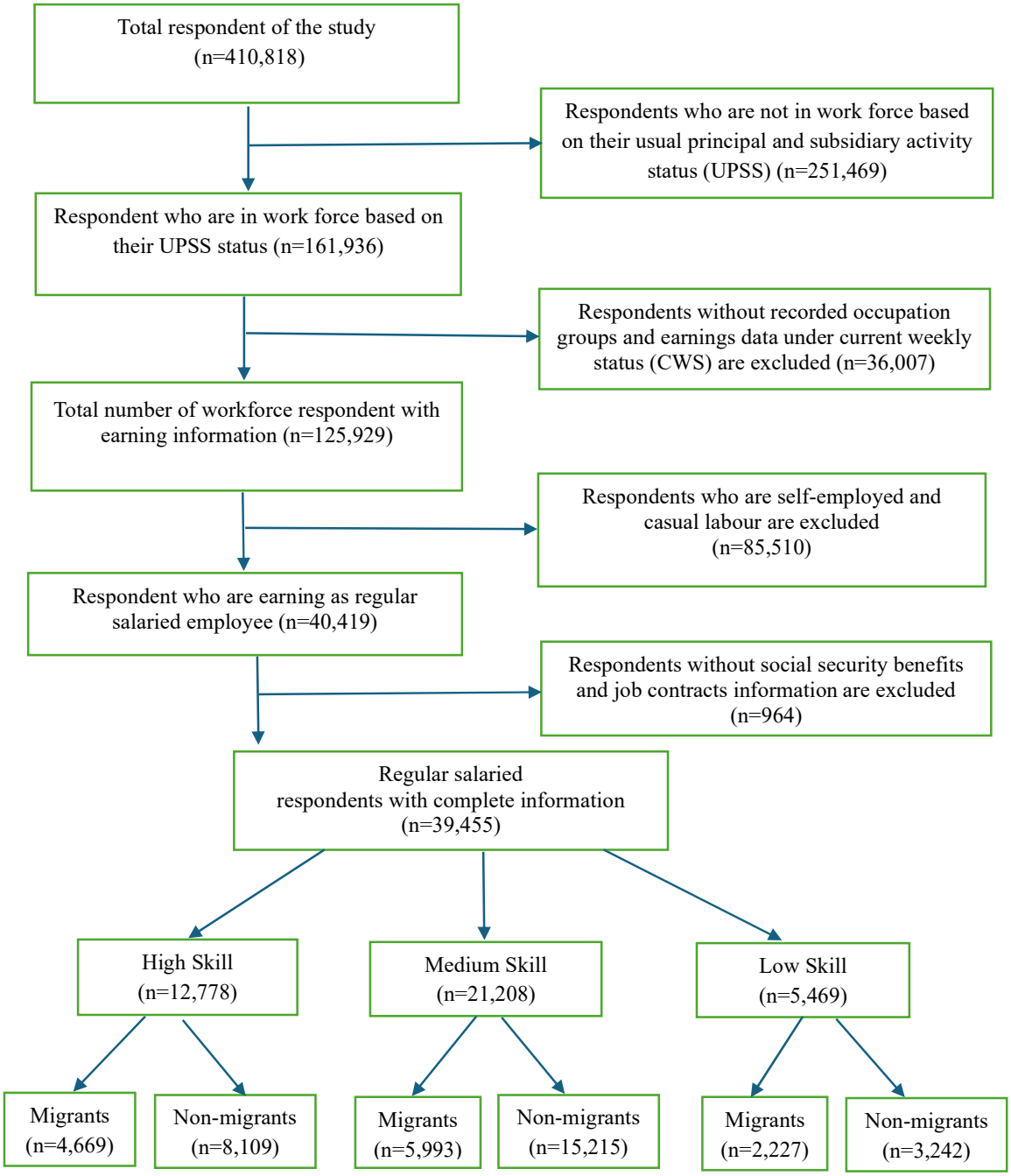


Figure 1: Sample selection flowchart

3.2 Empirical Specification

The decision to migrate is a binary variable, where migrant workers are assigned a value of one and non-migrants are assigned a value of zero. Migration is not a random decision, individuals choose to migrate

based on various personal, social, demographic, and economic factors, many of which are unobservable (like motivation, risk preference, and social networks). These unobserved factors may also influence wages, leading to selection bias if they are not properly accounted. When an independent variable related to the migration decision is represented as a dummy variable in the model, the method addresses the selectivity problem (Maddala, 1993). Therefore, we have used the endogenous switching regression model (ESRM) to address the potential selection bias in the analysis of skill-based wage differentials between migrants and non-migrants. This method has proven useful in addressing endogeneity resulting from self-selection bias (Long et al., 2017). Moreover, this model accounts for the fact that individuals self-select into migration based on both observable and unobservable characteristics, which may simultaneously influence their wage outcomes. By estimating separate wage equations for migrants and non-migrants, conditional on the decision to migrate, ESRM effectively captures the structural differences in returns to characteristics across the two groups. It also estimates a selection equation that models the probability of migration, allowing for correlation between the error terms of the selection and outcome equations (Lokshin & Sajaia, 2004).

Several studies have employed the endogenous switching regression model in similar wage analysis contexts (Lee, 1978; Delattre & Sabatier, 2007; Long et al., 2017; Parhah et al., 2025). The use of an endogenous switching regression model has two advantages compared to other methods. First, this approach allows us to examine the impact of migration on both wages and the determinants of wages. Second, using maximum likelihood estimates without additional corrections, the results show that migration affects wages differently across skill levels (Parhah et al., 2025). The endogenous switching regression can be used to predict expected wages for migrant workers if they switched to not migrating and vice versa for non-migrants across skill levels (Long et al., 2017).

To analyse the propensity to migrate for the earnings, let's take L as a latent variable with the following index function:

$$L^* = \delta Z_i + u_i,\ u \sim N(0, \sigma^2) \qquad (1)$$

$$L = 1\ if\ L^* > 0,\ L = 0\ if\ L^* \leq 0$$

Where, $L = 1$ if the wage earner is a migrant and $L = 0$ if the wage earner is a non-migrant. L^* can be estimated using the model for binary data. Z_i represents the vectors of attributes that determine the likelihood of migration, such as age, caste, religion, gender, education, marital status, sector and household size. δ is the coefficient of the explanatory variables (Z) and u_i is the error term that follows the normal distribution. Within this specification, it is essential that at least one variable differs from the wage equation. Consequently, the earning equations for both the regimes (migrants and non-migrants) are given below:

Regime 1 (migrants): $lnY_{1i} = \beta_1 X_{1i} + \varepsilon_{1i},\ \varepsilon_{1i} \sim N(0, \sigma^2)\ \ if\ L_i = 1 \qquad (2)$

Regime 2 (non-migrants): $lnY_{0i} = \beta_0 X_{0i} + \varepsilon_{0i},\ \varepsilon_{0i} \sim N(0, \sigma^2)\ if\ L_i = 0$ (3)

Here, lnY_{1i} represents the natural logarithms of wages for migrants, X_{1i} is the vector (age, age square, caste, religion, marital status, gender, education attainments, job contract, social security benefits, sector and region) that determines the migrants' earnings, β_1 is the estimator of the wage equation for migrants. Similarly, lnY_{0i} represents the natural logarithms of wages for non-migrants, X_{0i} is the vector that determines the non-migrants' wages, β_0 is the estimator of the wage equation for non-migrants.

Assume that u_i, ε_{1i}, and ε_{0i} have a trivariate normal distribution with mean zero and covariance matrix:

$$\begin{bmatrix} \sigma_u^2 & \sigma_{1u} & \sigma_{0u} \\ \sigma_{1u} & \sigma_1^2 & . \\ \sigma_{0u} & . & \sigma_0^2 \end{bmatrix} \quad (4)$$

Where, σ_u^2 is the variance of the error term in the selection equation, normalising with $\sigma_u^2 = 1$. σ_1^2 and σ_0^2 are variances of the error terms in the wage equations. σ_{1u} is a covariance of u_i and ε_{1i}, while σ_{0u} is a covariance of u_i and ε_{0i}. The covariance between ε_{1i} and ε_{0i} is not defined, as lnY_{1i} and lnY_{0i} are not observed simultaneously. We can assume that $\sigma_u^2 = 1$ (δ is estimable only up to a scalar factor).

Using the direct maximum likelihood methods, the log-likelihood function associated with our model is written as:

$$Lnl = \sum_{L=1}\left[logF(\eta_1) - \frac{1}{2}\left\{log\ (2\pi\sigma_{1u}) - \left(\frac{Y_1-\beta_1 X_1}{\sigma_1}\right)^2\right\}\right] + \sum_{L=0}\left[logF(\eta_0) - \frac{1}{2}\left\{log\ (2\pi\sigma_{1u}) - \left(\frac{Y_0-\beta_0 X_0}{\sigma_0}\right)^2\right\}\right] \quad (5)$$

Where $F(.)$ is the cumulative normal distribution function and $f(.)$ is the standard normal density function. $\eta_1 = \frac{\delta Z\ \ (Y_1-\beta_1 X_1)\sigma_{1u}/\sigma_1^2}{\sqrt{1-\rho_{1u}^2}}$ and $\eta_0 = \frac{\delta Z+(Y_0-\beta_0 X_0)\sigma_{0u}/\sigma_0^2}{\sqrt{1-\rho_{0u}^2}}$. $\rho_{1u} = \sigma_{1u}^2/\sigma_u\sigma_1$ is the correlation coefficient between ε_{1i} and u_i, $\rho_{0u} = \sigma_{0u}^2/\sigma_u\sigma_0$ is the correlation coefficient between ε_{0i} and u_i.

After estimating the model parameters, the calculation of the unconditional expectation is as follows:

$$E(Y_1 L = 1) = \beta_1 X_1 \quad (6)$$

$$E(Y_0 L = 0) = \beta_0 X_0 \quad (7)$$

Furthermore, by taking expectations from the outcome equation, we can determine the conditional expected wages for migrants and non-migrants with the following scenario:

The conditional expected wages for migrants who self-selected into migration is as follows:

$$E(Y_1 L = 1) = \beta_1 X_1 + \rho_1\sigma_1 f(\delta Z_i)/F(\delta Z_i) \quad (8)$$

Where $f(\delta Z_i)/F(\delta Z_i)$ is referred to as the non-selection hazard ratio or the inverse Mills ratio.

In experimental studies, those assigned to status 1 differ only randomly from those assigned to status 0, so that there is an interchangeability across statuses. However, in non-experimental studies, one must adjust for selectivity when evaluating expected wages if individuals were assigned to alternative regimes of participation rather than the regimes they selected into. The expected outcome for migrants if they were non-migrants is:

$$E(Y_1 L = 0) = \beta_1 X_1 - \rho_1 \sigma_1 f(\delta Z_i)/\{1 - F(\delta Z_i)\} \quad (9)$$

Where $f(\delta Z_i)/\{1 - F(\delta Z_i\}$ is referred to as the selection hazard rate.

Similarly, the expected outcome for non-migrants, had they been migrants, is:

$$E(Y_0 L = 1) = \beta_0 X_0 + \rho_0 \sigma_0 f(\delta Z_i)/F(\delta Z_i) \quad (10)$$

Likewise, the conditional expected wages for non-migrants who self-selected into non-migration.

$$E(Y_0 L = 0) = \beta_0 X_0 - \rho_1 \sigma_1 f(\delta Z_i)/\{1 - F(\delta Z_i\} \quad (11)$$

This scenario enables the identification of the switching process for each regime. We will be able to see what would happen if a migrant is not a migrant, and vice versa. This is useful for establishing the role of migration in wage determination and for evaluating wage differentials between migrants and non-migrants across skill levels.

4. 4.1 Results and Discussion

4.1 Descriptive results

Table 1 shows the characteristics of the migrants and non-migrants across skill levels of regular salaried workers in India. Migrants' average age is higher than that of non-migrants across all skill levels. As skill levels increase, educational attainment also rises, highlighting the critical role of education and training in enhancing workers' skills. Among high- and medium-skilled categories, migrants with higher and primary education levels constitute a larger share compared to non-migrants. Conversely, among middle and secondary education levels, non-migrants exhibit a higher share than migrants. In the low-skill category, migrants tend to have lower educational attainment than their non-migrant counterparts. Migrants are generally more likely to possess technical education than non-migrants across all skill levels, except in the low-skill group, where non-migrants show a slightly higher share of technical education. However, the overall proportion of technically educated workers remains very low across both migrant and non-migrant groups, particularly within the medium- and low-skill categories.

Table 1. Characteristics of migrant and non-migrant workers across skill level

	Full sample		High skill		Medium skill		Low skill	
Variables	**M**	**NM**	**M**	**NM**	**M**	**NM**	**M**	**NM**
Age	38.68	36.73	38.642	37.76	38.28	36.01	39.86	37.55
General education								
Up to primary	19.4	13.73	2.06	1.57	21.27	15.77	50.7	34.58
Up to middle	15.63	18.55	4.45	4.86	21.26	23.97	23.93	27.36
Secondary and diploma	30.39	35.17	26.28	26.81	36.66	40.35	22.14	31.8
Graduation and above	34.58	32.55	67.21	66.77	20.81	19.91	3.23	6.26
Technical education								
Without technical education	83.5	90.09	64.15	78.30	92.22	94.68	98.47	98.03
With technical education	16.5	9.91	34.85	21.70	7.78	5.32	1.53	1.97
Availability of social security benefits								
Yes	51.19	45.95	72.54	67.51	44.15	37.34	25.37	32.45
No	48.81	54.05	27.46	32.49	55.85	62.66	74.63	67.55
Job contract								
No written job contract	55.19	61	37.18	44.99	60.77	67.24	77.91	71.75
Written job contract less than 3 years	11.2	9.58	14.11	10.51	10.13	8.83	7.95	10.76
More than 3 years	33.62	29.42	48.7	44.51	29.1	23.93	14.14	17.49
Gender								
Male	59.34	83.66	49.95	73.31	70.82	90.33	48.14	78.22
Female	40.66	16.34	50.05	26.69	29.18	9.67	51.86	21.78
Marital status								
Unmarried	16.29	28.83	17.26	29.88	17.24	20.25	11.67	24.28
Married	83.71	71.17	82.74	70.12	82.76	70.75	88.33	75.72
Caste								
ST	8.03	15.16	8.50	19.72	7.88	13.55	7.45	11.32
SC	17.40	16.56	12.10	10.64	17.09	16.92	29.37	29.67
OBC	36.50	35.47	35.19	30.55	38.83	38.53	32.96	33.37
Others	38.07	32.82	44.21	39.09	36.21	31.00	30.22	25.63
Religion								
Hindu	84.68	73.85	82.78	69.96	85.55	74.18	86.3	81.99
Islam	7.03	11.55	7.13	10.27	7.18	12.89	6.42	8.48
Others	8.29	14.6	10.09	19.77	7.28	12.93	7.27	9.53
Sector								
Rural	21.79	37.10	24.72	33.38	20.79	39.22	18.37	36.46
Urban	78.21	62.90	75.28	66.62	79.21	60.78	81.63	63.54
Regions								
North	18.24	20.28	14.46	16.66	18.59	21.5	25.24	23.6
Central	13.96	13.04	14.09	10.11	14.35	13.95	12.62	16.07
Northeast	6.36	19.26	7.67	27.8	6.41	17.01	3.5	8.48
East	10.89	11.85	12.79	11.56	9.94	11.76	9.43	12.95
West	15.79	14.31	13.04	11.89	16.09	14.62	20.75	18.91
South	34.77	21.27	37.95	21.99	34.62	21.16	28.47	19.99

Note: Figures in the tables are in percentages, except age figures are in years; M: migrants, NM: non-migrants, other religions include Christianity, Sikhism, Jainism, Buddhism, and Zoroastrianism, etc.

Regarding social security coverage, migrants have greater access to social security benefits in the high- and medium-skill levels, whereas low-skilled non-migrants exhibit higher availability. The availability of social security benefits increases consistently with the level of skill, indicating that more skilled workers are better protected through formal employment mechanisms. Similar pattern observed for job contract availability aligns with this trend, as migrants exhibit greater access to formal job contracts in the high- and medium-skill categories, while low-skilled non-migrants show relatively higher access compared to their migrant counterparts. Overall, migrants exhibit a more balanced gender distribution than non-migrants, with a higher share of females across all skill levels, especially in high- and low-skill groups. Most migrants are married, and their share of married workers exceeds that of non-migrants across all skill levels, indicating migration is more prevalent among married individuals. Table 1 also presents the caste and religious distribution of migrant and non-migrant workers across different skill levels. Migrants have a higher representation in the others caste group across all skill categories, while Scheduled Tribes (ST) show a lower share among migrants compared to non-migrants. The share of Scheduled Castes (SC) and Other Backward Classes (OBC) remains broadly similar between the two groups across skill levels. Although non-migrants show a slightly higher proportion in the low-skill category. In terms of religion, Hindus constitute the majority among both migrants and non-migrants, with a relatively higher proportion among migrants across all skill levels. Conversely, the share of Muslim and other religious groups is slightly higher among non-migrants. Furthermore, migrants are predominantly concentrated in urban areas across all skill levels, while non-migrants are more rural-based. Regionally, the southern region accounts for the largest share of migrants across skill groups, indicating availability of higher employment opportunities in southern India. In contrast, non-migrants are more represented in the northern and northeastern regions, reflecting limited mobility and region-specific employment patterns (Table 1).

Table 2 presents the caste-based wage-earnings disparities between migrant and non-migrant workers in the regular salaried market of India. Overall, migrants have higher wages than non-migrants across social groups except the Scheduled Tribes (ST). The wage pattern reveals a contrasting pattern in rural and urban areas between migrants and non-migrants. In rural areas, migrants earn less than their non-migrant counterparts across all social groups except the 'Others' caste in the full sample. Whereas in urban areas, migrants exhibit higher wages than non-migrants across all social groups except the ST. This suggests that migration offers better economic returns in urban labour markets, whereas in rural areas, local non-migrants often retain higher wages, possibly due to better social networks or stable employment opportunities (Hnatkovska & Lahiri, 2013). Similar pattern is found in high and medium skilled regular salaried workers. Conversely, low-skilled migrants consistently earn less than their non-migrant counterparts across both regions and social groups, except others caste migrants in rural areas. This indicates that migration provides limited earnings benefits for less-skilled workers. As skill levels rise, wages also increase, because workers

with higher skills tend to earn more as compared to medium and low skill levels across social groups. (Madan & Mor, 2020).

Table 2. Skill-based wage disparities in the regular salaried market across social groups

Full sample									
	Rural			**Urban**			**Total**		
SG	**M**	**NM**	**%gap**	**M**	**NM**	**%gap**	**M**	**NM**	**%gap**
ST	15252.34	19721.96	**-22.66**	24443.58	26395.18	**-7.39**	20820.37	23011.34	**-9.52**
SC	11666.71	13241.97	**-11.9**	16842.29	14734.48	**14.31**	15471.67	14107.49	**9.67**
OBC	13839.8	14144.63	**-2.16**	20307.08	17376.07	**16.87**	18951.48	16189.4	**17.06**
Others	17071.32	17009.67	**0.36**	26173.74	22358.26	**17.07**	24650.79	20820.19	**18.4**
χ^2**test stat**	80.13***	279.16***		519.41***	539.52***		698.37***	923.17***	
High skill									
ST	17768.01	23488.14	**-24.35**	36796.61	33385	**10.22**	26831.51	28047.43	**-4.34**
SC	15093.4	18973.17	**-20.45**	29522.54	22437.14	**31.58**	24569.63	20953.71	**17.26**
OBC	18139.06	19982.6	**-9.23**	31191.88	27434.72	**13.69**	28110.4	25127.33	**11.87**
Others	20461.84	23859.75	**-14.24**	38511.46	31557.84	**22.03**	35247.07	29779.33	**18.36**
χ^2**test stat**	16.6128***	5.407		144.553***	80.587***		1500***	138.68***	
Medium skill									
ST	14118	18057.42	**-21.82**	23218.77	23900.49	**-2.85**	20183.4	21019.79	**-3.98**
SC	11579.03	12196.75	**-5.06**	15585.08	13756.01	**13.3**	14516.46	13032.14	**11.39**
OBC	11332.04	12572.4	**-9.87**	16509.28	13889.87	**18.86**	15398.37	13350.63	**15.34**
Others	14957.09	14716.5	**1.63**	19245.51	17055.49	**12.84**	18533.06	16284.67	**13.81**
χ^2**test stat**	52.572***	290.183***		39.797***	80.587***		68.46***	440.96***	
Low skill									
ST	7448.649	9676.667	**-23.02**	7885.776	11622.86	**-32.15**	7715.526	10439	**-26.09**
SC	6653.312	9788.598	**-32.03**	9352.175	10802.31	**-13.42**	8727.217	10414.98	**-16.21**
OBC	7886.068	9325.404	**-15.43**	9319.247	9966.485	**-6.49**	8945.043	9649.99	**-7.31**
Others	12519.04	11323.61	**10.56**	11276.39	12345.38	**-8.66**	11498.48	12004.44	**-4.21**
χ^2**test stat**	135.283***	12.448***		65.186***	55.344***		103.303***	39.62***	

Note: Figures in the table are in Indian rupees (INR), M: migrants, NM: non-migrants, ST: scheduled tribe, SC: scheduled caste, OBC: other backward class, *** p<0.01, ** p<0.05, * p<0.1.

Table 3 presents the comparison of average monthly wages between migrants and non-migrants across religion, location, and skill categories. In rural areas, migrants have lower wages than non-migrants across religious groups and skill levels. High-skilled Muslim migrant workers have the highest earnings disadvantage compared to their non-migrant counterparts in rural areas. In urban areas, migrants have higher wages than non-migrants across religious groups except for other religions. A similar pattern is visible in the medium and high skill categories, but only medium-skilled migrant workers from other religions face an earnings disadvantage in urban areas. In the low skill categories, migrants have lower wages across religious groups in both rural and urban areas, with migrants from other religions having a higher earnings disadvantage than their non-migrant counterparts. Results of the chi-square test statistics

reported in Tables 2 and 3 are statistically significant in most cases, suggesting that the distribution of wages is not uniform across caste and religion categories. In most of the cases, caste and religious affiliation play an important role in shaping earning disparities in Indian labour market (Arabsheibani et al., 2018). Economic gains from migration are concentrated among high-skilled workers and urban migrants (Khan, 2017). While rural and low-skilled migrants, especially among minority religions, face persistent wage disadvantages.

Table 3. Skill-based wage disparities in the regular salaried market across religious groups

Full sample									
	Rural			**Urban**			**Total**		
Religion	**M**	**NM**	**%gap**	**M**	**NM**	**%gap**	**M**	**NM**	**%gap**
Hindu	14214.10	14634.58	**-2.87**	22335.24	19481.02	**14.65**	20646.13	17717.89	**16.53**
Islam	14696.14	17757.75	**-17.24**	21569.56	16668.16	**29.41**	19779.14	17056.21	**15.96**
Others	16766.58	19957.49	**-15.99**	23536.86	25029.50	**-5.96**	21617.87	22902.11	**-5.61**
χ^2**test stat**	**18.20*** **	**126.94*** **		**6.70** **	**58.91*** **		**7.90** **	**27.17*** **	
High skill									
Hindu	18105.79	20790.70	**-12.91**	35412.97	29634.96	**19.50**	31260.67	27014.32	**15.72**
Islam	16166.02	24309.93	**-33.50**	31320.93	26366.75	**18.79**	26449.71	25524.99	**3.62**
Others	21544.12	23723.24	**-9.19**	32325.97	31572.91	**2.39**	29368.92	28091.20	**4.55**
χ^2**test stat**	**5.27***	**0.77**		**13.90*** **	**38.61*** **		**17.52*** **	**65.38*** **	
Medium skill									
Hindu	12268.52	13042.95	**-5.94**	17695.94	15523.76	**13.99**	16578.19	14518.91	**14.18**
Islam	14489.14	15331.45	**-5.49**	18889.49	13870.23	**36.19**	17829.78	14388.49	**23.92**
Others	15312.56	17832.82	**-14.13**	18917.19	22165.51	**-14.65**	17921.39	20359.32	**-11.97**
χ^2**test stat**	**20.57*** **	**129.10*** **		**25.60*** **	**42.27*** **		**30.25*** **	**126.11*** **	
Low skill									
Hindu	8104.63	9754.20	**-16.91**	9952.11	10997.76	**-9.51**	9558.16	10460.22	**-8.62**
Islam	10981.48	11133.70	**-1.37**	9603.58	10648.31	**-9.81**	9863.74	10785.30	**-8.54**
Others	9226.72	10215.24	**-9.68**	8635.38	11603.28	**-25.58**	8866.48	10970.56	**-19.18**
χ^2**test stat**	**23.49*** **	**0.83**		**0.86**	**5.76***		**7.67** **	**3.16**	

Note: Figures in the table are in INR; M: migrants, NM: non-migrants, other religions include Christianity, Sikhism, Jainism, Buddhism, and Zoroastrianism, etc., *** p<0.01, ** p<0.05, * p<0.1.

4.2 Empirical Results

4.2.1 Kernel density plots

Before estimating the endogenous switching regression model to examine the determinants of wage earnings and the wage gap between migrants and non-migrants, kernel density plots are reported to observe the distribution and pattern of the dependent variable (wages) for both the groups. Figure 2(A) shows the wage disparities between migrants and non-migrants in the full sample. Non-migrants exhibit a higher density around lower earnings levels, while migrants' earning distribution shifts slightly right-skewed,

indicating relatively higher wages among migrants and suggesting the presence of a modest wage gap favouring migrants.

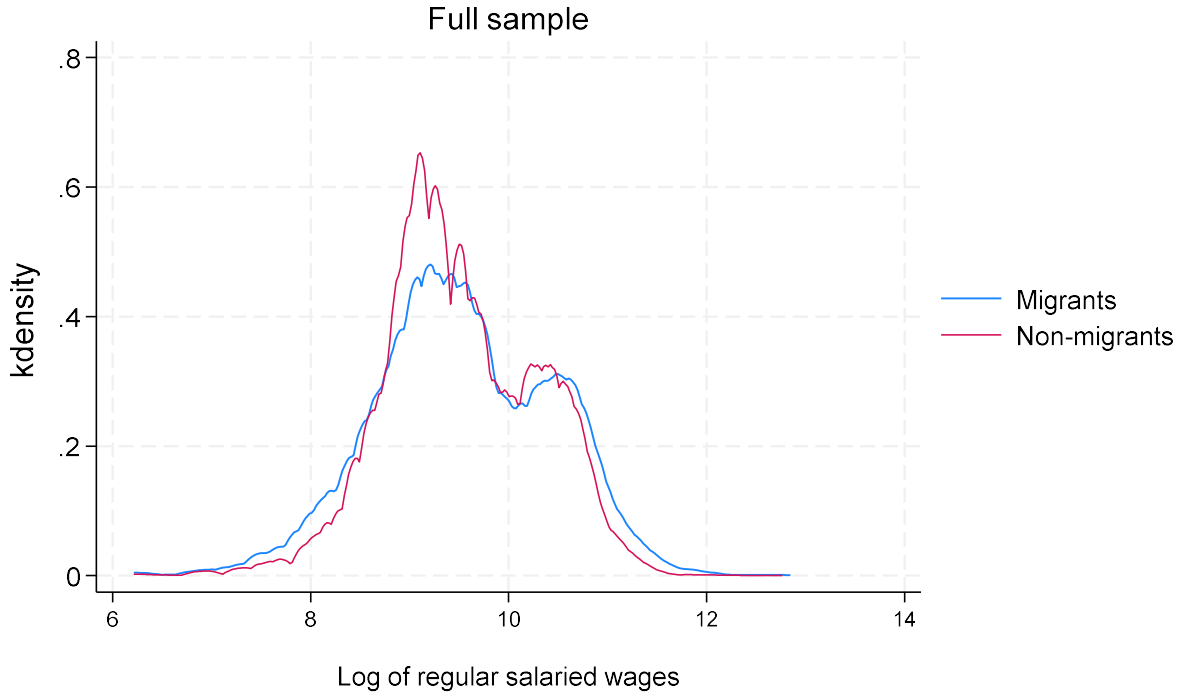


Figure: 2(A) kernel density graphs of regular salaried wages

Figure 2(B) shows the kernel density plot of wage distribution between migrants and non-migrants across skill levels. Among high-skilled workers, the wage distribution of migrants is slightly right-skewed compared to non-migrants, indicating marginally higher wages and reflecting the advantage for migrants, possibly due to access to more productive or formal sector jobs. Similarly, for medium-skilled workers, the migrants' curve also exhibits a right-skewed distribution, suggesting that migration is associated with relatively higher wages, possibly due to better employment opportunities. In contrast, among low-skilled workers, the density curve of non-migrants' peak is higher and located slightly right-skewed, indicating that non-migrants tend to earn higher wages compared to migrants, thus highlighting a wage gap between the two groups. Overall, the rightward shift of the wage distributions for migrants in the high- and medium-skill categories indicates that migration is generally associated with superior wage outcomes. In contrast, non-migrants exhibit higher wages at low skill levels, with the extent of this advantage depending on the specific skill category.

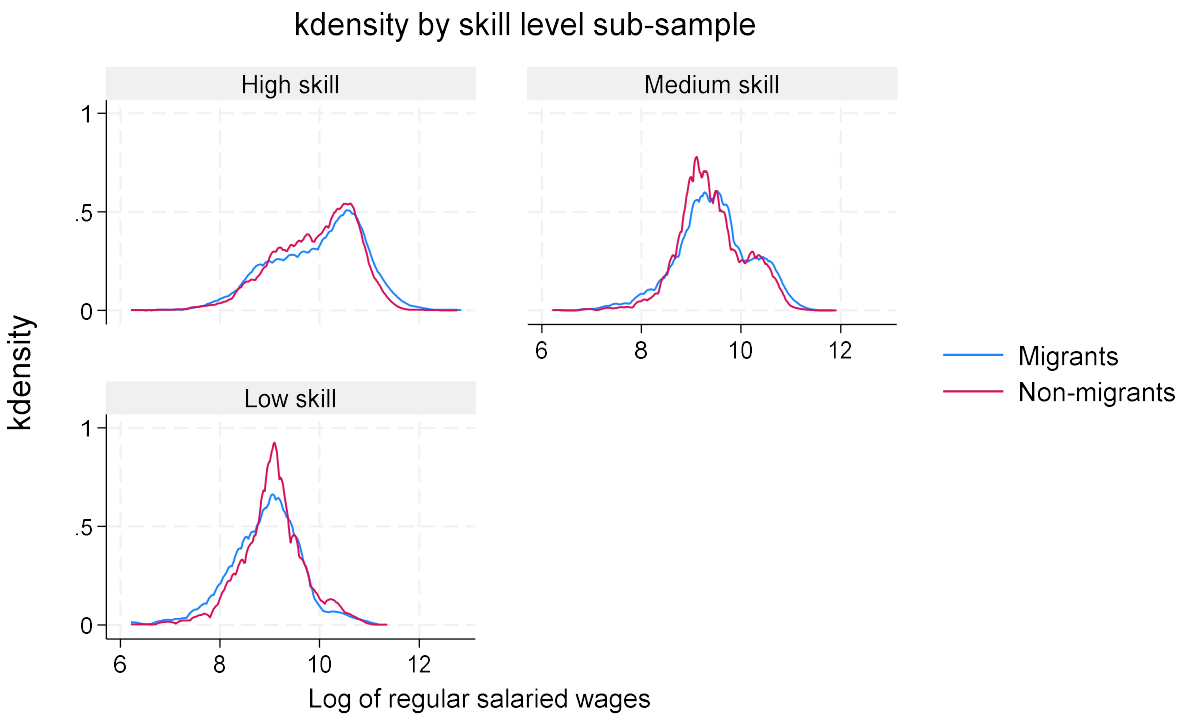


Figure: 2(B) Skill-based kernel density graphs of regular salaried wages

4.2.2 Baseline regression results with diagnostic test results

In this section, we examine how workers by their migration status influences wage earnings. To assess the wage differences between migrants and non-migrants, we first conduct the *Chow test*. The results indicate a statistically significant difference in the estimated coefficients, suggesting structural variation in the wage determination process between the two groups (Khan, 2016). Based on the OLS regression results presented in Table 4, migration appears to have a positive effect on wages. Regular salaried migrants earn, on average, 3.2 percent more than their non-migrant counterparts in the full sample. The sub-sample analysis further reveals that migrants earn significantly higher wages by 3.7 percent and 4.4 percent among high- and medium-skilled workers, respectively. However, migrants earn 1.1 percent more than non-migrants in the low-skill category, but the difference is statistically insignificant. Overall, when comparing the coefficients of migrant and non-migrant workers, it becomes evident that their characteristics differ, and these differences influence how wages are determined across skill levels. Diagnostic tests were conducted to assess multicollinearity, heteroskedasticity, normality, and model specification across the full sample and skill levels regression models (Table A3, Appendix). Nevertheless, since the OLS estimates do not account for sample selection bias, the results may be subject to potential estimation bias.

To examine the issue of sample selection between migrants and non-migrants, we first estimate the Heckman Selection Model using the two-step procedure. The results, presented in Table A4 (Appendix), show that the inverse Mills ratio (λ) is statistically significant in the full sample and across all skill levels except the low-skill category. This indicates the presence of selection bias in the data. Therefore, to account for this bias and to analyse the selected and non-selected samples more comprehensively, we employ the Endogenous Switching Regression Model (ESRM) for further analysis.

Table 4. OLS regression result

	Full sample			High skill			Medium skill			Low skill		
Variables	**Overall**	**M**	**NM**	**Overall**	**M**	**NM**	**Overall**	**M**	**NM**	**Overall**	**M**	**NM**
@Non-migrants												
Migrants	0.032***			0.037***			0.044***			0.011		
	(0.006)			(0.012)			(0.008)			(0.015)		
Age	0.031***	0.032***	0.033***	0.042***	0.034***	0.050***	0.030***	0.030***	0.032***	0.027***	0.029***	0.028***
	(0.002)	(0.003)	(0.002)	(0.004)	(0.007)	(0.004)	(0.002)	(0.005)	(0.002)	(0.004)	(0.007)	(0.005)
Age square	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Caste@ Others												
ST	0.009	-0.006	0.017	0.028	0.018	0.027	0.044***	0.027	0.050***	-0.049*	-0.048	-0.028
	(0.011)	(0.021)	(0.012)	(0.020)	(0.037)	(0.025)	(0.013)	(0.028)	(0.015)	(0.028)	(0.049)	(0.034)
SC	-0.107***	-0.102***	-0.100***	-0.118***	-0.092***	-0.125***	-0.057***	-0.066***	-0.050***	-0.087***	-0.055*	-0.084***
	(0.008)	(0.015)	(0.010)	(0.018)	(0.030)	(0.022)	(0.010)	(0.020)	(0.012)	(0.019)	(0.031)	(0.024)
OBC	-0.057***	-0.076***	-0.045***	-0.065***	-0.096***	-0.038**	-0.033***	-0.047***	-0.026***	-0.060***	-0.041	-0.063***
	(0.007)	(0.012)	(0.008)	(0.013)	(0.021)	(0.016)	(0.008)	(0.016)	(0.010)	(0.019)	(0.030)	(0.024)
Religion@ Hindu												
Islam	-0.012	0.022	-0.020*	-0.089***	-0.071**	-0.102***	0.018	0.074***	0.008	-0.016	0.017	-0.016
	(0.010)	(0.020)	(0.010)	(0.018)	(0.035)	(0.021)	(0.011)	(0.026)	(0.012)	(0.027)	(0.047)	(0.033)
Others	0.045***	0.042**	0.041***	0.038**	0.009	0.045**	0.047***	0.054**	0.042***	-0.018	0.033	-0.040
	(0.010)	(0.019)	(0.011)	(0.018)	(0.032)	(0.022)	(0.012)	(0.027)	(0.014)	(0.027)	(0.045)	(0.033)
Gender@ Male												
Female	-0.438***	-0.491***	-0.354***	-0.369***	-0.402***	-0.306***	-0.452***	-0.526***	-0.344***	-0.546***	-0.613***	-0.456***
	(0.007)	(0.011)	(0.009)	(0.011)	(0.019)	(0.014)	(0.010)	(0.015)	(0.013)	(0.017)	(0.025)	(0.023)
Marital status@ Unmarried												
Married	0.060***	0.003	0.084***	0.005	-0.021	0.025	0.083***	0.015	0.107***	0.054**	-0.035	0.081***
	(0.009)	(0.018)	(0.010)	(0.016)	(0.030)	(0.019)	(0.011)	(0.024)	(0.012)	(0.024)	(0.047)	(0.028)
Gen. Education@ Up to primary												
Middle	0.131***	0.159***	0.102***	-0.034	-0.080	-0.018	0.096***	0.142***	0.064***	0.130***	0.103***	0.148***
	(0.010)	(0.017)	(0.011)	(0.046)	(0.075)	(0.057)	(0.011)	(0.021)	(0.013)	(0.018)	(0.029)	(0.023)
Secondary and diploma	0.250***	0.293***	0.217***	0.302***	0.291***	0.294***	0.189***	0.253***	0.152***	0.191***	0.118***	0.234***
	(0.009)	(0.016)	(0.011)	(0.040)	(0.065)	(0.051)	(0.010)	(0.020)	(0.012)	(0.019)	(0.032)	(0.024)
Graduation and above	0.561***	0.681***	0.487***	0.610***	0.700***	0.539***	0.372***	0.479***	0.316***	0.334***	0.279***	0.363***
	(0.010)	(0.017)	(0.011)	(0.040)	(0.065)	(0.051)	(0.012)	(0.024)	(0.014)	(0.035)	(0.068)	(0.040)
@Without technical education												

With technical education	0.215***	0.221***	0.186***	0.227***	0.241***	0.202***	0.039***	0.026	0.037**	0.057	0.188**	0.001
	(0.010)	(0.015)	(0.011)	(0.012)	(0.020)	(0.016)	(0.015)	(0.026)	(0.018)	(0.054)	(0.095)	(0.065)
@Without social security benefits												
With social security benefits	0.572***	0.576***	0.564***	0.716***	0.697***	0.724***	0.491***	0.489***	0.483***	0.389***	0.417***	0.368***
	(0.007)	(0.013)	(0.008)	(0.013)	(0.022)	(0.015)	(0.009)	(0.017)	(0.010)	(0.018)	(0.030)	(0.022)
@No Job contracts												
Job contract less than 3 years	-0.051***	-0.050***	-0.049***	-0.060***	-0.107***	-0.020	-0.019	0.011	-0.030**	-0.018	0.013	-0.019
	(0.010)	(0.017)	(0.011)	(0.017)	(0.028)	(0.022)	(0.012)	(0.024)	(0.014)	(0.025)	(0.043)	(0.030)
Job contract more than 3 year	0.275***	0.302***	0.261***	0.217***	0.211***	0.220***	0.308***	0.346***	0.293***	0.323***	0.406***	0.282***
	(0.007)	(0.013)	(0.009)	(0.012)	(0.021)	(0.015)	(0.010)	(0.019)	(0.012)	(0.022)	(0.037)	(0.027)
Sector@ Rural												
Urban	0.150***	0.231***	0.117***	0.258***	0.330***	0.212***	0.119***	0.197***	0.091***	0.034**	0.084***	0.005
	(0.006)	(0.013)	(0.007)	(0.012)	(0.023)	(0.014)	(0.007)	(0.017)	(0.008)	(0.016)	(0.030)	(0.019)
Regions@ North												
Central	-0.217***	-0.187***	-0.239***	-0.210***	-0.156***	-0.239***	-0.231***	-0.176***	-0.255***	-0.187***	-0.188***	-0.188***
	(0.010)	(0.018)	(0.011)	(0.020)	(0.034)	(0.025)	(0.012)	(0.024)	(0.013)	(0.023)	(0.040)	(0.029)
Northeast	-0.014	-0.010	-0.033***	-0.083***	-0.013	-0.138***	0.026**	0.033	0.013	0.001	-0.081	-0.006
	(0.011)	(0.025)	(0.012)	(0.020)	(0.042)	(0.023)	(0.013)	(0.033)	(0.014)	(0.033)	(0.067)	(0.039)
East	-0.286***	-0.273***	-0.295***	-0.359***	-0.280***	-0.397***	-0.237***	-0.218***	-0.248***	-0.310***	-0.402***	-0.272***
	(0.010)	(0.020)	(0.012)	(0.020)	(0.035)	(0.024)	(0.013)	(0.027)	(0.014)	(0.025)	(0.043)	(0.031)
West	-0.092***	-0.031*	-0.128***	-0.066***	-0.009	-0.097***	-0.080***	-0.007	-0.115***	-0.094***	-0.033	-0.150***
	(0.010)	(0.017)	(0.011)	(0.020)	(0.034)	(0.024)	(0.012)	(0.023)	(0.013)	(0.022)	(0.034)	(0.028)
South	-0.042***	0.024	-0.090***	-0.088***	-0.006	-0.154***	-0.021*	0.041**	-0.053***	0.026	0.099***	-0.048*
	(0.009)	(0.015)	(0.010)	(0.017)	(0.029)	(0.022)	(0.011)	(0.020)	(0.012)	(0.021)	(0.033)	(0.028)
Constant	8.171***	8.072***	8.195***	7.748***	7.799***	7.691***	8.284***	8.218***	8.311***	8.444***	8.489***	8.401***
	(0.034)	(0.066)	(0.039)	(0.084)	(0.150)	(0.102)	(0.041)	(0.086)	(0.045)	(0.0745)	(0.128)	(0.091)
Observations	**39,455**	**12,889**	**26,566**	**12,778**	**4,669**	**8,109**	**21,208**	**5,993**	**15,215**	**5,469**	**2,227**	**3,242**
Chow test	**26.04*** **			**8.18*** **			**14.35 *** **			**4.29 *** **		
R-squared	0.554	0.591	0.541	0.550	0.570	0.546	0.503	0.533	0.497	0.423	0.467	0.386

Note: M: Migrants, NM: Non-migrants, Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2.3 Switching Regression Results

Since the OLS estimates may be biased due to sample selection between migrants and non-migrants, we employ the Endogenous Switching Regression Model as an alternative approach. This model consists of two components: the selection equation (Equation 1) and the wage equations (Equations 2 and 3). It is essential that at least one variable in the selection equation differs from those in the wage equations, a variable that influences the migration decision but does not directly affect earnings. In this study, the number of members in the household is used as the instrumental variable, as it is included in the selection equation but excluded from the wage equations.

Table 5 presents the results of the selection equation. Age has a positive effect on migration up to a threshold; after that, this effect becomes negative in the full sample and across skill levels, except for the low-skill group, where the pattern is insignificantly reversed. This suggests that younger and middle-aged individuals are more likely to migrate for employment opportunities, while older individuals are less mobile. The findings also indicate that individuals belonging to Scheduled Tribes (ST), Scheduled Castes (SC), and Other Backward Classes (OBC) are less likely to migrate compared to those from the Others caste. Moreover, the coefficient values decrease as the social hierarchy rises, suggesting that the likelihood of being a regular salaried migrant increases with higher social status. This pattern suggests that social and economic disadvantages, limited access to information, and weaker social networks restrict their migration opportunities (Navita & Pal, 2022; Kumar & Pradhan, 2025b).

Regular salaried workers belonging to Islam and other religious groups are less likely to migrate compared to their Hindu counterparts across all skill levels. This difference may be attributed to variations in social networks, community attachment, or occupational preferences. Female workers are found to be more likely to migrate than male workers across skill levels, primarily due to marriage-related migration, which remains a common social norm in India. General education shows a negative association with migration among regular salaried workers across all skill levels. As education levels rise, the likelihood of migration decreases, possibly because better-educated individuals have improved employment opportunities in their local areas (Keshri & Bhagat, 2012). In contrast, technical education has a positive impact on migration, indicating that individuals with technical skills are more inclined to move in search of better job prospects that match their qualifications. Regular salaried workers in urban areas are more likely to migrate than those in rural areas across all skill levels. The selection variable results show that household size has a significant negative effect on the likelihood of migration for employment. As household size increases, the probability of migration decreases (Kumar & Pradhan, 2025b). This may happen because individuals in larger households face greater family responsibilities and dependents, which reduce their willingness or ability to migrate for work (Table 5).

Table 5. Switching regression results: Selection equation

Variables	Full sample	High skill	Medium skill	Low skill
Age	0.002	0.009	0.013**	-0.010
	(0.005)	(0.009)	(0.006)	(0.010)
Age square	-0.001	-0.001	-0.001**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Caste@ Others				
ST	-0.307***	-0.411***	-0.244***	-0.356***
	(0.027)	(0.045)	(0.036)	(0.072)
SC	-0.070***	0.020	-0.078***	-0.189***
	(0.021)	(0.040)	(0.028)	(0.048)
OBC	-0.072***	0.002	-0.060***	-0.152***
	(0.016)	(0.028)	(0.022)	(0.046)
Religion@ Hindu				
Islam	-0.261***	-0.217***	-0.307***	-0.185***
	(0.025)	(0.043)	(0.032)	(0.070)
Others	-0.331***	-0.296***	-0.341***	-0.169**
	(0.025)	(0.041)	(0.035)	(0.068)
Gender@ Male				
Female	0.792***	0.719***	0.785***	0.740***
	(0.016)	(0.025)	(0.025)	(0.041)
Marital status@ Unmarried				
Married	0.515***	0.627***	0.393***	0.434***
	(0.023)	(0.038)	(0.030)	(0.065)
General education@ Up to primary				
Middle	-0.147***	-0.189*	-0.163***	-0.113**
	(0.024)	(0.104)	(0.029)	(0.046)
Secondary and diploma	-0.165***	-0.193**	-0.181***	-0.140***
	(0.021)	(0.091)	(0.027)	(0.048)
Graduation and above	-0.222***	-0.248***	-0.265***	-0.313***
	(0.022)	(0.090)	(0.031)	(0.092)
@Without technical education				
With technical education	0.373***	0.395***	0.297***	0.104
	(0.021)	(0.027)	(0.039)	(0.139)
Sector@ Rural				
Urban	0.400***	0.205***	0.459***	0.457***
	(0.016)	(0.028)	(0.021)	(0.041)
Household size@ Small				
HH size medium-small	-0.294***	-0.302***	-0.204***	-0.249***
	(0.014)	(0.024)	(0.017)	(0.033)
HH size medium	-0.467***	-0.464***	-0.346***	-0.344***
	(0.020)	(0.035)	(0.024)	(0.047)
HH size large	-0.595***	-0.627***	-0.450***	-0.414***
	(0.031)	(0.054)	(0.036)	(0.074)
Constant	-0.847***	-0.868***	-1.103***	-0.483**
	(0.086)	(0.194)	(0.115)	(0.191)
Observations	**39,455**	**12,778**	**21,208**	**5,469**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the wage equation (Table 6), the *rho* values are significant, and their signs vary across skill levels. The *rho* value for migrants is highly significant and negative in the full sample and across skill levels. Whereas for non-migrants, it is negative but insignificant in the full sample, among the high-skill group, the *rho* values are negative and significant. In contrast, for the medium- and low-skill groups, the rho values for non-migrants are positive and highly significant. The *rho* value represents the correlation coefficient between the error terms of the selection equation (u) and the wage equation (ε). A significant *rho* value indicates that the migration decision is endogenous to earnings. Therefore, the endogenous switching regression model is more appropriate than the ordinary least squares (OLS) regression model. The negative and significant rho_1 implies that, conditional on observable characteristics, individuals who choose to migrate tend to have unobserved traits that lower their wages than if they get work in their native places across skill levels. Similarly, negative rho_0 values for high skilled non-migrants, analysis show that non-migrant workers will receive lower wages if they do not migrate. However, the rho_0 value for high-skilled non-migrants is very small (-0.111*), which suggests that the migration condition has a limited effect on their wages. Contrastingly, a positive and significant rho_0 suggests that unobserved factors u positively correlated with the unobserved factors ε_0 wages for non-migrants in medium and low skill analysis. The positive rho_0 for non-migrants in medium and low skill analysis implies that, conditional on observable characteristics, individuals who choose to stay possess unobserved traits that enhance their wages if they stay non-migrants. Our findings are not aligned with Parhah et al. (2025) and Long et al. (2017) findings that network users will receive higher income when they switch to non-users of the network. However, to earn higher wages, non-migrants with medium and low skills should maintain their position as non-migrants.

Although the rho_1 values for migrants are negative and significant across skill levels, this does not necessarily imply lower wages for migrants. Since the dependent variable is expressed in logarithmic form, the negative sign of rho_1 indicates that unobserved factors increasing the likelihood of migration are negatively correlated with the unobserved determinants of log wages (Lokshin & Sajaia, 2004). However, the overall wage outcome depends on both the structural effects of observable variables and the selection correction term (*rho*). Thus, the mixed signs of *rho* across skill levels indicate that the nature and direction of unobserved factors influence migration and wages differently across groups. The Likelihood Ratio (LR) test of independent equations is highly significant across all samples, full, high-, medium-, and low-skill groups, indicating that the selection (migration decision) and wage equations are not independent. Additionally, it also supports the inclusion of household size variables as exclusion restrictions in the selection equation. This justifies the use of the Endogenous Switching Regression Model, as it accounts for selection bias and confirms that migration status has a significant influence on earning outcomes.

Table 6. Switching regression results: Wage equation

excel	Full sample		High skill		Medium skill		Low skill	
Variables	**M**	**NM**	**M**	**NM**	**M**	**NM**	**M**	**NM**
Age	0.030***	0.033***	0.0287***	0.0495***	0.0240***	0.0320***	0.0258***	0.0327***
	(0.004)	(0.002)	(0.00793)	(0.00473)	(0.00536)	(0.00271)	(0.00521)	(0.00767)
Age square	-0.001***	-0.001***	-0.001	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Caste@ Others								
ST	0.143***	0.018	0.217***	0.0397	0.164***	-0.00415	-0.110***	0.0960*
	(0.023)	(0.013)	(0.041)	(0.0255)	(0.0323)	(0.0166)	(0.0384)	(0.0554)
SC	-0.058***	-0.099***	-0.090***	-0.124***	-0.0173	-0.075***	-0.133***	0.0527
	(0.017)	(0.010)	(0.033)	(0.022)	(0.0236)	(0.0131)	(0.0268)	(0.0361)
OBC	-0.036***	-0.044***	-0.089***	-0.037**	-0.008	-0.050***	-0.105***	0.039
	(0.014)	(0.008)	(0.024)	(0.016)	(0.019)	(0.010)	(0.026)	(0.034)
Religion@ Hindu								
Islam	0.166***	-0.018*	0.056	-0.093***	0.261***	-0.057***	-0.057	0.117**
	(0.022)	(0.011)	(0.039)	(0.022)	(0.030)	(0.013)	(0.035)	(0.053)
Others	0.192***	0.042***	0.159***	0.054**	0.219***	-0.024	-0.075**	0.104**
	(0.022)	(0.012)	(0.036)	(0.022)	(0.0313)	(0.015)	(0.035)	(0.052)
Gender@ Male								
Female	-0.793***	-0.358***	-0.685***	-0.330***	-0.847***	-0.135***	-0.284***	-0.885***
	(0.015)	(0.012)	(0.024)	(0.019)	(0.021)	(0.0153)	(0.035)	(0.032)
Marital status@ Unmarried								
Married	-0.193***	0.082***	-0.253***	0.008	-0.175***	0.172***	0.150***	-0.202***
	(0.020)	(0.010)	(0.035)	(0.021)	(0.027)	(0.013)	(0.032)	(0.052)
Gen. education@ Up to primary								
Middle	0.210***	0.103***	0.012	-0.011	0.206***	0.034**	0.116***	0.117***
	(0.020)	(0.012)	(0.085)	(0.057)	(0.025)	(0.014)	(0.025)	(0.034)
Secondary and diploma	0.348***	0.218***	0.385***	0.300***	0.314***	0.118***	0.195***	0.156***
	(0.018)	(0.011)	(0.074)	(0.052)	(0.023)	(0.013)	(0.026)	(0.036)
Graduation and above	0.762***	0.489***	0.810***	0.547***	0.567***	0.271***	0.304***	0.390***
	(0.019)	(0.012)	(0.074)	(0.051)	(0.027)	(0.015)	(0.044)	(0.074)
@Without technical education								
With technical education	0.062***	0.184***	0.060**	0.189***	-0.122***	0.106***	0.024	0.157
	(0.018)	(0.012)	(0.024)	(0.017)	(0.032)	(0.019)	(0.069)	(0.107)
@Without social security benefits								
With social security benefits	0.572***	0.564***	0.685***	0.724***	0.497***	0.492***	0.378***	0.394***
	(0.012)	(0.008)	(0.022)	(0.015)	(0.017)	(0.010)	(0.022)	(0.028)
@No Job contracts								
Job contract less than 3 year	-0.043**	-0.049***	-0.102***	-0.020	0.020	-0.032**	-0.025	0.023
	(0.017)	(0.011)	(0.027)	(0.022)	(0.022)	(0.014)	(0.030)	(0.040)
Job contract more than 3 year	0.307***	0.261***	0.202***	0.220***	0.369***	0.301***	0.289***	0.483***
	(0.013)	(0.009)	(0.021)	(0.015)	(0.018)	(0.011)	(0.027)	(0.037)
Sector@ Rural								
Urban	0.033**	0.116***	0.221***	0.205***	-0.072***	0.177***	0.085***	-0.130***
	(0.015)	(0.008)	(0.026)	(0.014)	(0.021)	(0.009)	(0.023)	(0.035)
Regions@ North Central								
	-0.181***	-0.239***	-0.166***	-0.239***	-0.171***	-0.266***	-0.196***	-0.161***
	(0.018)	(0.011)	(0.033)	(0.025)	(0.022)	(0.013)	(0.029)	(0.037)

Northeast	-0.021	-0.033***	-0.055	-0.140***	0.025	0.010	-0.002	-0.052
	(0.024)	(0.012)	(0.040)	(0.023)	(0.031)	(0.014)	(0.038)	(0.064)
East	-0.271***	-0.296***	-0.298***	-0.398***	-0.204***	-0.246***	-0.276***	-0.364***
	(0.019)	(0.012)	(0.034)	(0.024)	(0.025)	(0.014)	(0.030)	(0.041)
West	-0.048***	-0.128***	-0.040	-0.098***	-0.033	-0.119***	-0.152***	-0.055*
	(0.017)	(0.011)	(0.033)	(0.024)	(0.022)	(0.013)	(0.028)	(0.032)
South	0.003	-0.091***	-0.030	-0.156***	0.009	-0.060***	-0.047*	0.061**
	(0.015)	(0.010)	(0.028)	(0.022)	(0.019)	(0.012)	(0.027)	(0.031)
Constant	9.033***	8.192***	8.812***	7.679***	9.373***	8.413***	9.238***	8.580***
	(0.079)	(0.039)	(0.174)	(0.102)	(0.105)	(0.0499)	(0.150)	(0.101)
lns	-0.286***	-0.657***	-0.241***	-0.582***	-0.281***	-0.613***	-0.342***	-0.592***
	(0.013	(0.004	(0.021)	(0.008)	(0.018)	(0.009)	(0.027)	(0.031)
r	-1.141***	-0.019	-1.124***	-0.111*	-1.407***	0.996***	-1.315***	0.744***
	(0.034)	(0.037)	(0.054)	(0.060)	(0.043)	(0.035)	(0.074)	(0.114)
rho	**-0.815*** **	**-0.019**	**-0.809*** **	**-0.111***	**-0.886*** **	**0.759*** **	**-0.865*** **	**0.631*** **
	(0.011)	**(0.037)**	**(0.019)**	**(0.059)**	**(0.009)**	**(00.015)**	**(0.018)**	**(0.069)**
LR test of independent equation	**265.73*** **		**115.02*** **		**328.66*** **		**76.50*** **	
Observations	**39,455**	**39,455**	**12,778**	**12,778**	**21,208**	**21,208**	**5,469**	**5,469**

Note: M: Migrants, NM: Non-migrants, LR: Likelihood ratio, Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The endogenous switching regression model (ESRM) captures how explanatory variables affect wages differently for migrants and non-migrants. However, comparing the wage equations for migrants and non-migrants reveals few differences (Table 6). Age has a positive and statistically significant effect on earnings for both migrant and non-migrant groups across skill levels, reflecting the growth of experience and productivity. However, the positive effect diminishes over time, suggesting a non-linear (inverted U-shaped) relationship between age and wage earnings (Khan, 2021). The results indicate significant wage differentials across caste and religion groups. Scheduled Tribes (ST) migrants consistently earn higher wages than the Other caste, particularly in the full and high and medium skill levels, while low-skilled ST migrants earn significantly less. Scheduled Castes (SC) and Other Backward Classes (OBC) generally earn lower wages compared to the Other group for both migrants and non-migrants across all skill levels, showing a persistent disadvantage for these castes (Arabsheibani et al., 2018; Sengupta and Guchhait, 2021; Kumar & Pradhan, 2025a). Considering Hindus religion as the reference group, Islamic migrants significantly earn higher wages in the full and medium-skill samples, whereas non-migrant Islamic workers earn less, particularly in the high- and medium-skill categories. Individuals from other religions exhibit a significant wage advantage across all skill levels, except for the low-skilled migrants and medium skilled non-migrants. Whereas non-migrants belonging to Islam and other religious groups earn higher wages than their Hindu counterparts. Female workers earn substantially lower wages than their male counterparts across skill levels and groups, indicating a persistent gender wage gap in the Indian labour market. Marital

status is associated with lower wages for migrants and higher wages for non-migrants across all skill levels, except in the low-skill group, where this pattern is reversed.

The results show that higher educational attainment significantly increases wage for both migrants and non-migrants across all skill levels (Becker, 1974; Khan, 2016). Earnings rise steadily from middle to graduation and above, with the highest returns observed for graduates. Regarding technical education, individuals with technical qualifications generally earn more than those without, particularly among non-migrants. Conversely, among medium-skilled migrants, those with technical education earn less than migrants without technical education. Moreover, workers with social security benefits earn significantly higher wages than those without receiving it, across all skill levels and migration statuses, highlighting the strong positive impact of employment protection and benefits on earnings (ILO, 2018). Workers with job contracts shorter than three years generally earn less, reflecting lower job stability and bargaining power. In contrast, those with contracts longer than three years earn substantially more, suggesting that long-term employment stability enhances income security, productivity, and wage returns for both migrants and non-migrants. The results indicate that both migrants and non-migrants earn more in urban areas compared to their rural counterparts. In addition, notable regional differences in wage exist across North, South, West, East, Central, and Northeast India. Workers in the Central, East, and West consistently experience significantly lower earnings compared to those in the North, suggesting regional disparities in labour markets that affect both groups. These findings are statistically robust, as indicated by several significant coefficients. They reflect underlying structural differences in regional economies and sectoral opportunities due to variations in economic development, industrialisation, infrastructure, and income-generating opportunities. (Kumar& Pradhan, 2025b).

4.2.4 Earnings Differentials

Table 7 presents a comparison of observed and predicted log wages between migrants and non-migrants based on the wage equations reported in Table 6. Unconditional log wages are predicted using the ESRM, as outlined in Equations (6) and (7). Conditional log wages are predicted using the ESRM, as outlined in Equations (8–11). The predicted unconditional log wages are the most useful for calculating the effect of migration on earnings, since they are not subject to any selectivity bias. The observed mean wages indicate that migrants earn approximately 2.33% more than non-migrants in the full sample. The wage gap widens for high-skilled (5.03%) and medium-skilled (4.71%) workers, indicating migration benefits skilled labour. However, low-skilled migrants earn 16.12% less than non-migrants. The unconditional value represents the average wage differences between migrants and non-migrants, without adjusting for selection bias or unobserved individual characteristics. In the full sample, migrants earn about 84% higher wages than non-

migrants, indicating a strong overall migration advantage. This advantage is particularly pronounced for high-skilled workers (91.20%) and remains significant for medium-skilled workers (78.27%), indicating strong earnings returns to migration among skill groups. For low-skilled workers, migrants earn about 14.23% more, showing a small but positive migration benefit. This suggests that migrants may possess certain unobserved characteristics that enable them to earn higher wages compared to non-migrants. Such factors may include greater adaptability, stronger work motivation, better job-search skills, wider social exposure, and a willingness to relocate for better opportunities. Since these factors are typically not measured in standard wage models, failing to account for them can lead to omitted variable bias. As a result, the raw wage gap may partly reflect the influence of these unobserved competencies, rather than just the effect of migration itself (Freeman & Schettkat, 2001; Behrens & Sato, 2011; Dustmann et al., 2013; Long et al., 2017).

Table 7. Observed and predicted log of monthly wages

		Full sample		High skill		Medium skill		Low skill	
	Variable	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
Migrants	Observed	9.554	0.891	9.968	0.921	9.458	0.756	8.942	0.718
	Unconditional	10.137	0.742	10.535	0.734	10.160	0.640	9.448	0.605
	Conditional on migrants	9.556	0.683	9.969	0.689	9.460	0.551	8.943	0.485
	Conditional on non-migrants	10.593	0.634	11.017	0.659	10.610	0.519	10.153	0.461
Non-migrants	Observed	9.531	0.765	9.919	0.827	9.412	0.664	9.118	0.631
	Unconditional	9.527	0.562	9.887	0.611	9.582	0.482	9.315	0.360
	Conditional on migrants	9.531	0.562	9.918	0.612	9.411	0.475	9.117	0.395
	Conditional on non-migrants	9.518	0.572	9.844	0.603	10.098	0.468	9.516	0.399

Note: Figures in the table are in log of INR

The conditional expected wage estimates reveal a consistent and substantial earnings disadvantage for migrants across all skill levels. For the full sample, migrants earn about 64.50% less than what they would have earned had they remained non-migrants, after accounting for observable characteristics and self-selection bias. This disadvantage persists across all skill groups, approximately 65% for high-skilled, 68% for medium-skilled, and 70% for low-skilled workers, indicating that migration is associated with significant wage losses. These results suggest that migrants may be concentrated in lower-paying or informal sectors at the destination, where returns to education and skills are limited. Additionally, the widening wage gap among migrants and non-migrants across low, medium and high skill levels indicates that migration does not necessarily lead to improve the economic outcomes. Instead, it reflects structural constraints at destination labour markets, including underemployment, occupational downgrading, skill

underutilisation, and imperfect skill transferability (Wang et al., 2015; Williams & Bol, 2018; Morlin et al., 2026). Overall, from the migrants' perspective, the ESRM-based conditional wages indicate that the economic returns to migration are negative across all skill levels, with the largest penalties observed among low-skilled workers (Table 7).

The conditional mean wage estimates for the non-migrant group highlight a distinct skill-based pattern in potential migration outcomes. For the full sample, the conditional log wage difference implies that non-migrants would earn approximately 1.30% less if they had chosen to stay, suggesting almost no difference in predicted earnings between the two regimes. Among high-skilled non-migrant workers, the negative wage gap indicates that migration would improve their earnings by 7.10%, possibly due to better destination employment matches and sectoral stability at the destination. In contrast, the results for medium- and low-skilled non-migrants reveal significant potential wage gains under the non-migrant scenario, approximately 98.80% and 49.90% higher, respectively, if they stay in the same channel (non-migrants). These findings suggest that migration provides economic benefits for high-skilled non-migrants, whereas lower- and medium-skilled non-migrant workers face substantial wage penalties for relocating. Overall, the results underscore that the returns to migration are highly skill-sensitive, favouring workers in the high skill spectrum, for whom migration substantially enhances earning opportunities (Table 7).

5. Conclusion

The study highlights that skill-based wage differences between migrants and non-migrants in the Indian labour market persist even within comparable skill groups using the Periodic Labour Force Survey data 2020-21. This aspect has not been widely examined in previous research on internal migration. By highlighting skill-specific wage disparities, our findings contribute new evidence to the literature on internal migration in India. It shows that labour mobility interacts with skill levels to shape earning outcomes in ways that have not been adequately explored.

The empirical findings of ordinary least squares (OLS) regression results illustrate that migrants have a positive effect on wages compared to their non-migrant counterparts across all skill levels. However, these results do not account for selection bias, as Heckman's findings indicate that it is present. For this endogenous switching regression model (ESRM) is used (Long et al., 2017; Parhah et al., 2025). The ESRM Selection equation results show how socio-economic and demographic variables affect migration probability differently, such that Other castes in society have a higher propensity to migrate to respective lower social groups. Also, the selection variable household size has a negative impact on the migration propensity across skill levels (Kumar & Pradhan, 2025b). Moreover, the wage equations show that the *rho* and Likelihood Ratio test of independent equations yield highly significant values, indicating that the

ESRM is more appropriate than OLS (Lokshin & Sajaia, 2004; Long et al., 2017). Caste and religion significantly influence wages for both migrants and non-migrants across skill levels, reflecting the persistent role of social hierarchy and discrimination in India's labour market (Sengupta & Guchhait, 2021; Motkuri, 2025). Education positively affects wage earnings, as higher qualifications enhance workers' skills, productivity and employability. Similarly, access to social security benefits and long-term job contracts improves earnings by providing greater stability, reducing employment-related risks, and strengthening workers' bargaining power (Srivastava & Sutradhar, 2016; ILO, 2018). The earnings results reveal notable wage disparities between migrants and non-migrants, driven by variation in task-based skill requirements and unequal returns to these occupational tasks across the wage distribution, indicating pronounced within-occupation wage inequality (Williams & Bol, 2018). The observed mean wage values show that migrants with medium and high skills have higher earnings, while migrants with low skills have lower earnings than their non-migrant counterparts. Unconditional wages show that migrants have earnings advantages across skill levels, particularly for higher and medium skill levels. The conditional value for migrants shows lower earnings compared to those of non-migrants. This shows the structural barriers and discrimination in the labour market due to their migration status. Similarly, conditional values for non-migrants indicate that migration is beneficial only for high-skilled workers, while medium- and low-skilled workers will face substantial wage disadvantages if they relocate.

The conditional mean wages suggest that migration is largely driven by the lack of adequate employment opportunities and the absence of suitable jobs in migrants' native regions. Individuals move in search of higher wages and better-quality work. However, upon migrating, they frequently encounter wage discrimination and structural constraints that vary systematically by skill level and occupation. These findings highlight the need for policies that promote local employment generation, expand market-oriented skill development, and enforce fair wage and anti-discrimination regulations. Strengthening social protection mechanisms is also essential to ensure more equitable labour-market outcomes for all workers, especially those with low and medium skills. In this context, local governments and administrative bodies should adopt a proactive approach to strengthening the enforcement of labour rights and expanding access to essential services such as education, training and healthcare (Rajput & Rajan, 2023). Additionally, enhancing awareness and registration under the *e-Shram portal* is crucial for addressing skill-based earning disparities between migrants and non-migrants. Its integration with skill development initiatives and employment platforms facilitates access to training, job-skill matching, and social security, thereby improving overall labour-market outcomes. These results also support progress toward Sustainable Development Goals (SDG) 8, which calls for decent work and stronger social protection, and SDG 10, which aims to reduce inequalities within and between population groups.

Acknowledgement:

The authors declare no external funding and no competing financial or personal interests related to this research.

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Appendix

Table A1: Assigned skill level based on broader national code of occupation (NCO) 2004 categories

NCO code-2004	Broader occupation category	Require educational attainments	NCO-based skill level	Skill-based broader category (Ankita & Singh, 2025)
111/130	Legislators, senior officials, and managers	Not defined	Skill not defined*	**High skill**
211/246	Professionals	Postgraduate university degree and above	IV	
311/348	Technicians and associate professionals	First university degree	III	
411/422	Clerks	Secondary education	II	**Medium skill**
511/523	Service workers and shop & market sales workers	Secondary education	II	
611/620	Skilled agricultural and fishery workers	Secondary education	II	
711/744	Craft and related trades workers	Secondary education	II	
811/834	Plant and machine operators and assemblers	Secondary education	II	
911/933	Elementary occupations	Primary education/ informal skills	I	**Low skill**

Source: Ankita & Singh (2025); NCO (2004); *The concept of skill level has not been applied in the case of legislators, senior officials & managers as skills for executing tasks and duties of these occupations vary to such an extent that it would be impossible to link them with any of the four broad skill levels.

Table A2: Description of the covariates

Variables	Variable description	Unit of measurement
Wage	Log of individual monthly wages	Log of INR
Age	Age of the individuals	No. of years
Age squares	Age square of the individuals	Square of age
Household size	Number of members in the household	In number
General education	Categorized the educational attributes into the following categories: Up to primary, Up to Middle, Senior secondary and diploma, Graduation and above	
Technical education	Those having a technical degree and diploma come under "with technical education; otherwise, "without technical education."	

Availability of social security benefits	Yes or no (social security benefits include only PF/ pension, only gratuity, only health care & maternity benefits)	
Type of job contract	No written job contract, written job contract less than 3 years, more than 3 years	
Occupations	Based NCO-2004 classification, we have categorized it into ten broader occupation categories, and then as per skill level, we have categories it into three categories: High skill, medium skill, and low skill	National Occupation Code 2004
Gender	Male, Female	
Marital status	Unmarried, Married	
Caste	Scheduled Castes (SC), Scheduled Tribes (ST), Other Backward Classes (OBC), Others	
Sector	Rural, Urban	
Religion	Hindu, Muslim, Others (Others include the following religions: Christianity, Sikhism, Buddhism, Jainism, Zoroastrianism, and others)	
Regions	Based on the literature and the Indian geographical structure, we have divided India into six major regions: North, Central, Northeast, East, West, and South	

Table A3: Diagnostic tests for regression

Wage-earning Determinants		VIF	Het. test (BP)	AIC	BIC	Ramsey test	Cameron and Trivedi's decomposition of IM-test		
							Skewness	Kurtosis	Hetero-scedasticity
Full sample	Overall	1.58	2.71*	63453.11	63650.52	64.65***	466.65***	161.32***	2037.77***
	M	1.5	0.23	22152.65	22316.86	3.79***	128.23***	43.23***	785.13***
	NM	1.64	4.99**	40642.51	40822.63	103.18***	368.5***	120.21***	1369***
High Skill	Overall	2.63	184.91***	22366.52	22538	10.33***	194.95***	58.48***	969.41***
	M	2.42	28.5***	8593.669	8735.54	6.92***	60.94***	14.4***	472***
	NM	2.89	196.04***	13615.25	13769.26	5.39***	154.59***	43.91***	716.45***
Medium skill	Overall	1.53	6.15**	29903.3	30086.43	23.44***	271.11***	81.96***	1243.28***
	M	1.47	2.26	9165.714	9313.078	4.7***	71.88***	17.77***	594.37***
	NM	1.58	22.38***	20417.5	20585.36	46.89***	222.67***	64.94***	853.03***
Low skill	Overall	1.37	13.87***	8269.509	8421.466	23.25***	80.09***	36.37***	599.89***
	M	1.32	20.69***	3501.803	3627.388	13.37***	46.74***	14***	302.53***
	NM	1.41	0.01	4705.794	4839.641	9.94***	58.67***	20.39***	450.25***

Note: M: Migrants, NM: Non-migrants
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Heckman model equation

	Full sample		High skill		Medium skill		Low skill	
Variables	**Wage equation**	**Selection equation**	**Wage equation**	**Selection equation**	**Wage equation**	**Selection equation**	**Wage equation**	**Selection equation**
Age	0.032***	0.005	0.032***	0.011	0.030***	0.011*	0.029***	-0.011
	(0.003)	(0.005)	(0.007)	(0.009)	(0.004)	(0.006)	(0.007)	(0.010)
Age square	-0.001***	-0.001*	-0.001*	-0.001*	-0.001***	-0.001**	-0.001***	0.001

	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Caste@ Others								
ST	0.031	-0.304***	0.103**	-0.400***	0.052*	-0.255***	-0.041	-0.348***
	(0.023)	(0.027)	(0.042)	(0.046)	(0.030)	(0.038)	(0.052)	(0.074)
SC	-0.091***	-0.065***	-0.090***	0.030	-0.056***	-0.080***	-0.051	-0.224***
	(0.015)	(0.021)	(0.030)	(0.041)	(0.020)	(0.030)	(0.034)	(0.050)
OBC	-0.067***	-0.069***	-0.094***	0.005	-0.038**	-0.089***	-0.038	-0.184***
	(0.012)	(0.017)	(0.022)	(0.028)	(0.017)	(0.023)	(0.032)	(0.047)
Religion@ Hindu								
Islam	0.056***	-0.261***	-0.017	-0.210***	0.105***	-0.319***	0.021	-0.179**
	(0.021)	(0.025)	(0.038)	(0.044)	(0.028)	(0.034)	(0.048)	(0.072)
Others	0.079***	-0.328***	0.070**	-0.301***	0.089***	-0.362***	0.036	-0.188***
	(0.021)	(0.025)	(0.035)	(0.041)	(0.030)	(0.037)	(0.046)	(0.069)
Gender@ Male								
Female	-0.568***	0.777***	-0.525***	0.714***	-0.590***	0.812***	-0.625***	0.740***
	(0.020)	(0.016)	(0.035)	(0.025)	(0.026)	(0.026)	(0.043)	(0.041)
Marital status@ Unmarried								
Married	-0.045**	0.543***	-0.121***	0.649***	-0.016	0.459***	-0.043	0.477***
	(0.021)	(0.023)	(0.039)	(0.038)	(0.026)	(0.032)	(0.052)	(0.066)
Gen. education@ Up to primary								
Middle	0.173***	-0.137***	-0.041	-0.175*	0.154***	-0.151***	0.105***	-0.096**
	(0.018)	(0.024)	(0.078)	(0.105)	(0.021)	(0.031)	(0.029)	(0.048)
Secondary and diploma	0.309***	-0.152***	0.329***	-0.186**	0.266***	-0.151***	0.121***	-0.147***
	(0.016)	(0.022)	(0.067)	(0.093)	(0.020)	(0.029)	(0.032)	(0.050)
Graduation and above	0.704***	-0.211***	0.749***	-0.230**	0.497***	-0.208***	0.285***	-0.310***
	(0.018)	(0.023)	(0.067)	(0.092)	(0.024)	(0.033)	(0.070)	(0.094)
@Without technical education								
With technical education	0.182***	0.383***	0.166***	0.416***	-0.002	0.339***	0.186*	0.150
	(0.017)	(0.022)	(0.027)	(0.028)	(0.028)	(0.040)	(0.095)	(0.142)
@Without social security benefits								
With social security benefits	0.574***		0.692***		0.487***		0.416***	
	(0.013)		(0.022)		(0.017)		(0.029)	
@No Job contracts								
Job contract less than 3 year	-0.049***		-0.107***		0.011		0.014	
	(0.017)		(0.028)		(0.024)		(0.043)	
Job contract	0.303***		0.210***		0.346***		0.407***	

more than 3 year	(0.013)		(0.021)		(0.019)		(0.037)	
Sector@ Rural								
Urban	0.184***	0.419***	0.286***	0.216***	0.150***	0.518***	0.075*	0.494***
	(0.016)	(0.016)	(0.025)	(0.029)	(0.023)	(0.022)	(0.039)	(0.042)
Regions@ North								
Central	-0.185***		-0.158***		-0.172***		-0.188***	
	(0.018)		(0.034)		(0.024)		(0.040)	
Northeast	-0.012		-0.020		0.031		-0.081	
	(0.025)		(0.042)		(0.033)		(0.066)	
East	-0.277***		-0.291***		-0.220***		-0.403***	
	(0.020)		(0.035)		(0.027)		(0.043)	
West	-0.031*		-0.016		-0.006		-0.034	
	(0.017)		(0.034)		(0.023)		(0.034)	
South	0.022		-0.010		0.040**		0.098***	
	(0.015)		(0.029)		(0.020)		(0.033)	
HH size@ Small								
HH size medium-small		-0.390***		-0.366***		-0.411***		-0.375***
		(0.016)		(0.027)		(0.022)		(0.041)
HH size medium		-0.574***		-0.535***		-0.612***		-0.530***
		(0.023)		(0.040)		(0.032)		(0.057)
HH size large		-0.753***		-0.730***		-0.759***		-0.801***
		(0.035)		(0.063)		(0.048)		(0.096)
Lambda/ Mills		-0.157***		-0.278***		-0.121***		-0.022
		(0.033)		(0.066)		(0.040)		(0.080)
Constant	8.302***	-0.861***	8.225***	-0.892***	8.407***	-1.021***	8.519***	-0.380*
	(0.0826)	(0.087)	(0.183)	(0.196)	(0.107)	(0.119)	(0.155)	(0.196)
Observations	**39,455**	**12,889**	**12,778**	**4,669**	**21,208**	**5,993**	**5,469**	**2,227**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1