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Internal Labour Migration and Skill Heterogeneity: Evidence from Major Industrial Regions of India

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Abstract

Internal labour migration is an important component of labour market transformation in India, shaped by rapid industrialisation, urbanisation, and regional economic inequalities. Despite extensive literature on rural–urban migration and informal labour mobility, limited evidence exists on the heterogeneity of skills and migration patterns across industrial regions. This study examines skill-based migration patterns and their determinants across six major industrial regions of India: Delhi NCR, Surat-Ahmedabad, Mumbai-Pune, Chennai, Bengaluru, and Hyderabad, using unit-level data from the Periodic Labour Force Survey 2020–21. Logistic regression models identify the determinants of migration across skill levels and industrial regions. Descriptive tables and figures examine migration patterns, distance, and industrial employment across skill groups and regions. The findings reveal substantial differences in migration patterns across skill groups and industrial regions. High-skilled workers are more concentrated in urban-oriented and interstate migration, whereas low-skilled workers exhibit relatively localised and rural mobility. Interstate migration is particularly concentrated towards Delhi NCR and Mumbai–Pune, while southern industrial regions show stronger intra-state migration linkages. The results further indicate that urban residence and technical education significantly increase the probability of migration, particularly among medium- and high-skilled workers. Overall, migration in India is increasingly differentiated by occupational skill, industrial structure, and regional labour demand, with implications for employment policy, regional development, urban planning, and skill formation.

Keywords: Internal labour migration; Skill-based migration; Industrial regions; Occupational skill categories; India.

Jel classifications: J01, J21, J24, J61, J62

1. Introduction

The pace of industrialisation, urbanisation, regional inequality and structural economic change has increased labour mobility across regions, sectors and occupations in India (Tumbe, 2018; Parida & Raman, 2020). However, labour migration is no longer a simple rural-urban phenomenon. It increasingly reflects differences in education, occupational specialisation, technical capability and the changing demand for skills in regional labour markets (Hofmann, 2015; De et al., 2025). As economies grow more integrated and production systems more specialised, the interaction between migration and skill has become a central issue when trying to understand labour allocation, productivity, employment structures and regional development (Sjaastad 1962; De Haas et al., 2020).

The existing literature highlights that migration is highly selective by human capital. Workers with higher education, technical training and occupational skills move longer distances to locations with higher skill return, better employment opportunities and stronger labour market networks (Borjas, 1987; Hunt & Mueller, 2004; Hanson, 2010; Grogger & Hanson, 2011). Conversely, low-skilled labour migration remains concentrated in labour-intensive sectors characterised by informal employment, low wages and employment insecurity (Piore, 1979; Ruhs & Vargas-Silva, 2015). Thus, migration has become differentiated across skill groups in terms of migration distance, employment prospects, occupational concentration and spatial mobility.

Since the 1990s, rapid expansion of manufacturing, construction, logistics, finance, information technology and the service sector have created large-scale demand labour in major industrial and metropolitan regions (Kundu, 2009; Chandrasekhar & Sharma, 2015). Six regions have emerged as principal economic growth poles, i.e., Delhi NCR, Mumbai–Pune, Bengaluru, Hyderabad, Chennai, and Surat–Ahmedabad. These regions attract migrants from less economically developed states such as Uttar Pradesh, Bihar, Jharkhand, Odisha, Rajasthan and Madhya Pradesh, resulting in complex systems of labour mobility shaped by regional disparities, industrial demand and occupational specialisation (Tumbe, 2018; Rajan & Bhagat, 2021). Industrial clusters and metropolitan growth regions are increasingly acting as specialised labour markets which require different kinds of labour (Riggi & Maggioni, 2004; Narayana, 2014). Knowledge-intensive metropolitan economies such as Bengaluru and Hyderabad attract the highly educated and technically skilled, while manufacturing and construction hubs are absorbing large numbers of medium and low skilled migrants. At the same time, informal labour systems are the dominant

form of work in sectors such as construction, domestic work, transport and low-end services, especially for low-skilled migrants (Breman, 1996; Srivastava, 2011). These trends indicate a deepening segmentation of the skill, occupational and industrial structure of labour in India.

Despite the extensive literature on internal labour migration in India, important gaps remain in understanding the relationship between occupational skills and regional migration patterns. Existing studies have largely focused on rural–urban migration, informal employment, demographic characteristics and economic disparities, often treating migrants as a relatively homogeneous group (Singh, 1980; Kundu & Saraswati, 2012; Mitra, 2019; Kumar & Pradhan, 2025). Consequently, limited attention has been given to how skill heterogeneity shapes migration patterns and determinants across high-, medium- and low-skilled workers. Furthermore, comparative evidence on skill-based migration across major industrial and metropolitan regions remains limited. These regions differ considerably in their industrial composition, occupational requirements and employment opportunities, potentially generating distinct patterns of labour mobility across skill groups. In addition, the socioeconomic and demographic factors influencing migration may operate differently across occupational skill categories and regional labour markets (Parida & Madheswaran, 2011; Tripathi & Kaur, 2017). In particular, the combined role of education, technical training, gender, social identity, household characteristics and employment structure in shaping skill-based migration requires further empirical investigation. Addressing these gaps is important for understanding how occupational skills interact with regional industrial structures to shape internal labour mobility in India.

The study examines the pattern and determinants of occupational skill-based labour migration in six major industrial regions of India, i.e., Delhi NCR, Surat-Ahmedabad, Mumbai-Pune, Chennai, Bengaluru and Hyderabad, which constitute the principal growth poles in India for the absorption of labour. Using unit-level data of Periodic Labour Force Survey (PLFS) 2020-21, we analyse migration streams, migration distance pattern across regions, industrial employment concentration by skill and region, and socio-economic and demographic determinants of migration using logistic regression models with regional and district-level heterogeneity. The study proposes a skill-based framework for the analysis of internal labour migration in India, systematically differentiating high, medium and low skilled workers based on occupational categories. Finally, the study contributes to a wider understanding of labour market segmentation and regional inequality by

illustrating variation of migration patterns across occupational skill categories and industrial regions.

The rest of the paper is organised as follows. In section 2, synthesises existing literature on, determinants of migration, skill heterogeneity, industrial labour markets and labour market outcomes. Section 3 describes the data, variable construction and the empirical methodology. Section 4 presents the descriptive and empirical results for migration patterns and determinants across skill groups and regions. The section 5 concludes with findings, policy implications and future research directions.

2. Literature review

Migration decisions by individuals are influenced by income differentials, expected returns to education, occupational mobility, labour market segmentation, and regional differences in economic development, as documented in theoretical and empirical studies (Borjas, 1987; Hanson, 2010). The classical push-pull framework views migration as the result of negative circumstances in the origin regions and positive opportunities in the destination regions (Lee, 1966). Rural poverty, agrarian distress, unemployment and underemployment are major push factors, while industrial growth, urban employment opportunities, higher wages and better infrastructure pull migrants towards economically advanced regions (Singh, 1980). An alternative explanation for migration behaviour is provided by human capital theory. According to this theory, migration is an investment decision, where people migrate to maximise the returns on their education, skills and labour market experience (Sjaastad, 1962). Migration is positively self-selected more educated and skilled individuals are more likely to migrate if destination regions provide higher returns to human capital (Borjas, 1987). Grogger and Hanson (2011) find that regional differences in the returns to skill shape the composition of migration flows. Typically, high-skilled migration involves long-distance mobility, interstate migration, formal employment, and higher earnings (Hunt & Mueller, 2004; Ruhs & Vargas-Silva, 2015). High-skilled migrants concentrate in knowledge-intensive industries such as information technology, financial services, health care, education and corporate services, where they access stable employment and career advancement.

By contrast, low-skilled migration is linked to informal labour markets, short-distance mobility, seasonal migration and employment insecurity. Most low-skilled migrants work in labour-intensive sectors such as construction, agriculture, domestic work, informal manufacturing and

urban services. This migration is often motivated by rural distress and lack of stable livelihood opportunities in origin regions. Informal recruitment systems, labour contractors and social networks play a critical role in facilitating the mobility of low-skilled labour. Labour market segmentation theory provides a framework for understanding these differentiated outcomes. Under this approach, labour markets segment into formal and informal sectors with unequal wages, job security and working conditions. Skilled migrants are more likely to access formal labour markets with stable employment and higher wages, whereas low-skilled migrants are over-represented in insecure, informal occupations with weak labour protection. Within India's context, job opportunities and wage differentials remain primary determinants of migration (Parida & Madheswaran, 2011; Tripathi & Kaur, 2017). Industrial growth in major metropolitan regions creates labour demand that pulls migrants from less-developed states such as Uttar Pradesh, Bihar, Jharkhand, Odisha and Rajasthan. The literature documents high educational and skill selectivity of migration: more educated and technically trained people are more likely to migrate longer distances and across state boundaries, leveraging better access to labour market information and stronger networks (Hunt & Mueller, 2004). However, this evidence comes largely from national-level or single-city studies, with limited systematic comparison across major regional labour markets. Socio-demographic factors caste, religion, gender, and household structure also influence migration costs, network access, and social outcomes, though these remain underexplored in Indian migration literature (Parida & Raman, 2020).

Studies on industrial labour systems show that industrial clusters and metropolitan regions act as labour magnets by concentrating economic activity, infrastructure and specialised labour demand (Narayana, 2014). Agglomeration economies create productivity gains and employment, attracting migrants to manufacturing and service sectors. However, these clusters operate as segmented labour markets, each drawing different skill types: knowledge-intensive cities attract highly educated workers; manufacturing hubs absorb medium-skilled workers; service hubs employ both skilled professionals and large numbers of informal workers. This clustering pattern reflects deepening skill-based labour market segmentation in India's economy. There is growing research on migration outcomes and labour market performance. Migrants generally experience better job prospects and wage gains compared to non-migrants, but these advantages differ substantially across skill levels (Khan, 2021). High-skilled migrants achieve higher formal sector wages and career progression, while low-skilled migrants concentrate in precarious informal jobs with low

earnings, casual contracts and weak protection. This outcome heterogeneity reflects both who migrates and what opportunities exist at destination. These mechanisms that remain incompletely understood in the Indian context, particularly when examined across different regional and industrial structures. Addressing this gap is important for understanding how individual characteristics, occupational skills and regional industrial structures jointly shape internal labour mobility in India.

Against this background, the present study contributes by examining occupational skill-based labour migration patterns and socioeconomic and demographic determinants across India's six major industrial regions. The study contributes to the existing literature in three ways. First, it provides a comparative assessment of migration patterns across high-, medium- and low-skilled workers, with particular attention to migration streams and distance. Second, it examines the industrial employment distribution of migrant and non-migrant workers across occupational skill categories and regional labour markets. Third, it investigates the socioeconomic and demographic factors associated with migration across skill groups, accounting for regional and district-level heterogeneity. By integrating migration theory, labour market segmentation, industrial geography and occupational skill heterogeneity, the study provides a systematic comparison of how migration and skill interact within India's evolving labour market structure.

3. Data and methodology

3.1 Data

This study is based on the Periodic Labour Force Survey (PLFS) 2020-21, which was conducted by the National Statistical Office (NSO). The PLFS is the national representative data that collects information across Indian states. This survey also contains detailed information on socio-economic and demographic characteristics of individuals, such as age, gender, marital status, social groups, religion, education, place of living, along with detailed information on employment (by industry and occupation) and unemployment of workers. As per this survey, *an individual is classified as a migrant if his/her present place of enumeration is different from their last usual place of residence*. To generalise the results, we have removed those observations, who migrated after March 2020 (COVID-19 induced migrants) as the lockdown was imposed on 25th March 2020 (Mitra & Shrivastav, 2024; Kumar & Pradhan, 2025). The survey comprises a total of 410,818 observations across India, out of which 17,824 observations are selected for the present analysis based on

defined sampling criteria and the specific objectives of the study, focusing on six major industrial regions. These six regions are classified based on patterns of in-migration and industrial development. Drawing on evidence from the Census of India 2011 migration tables and the Economic Survey of India, along with official Metropolitan and Regional Development Authority plans. The study clusters districts and their sub-districts into six major industrial regions: Delhi NCR[1], Ahmedabad[2]–Surat, Mumbai[3]–Pune[4], Chennai[5], Bengaluru[6], and Hyderabad[7] (Census, 2011; Government of India, 2016). These regions represent the principal economic growth poles and major in-migration destinations in India. The delineation follows a core-periphery framework, wherein metropolitan core districts and their surrounding spillover areas are grouped to capture functional economic regions. In total, the selected clusters comprise 52 districts, reflecting integrated labour markets and regional industrial linkages. The complete list of districts and their regional classification is presented in Table A1 (Appendix). The variables used in this study are primarily drawn from existing literature and include demographic and socio-economic characteristics. A detailed description of the variables and their units of measurement is provided in Table A2 (Appendix).

3.2 Empirical strategy

The migration decision is a binary outcome, indicating whether an individual is a migrant or not. Therefore, this study employs logistic regression to examine how socio-demographic and economic factors influence skill-based migration decisions across six major industrial regions of India (Cameron & Trivedi, 2005; Gujarati, 2012). Our major explanatory variables in the logistic regression are individual and household characteristics such as age, age square, gender, sectors, religion, social groups, education, marital status, industry of employment, occupation-based skill level, and household size. The broader classifications of occupation-based skill levels and industry of employment are presented in Tables A3 and A4 (Appendix). This framework examines the

[1] https://ncrpb.nic.in/
[2] https://www.auda.org.in/
[3] https://www.mmrda.maharashtra.gov.in/mr#gsc.tab=0
[4] https://www.pmrda.gov.in/en/home/
[5] https://www.cmdachennai.gov.in/index.html
[6] https://bmrda.karnataka.gov.in/en
[7] https://www.hmda.gov.in/

impact of socio-economic variables on the probability of migration. The dependent variable M_i, is binary, $M_i = 1$ if the individual i is a migrant, otherwise, $M_i = 0$. The binomial logit model assumes that the probability of migration can be modeled $P(M_i = 1)$ as a logistic function of a set of independent variables X_i:

$$P(M_i = 1|\, X_i) = \frac{1}{1 + e^{-Z_i}} = \frac{e^{Z_i}}{1 + e^{Z_i}} \qquad (1)$$

where: $Z_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} \ldots\ldots + \beta_k X_{ik}$ (2)

β_0 is the intercept and $\beta_1, \beta_2, \ldots\ldots, \beta_k$ are the coefficients for the independent variables $X_{i1}, X_{i2}, \ldots\ldots, X_{ik}$. Therefore, $\frac{P}{1-P}$ is the odds ratio of migration likelihood. Now taking log of odds ratio,

$$ln\left(\frac{P(M=1)}{1-P(M=1)}\right) = Z_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} \ldots\ldots + \beta_k X_{ik} \qquad (3)$$

Equation 3 is baseline regression, thus allowing the estimation of how the explanatory variables influence the likelihood of migration.

To account for spatial heterogeneity, three alternative model specifications are estimated. The first model includes both industrial region and district fixed effects to control for unobserved regional and local characteristics. The second model controls only industrial regions, while the third model includes district-level controls alone. These specifications help to assess the robustness of the results and understand how different levels of geographic control affect the determinants of decision to migrate.

Model 1: Controlling for both industrial regions and districts

$$M_i = \beta_0 + \beta_k \sum_{k=1}^{n} X_{ik} + \delta Regions_i + \theta Districts_i + \varepsilon_i \qquad (4)$$

Model 2: Controlling for Industrial Regions Only

$$M_i = \beta_0 + \beta_k \sum_{k=1}^{n} X_{ik} + \delta Regions_i + \varepsilon_i \qquad (5)$$

Model 3: Controlling for Districts Only

$$M_i = \beta_0 + \beta_k \sum_{k=1}^{n} X_{ik} + \theta Districts_i + \varepsilon_i \qquad (6)$$

Where, $\sum_{k=1}^{n} X_{ik}$ is the vector of the explanatory variables, β_k is the coefficients of explanatory variables, δ is the coefficients of regions, θ is the coefficient of districts and ε_i is the error term. To examine the robustness and heterogeneity of the estimated effects, we implement the above logistic regression specifications for both the pooled sample and across skill-specific sub-samples. In the pooled specification, skill level is included as a control variable to account for systematic differences in migration behaviour across workers. To further explore heterogeneity, the sample is stratified into high-, medium-, and low-skilled workers, and each of the three model specifications is estimated separately for these groups. This empirical strategy allows us to assess whether the determinants of migration and the role of spatial controls vary across skill categories, thereby providing additional insights into the structure of labour mobility.

The results are reported in terms of marginal effects (Table 4), which allow for a direct interpretation of changes in the probability of migration associated with variations in the covariates. In addition, we present odds ratios in Table S1 (Supplementary) to facilitate comparison with the existing literature and to provide an alternative scale of interpretation. Reporting both marginal effects and odds ratios enhances the transparency and robustness of the empirical findings.

4. Results & Discussion

4.1 Descriptive Results

4.1.1 Stylized facts

Table 1 shows descriptive statistics of the variables used in the study. In addition, the chi-square test was used to determine if there are statistically significant associations between categorical variables, specifically across skill levels and between migrant and non-migrant workers. The results indicate that migrant workers are on average older than non-migrant workers in all skill groups, i.e., high, medium and low. Additionally, migrants tend to be more concentrated in urban areas and non-migrants are somewhat more represented in rural areas. This pattern suggests that migration is mainly towards urban labour markets where employment opportunities are generally better, especially for medium and high-skilled workers. Although, low-skilled migrants have a higher share of urban residents than non-migrants but a lower share than high-skilled migrants, indicating some limited mobility or constraints to access urban labour markets. With respect to

household size, migrants tend to reside in the smaller household sizes, whereas non-migrants are more concentrated in the higher household size categories. The migrants are relatively more concentrated in the OBC and general categories, while ST and SC groups are relatively more represented among non-migrants, especially in the low-skilled segment. However, these differences are not strongly statistically significant. The religious composition shows a relatively stable pattern between migrants and non-migrants and therefore the limited role of religion in migration decisions. Gender differences, in contrast, are large and statistically significant. For all skill levels, for both migrants and non-migrants, males constitute a higher share than females, except for low-skilled migrants. Representation of females is low in higher-skilled occupations, indicating limited participation at the upper end of the skill distribution. Most workers are married, regardless of skill level, with migrants have lower proportion of married workers. In addition, as the skill level declines, the level of education decreases, suggesting a clear positive relationship between skill level and education. Workers are predominantly concentrated in the lower education levels, especially at the primary and middle school levels.

Table 1: Characteristics of migrant and non-migrant workers across skill levels

	Full sample		**High skill**		**Medium skill**		**Low skill**		
Variables	**M**	**NM**	**M**	**NM**	**M**	**NM**	**M**	**NM**	**χ^2test stat**
Age	39.84	39.62	39.31	38.38	39.60	38.53	41.14	39.00	345.28***
Sector									
Rural	25.76	42.23	9.28	21.22	30.07	48.32	39.43	59.02	43.85***
Urban	74.24	57.77	90.72	78.78	69.93	51.68	60.57	40.98	50.87***
HH Size									
Small	38.56	26.29	41.48	28.67	35.72	24.94	38.18	26.24	14.63***
Medium small	47.69	49.82	47.41	50.32	49.18	49.51	47.19	49.90	12.54***
Medium	11.08	17.42	9.14	14.85	11.88	18.67	12.06	18.05	7.79**
Large	2.67	6.47	1.98	6.16	3.22	6.88	2.56	5.80	3.45
Social groups									
ST	4.49	6.84	1.93	2.92	4.93	7.04	7.14	12.63	0.11
SC	17.09	19.79	9.19	12.44	16.68	19.32	29.11	33.02	14.39***
OBC	42.42	38.40	40.40	36.46	45.45	41.41	38.60	33.02	23.88***
Others	36.00	34.98	48.49	48.18	32.94	32.24	25.16	21.32	24.70***
Religion									
Hindu	90.41	87.34	88.64	84.49	90.90	88.06	91.82	89.90	35.23***
Islam	6.32	9.90	6.57	11.66	6.70	9.60	5.13	7.90	2.78
Others	3.27	2.76	4.79	3.85	2.40	2.34	3.05	2.20	5.33*
Gender									
Male	58.50	84.78	68.94	83.56	59.10	88.56	42.55	76.05	59.05***
Female	41.50	15.22	31.06	16.44	40.90	11.44	57.45	23.95	50.13***
Marital status									
Unmarried	13.16	23.52	18.12	26.45	12.92	22.85	6.72	20.68	26.38***
Married	86.84	76.48	81.88	73.55	87.08	77.15	93.28	79.32	45.74***
General education									

Up to primary	33.51	26.73	12.94	12.47	36.01	27.83	56.90	46.73	15.18***
Up to middle	18.89	21.40	9.78	12.68	23.22	25.58	22.18	23.71	13.43***
Secondary and diploma	27.01	31.74	26.42	29.97	31.02	34.61	19.06	26.49	2.05
Graduation and above	20.59	20.13	50.86	44.88	9.76	11.97	1.87	3.07	33.42***
Technical education									
Without technical education	91.06	93.42	77.04	84.76	96.34	96.49	99.31	98.78	43.78***
With technical education	8.94	6.58	22.96	15.24	3.66	3.51	0.69	1.22	16.80***
Industry									
Agriculture mining	17.14	23.26	1.63	5.92	22.14	28.32	27.93	37.07	38.26***
Manufacturing	20.43	17.97	15.65	14.31	25.55	20.95	15.87	15.46	0.77
Construction	9.04	9.84	3.60	4.51	9.19	10.20	16.35	17.46	7.94**
Trade	14.12	15.27	20.59	22.42	13.58	14.54	6.24	5.76	7.30**
TIAFF	16.55	16.60	26.81	25.97	15.63	15.05	4.16	5.80	2.87
PSTPA	7.19	6.40	11.11	10.22	5.21	4.35	6.03	6.00	0.23
Basic services	15.53	10.65	20.59	16.65	8.69	6.59	23.42	12.44	37.06***
Regions									
Delhi	13.90	19.96	11.11	21.28	14.78	19.44	15.87	19.32	28.40***
Bengaluru	14.21	10.48	20.44	15.00	12.38	9.20	9.49	6.78	5.05*
Chennai	21.40	17.71	20.49	14.40	22.14	19.44	21.07	18.20	19.83***
Surat-Ahmedabad	10.10	14.91	12.25	14.43	9.79	14.79	7.76	16.00	15.30***
Mumbai-Pune	29.32	25.46	28.00	24.35	28.21	24.67	33.61	29.51	11.82***
Hyderabad	11.06	11.47	7.70	10.55	12.70	12.45	12.20	10.20	21.61***

Note: Numerical figures in the tables are in percentage, except age are in years; M: migrants, NM: non-migrants, other religions include Christianity, Sikhism, Jainism, Buddhism, and Zoroastrianism, etc.; TIAFF- Transport information accommodation food financial, PSTPA- Professional scientific technical and public administration, Basic services- Education, human health, social work, water sanitation, gas supply and other basic services; *** p<0.01, ** p<0.05, * p<0.1

The majority of workers have no formal technical education. However, migrants exhibit higher share of technical education, especially among medium- and high-skilled workers, than their non-migrant counterparts. A large proportion of high-skilled workers are employed in the service-oriented sectors of Trade, Information, Accommodation and Food, and Financial Activities (TIAFF), as well as in basic services such as Education, Health, and Public Utilities. Meanwhile, medium-skilled workers are largely employed in agriculture and manufacturing. The low-skilled workers are mainly employed in agriculture and construction work. It is worth noting that a substantial number of low-skilled migrants also work in basic services, which means they are working in informal and low-end service sector jobs. The Mumbai-Pune industrial cluster is the dominant cluster, attracting substantial proportion of workers across all skill levels and migration status, underscoring its importance as a major employment hub. But there are huge regional differences by skill level. Among the high-skilled workers, migrants are relatively more concentrated in Delhi and Chennai, whereas non-migrants are relatively more concentrated in Bengaluru and Chennai. Among medium-skilled workers, Delhi has a relatively higher

concentration of migrants and Chennai has a large share of non-migrants. Low-skilled workers are more concentrated in Chennai and Delhi than in the other regions, with a similar regional distribution among migrants and non-migrants.

4.1.2 Skill-endowment and migration streams

Table 2 shows dominant migration streams are rural-to-urban and urban-to-urban across industrial regions. High-skilled workers exhibit strong urban-oriented migration patterns, with rural-to-urban flows accounting for 50.45% in Delhi NCR, 51.82% in Surat, and 46.25% in Bengaluru. Urban-to-urban migration is also substantial among high-skilled workers, ranging from 35.22% to 72.71% across regions. Medium-skilled workers show mixed patterns: high rural-to-urban in northern regions (Delhi NCR 76.77%) but higher rural-to-rural in southern regions (Hyderabad 43.28%, Chennai 30.14%). Low-skilled workers display localized mobility, with high rural-to-rural migration in Chennai (62.05%) and Surat (43.24%), reflecting constrained movement and network dependence. Although rural-to-urban migration also accounts for a substantial share among low-skilled workers, particularly in Delhi (75.11%).

Table 2: Sectors wise migration pattern across six major industrial regions and skill levels

Region	Delhi NCR region	Bengaluru region	Chennai region	Surat-Ahmedabad region	Mumbai-Pune region	Hyderabad region
Full sample						
Rural to rural	10.48	13.27	13.27	24.55	21.82	30.87
Rural to urban	69.98	52.44	52.44	46.71	37.91	42.62
urban to rural	1.86	2.23	2.23	3.29	2.78	1.50
urban to urban	17.69	32.06	32.06	25.45	37.49	25.00
High skill						
Rural to rural	3.60	6.05	7.49	11.34	7.98	5.77
Rural to urban	50.45	46.25	15.94	51.82	36.17	41.03
urban to rural	0.90	1.21	3.86	1.62	2.30	1.28
urban to urban	45.05	46.49	72.71	35.22	53.55	51.92
Medium skill						
Rural to rural	11.40	14.03	30.14	28.39	26.71	43.28
Rural to urban	76.77	58.93	20.14	48.71	37.04	36.32
urban to rural	1.72	3.57	9.43	3.87	2.81	1.74
urban to urban	10.11	23.47	40.29	19.03	33.45	18.66
Low skill						
Rural to rural	15.28	32.85	62.05	43.24	28.93	24.71
Rural to urban	75.11	52.55	8.91	29.73	41.53	58.62
urban to rural	3.06	1.46	11.55	5.41	3.31	1.15
urban to urban	6.55	13.14	17.49	21.62	26.24	15.52

Note: Numerical figures in the tables are in percentage.

Figure 1 shows clear differences in distance-wise migration patterns across regions and skill levels. For the full sample, intra-district migration is the highest in the Chennai region (55.09%), indicating strong local labour absorption. In contrast, the Bengaluru (51.59%) and Hyderabad (46.60%) regions report relatively higher intra-state migration. Delhi NCR stands out with a higher share of inter-state migration (69.31%), highlighting its role as a major national labour market drawing workers from distant states. Overall, except for Chennai, most regions show a significant share of inter-state migrants, indicating that economically advanced regions tend to attract labour over longer distances. A similar pattern is observed across skill levels, with some variations. High-skilled workers display relatively balanced mobility, with a strong presence in intra-state migration across regions. This suggests that they respond to regional job opportunities and firm-level demand, supported by better information and lower migration costs. Medium-skilled workers show mixed patterns, combining local mobility in southern regions with high inter-state migration in Delhi NCR (76.52%). Low-skilled workers are more spatially concentrated, with high intra-district migration in Chennai (66.12%) and Surat-Ahmedabad (61.95%), reflecting reliance on local networks and higher mobility constraints. However, Delhi NCR again records high inter-state migration (71.54%), indicating strong demand for low-skilled labour in construction and informal services, relatively higher wages, proximity to major migrant-sending states, and well-established migrant networks that facilitate labour mobility. Overall, migration patterns reflect labour demand, costs, and network effects (Figure 1).

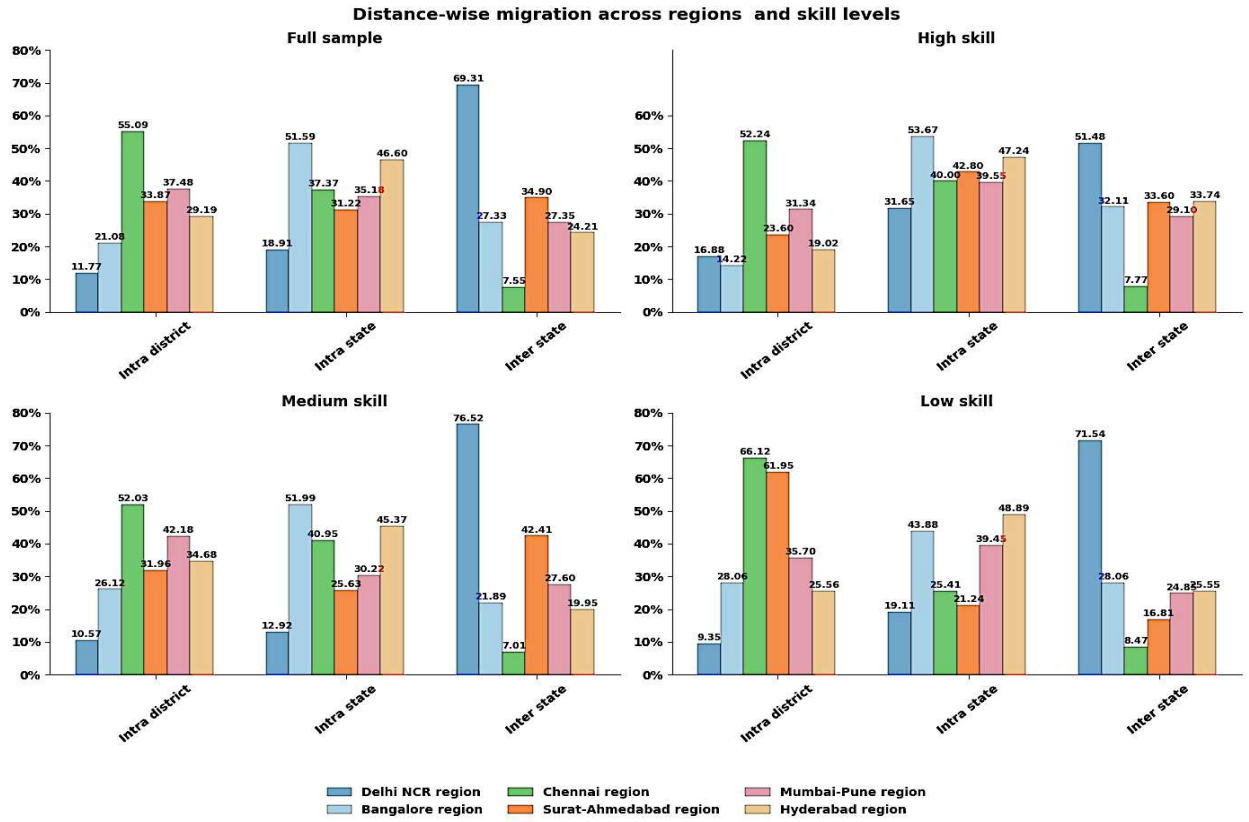

Figure 1: Distance-based migration pattern across six major industrial regions and skill level

4.1.3 Choices of destinations clusters an analysis of interstate migrants

Figure 2 presents inter-state migration flows for the full sample, including only origin states that contribute more than 1% of migrants to the six major industrial regions of India. The pattern shows that most inter-state migrants originate from Uttar Pradesh, Andhra Pradesh, Bihar, Rajasthan, Tamil Nadu, Maharashtra, Jharkhand and Odisha, Karnataka and West Bengal. Delhi NCR receives a large share of migrants from Uttar Pradesh and Bihar, with smaller contributions from several other states, highlighting its role as a major national destination. In Surat-Ahmedabad, migrants mainly come from Uttar Pradesh, Maharashtra, Rajasthan, and Bihar, reflecting both northern and western linkages. The Mumbai-Pune region is dominated by migrants from Uttar Pradesh, with a more diverse inflow from multiple states.

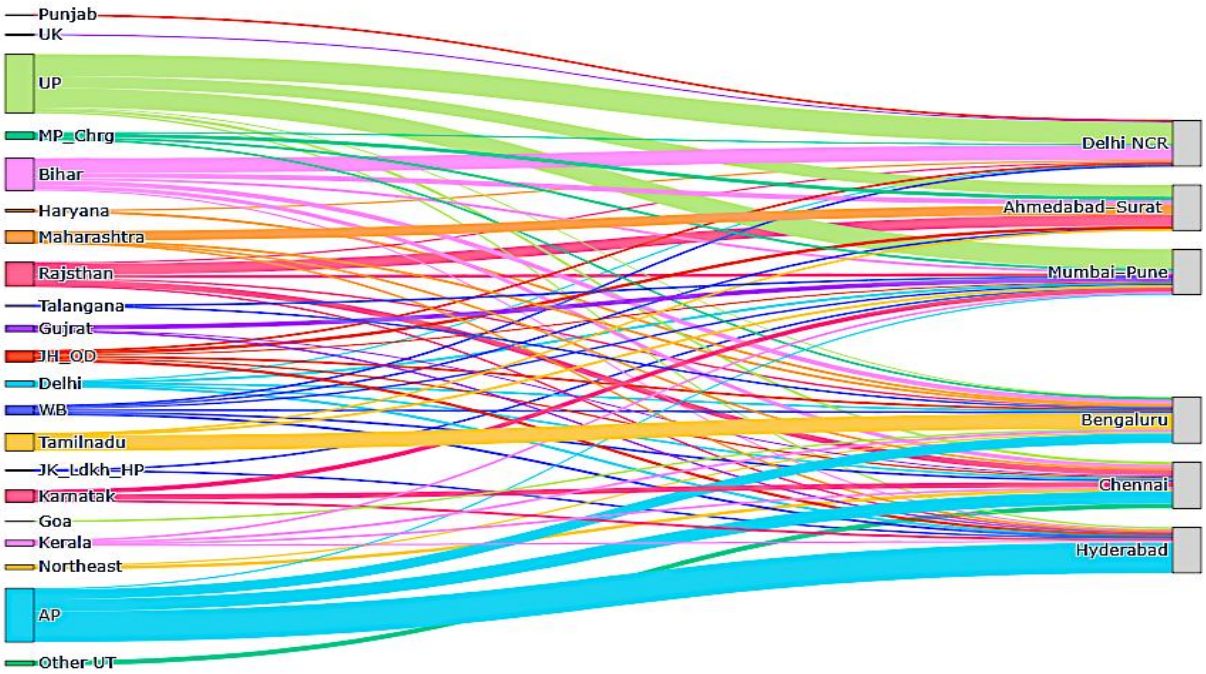

Figure 2: Interstate in-migration flow in six major industrial regions of India for the Full sample

Note: We present interstate in-migration flows exceeding 1% across the regions. UK: Uttarakhand; UP: Uttar Pradesh; MP_Chhattisgarh: Madhya Pradesh and Chhattisgarh; JH_OD: Jharkhand and Odisha; WB: West Bengal; JK_Ladakh_HP: Jammu & Kashmir, Ladakh, and Himachal Pradesh; AP: Andhra Pradesh; Other_UT: Other Union Territories (excluding Delhi). The Northeast includes Assam, Arunachal Pradesh, Meghalaya, Manipur, Nagaland, Mizoram, Tripura, and Sikkim.

In southern regions, migration is more regionally concentrated. Bengaluru attracts the highest number of migrants from Tamil Nadu and Andhra Pradesh, along with a notable share from other states. Chennai mainly receives migrants from Andhra Pradesh, along with flows from nearby states such as Karnataka, some Union Territories and Rajasthan. Hyderabad is largely dominated by migrants from Andhra Pradesh, indicating strong regional proximity and historical ties. A similar pattern is observed across skill levels when the distribution is measured as the percentage share of inter-state migrants within each industrial region (Figure 2).

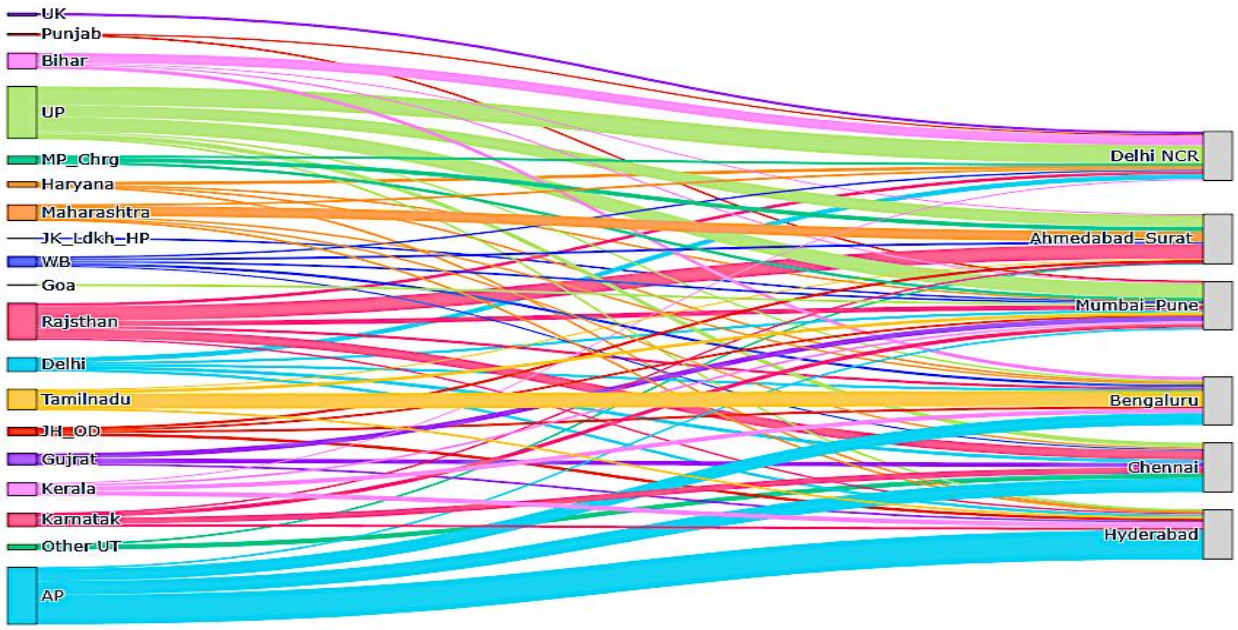

Figure 2 (a): Interstate in-migration flow in six major industrial regions of India for the high skill

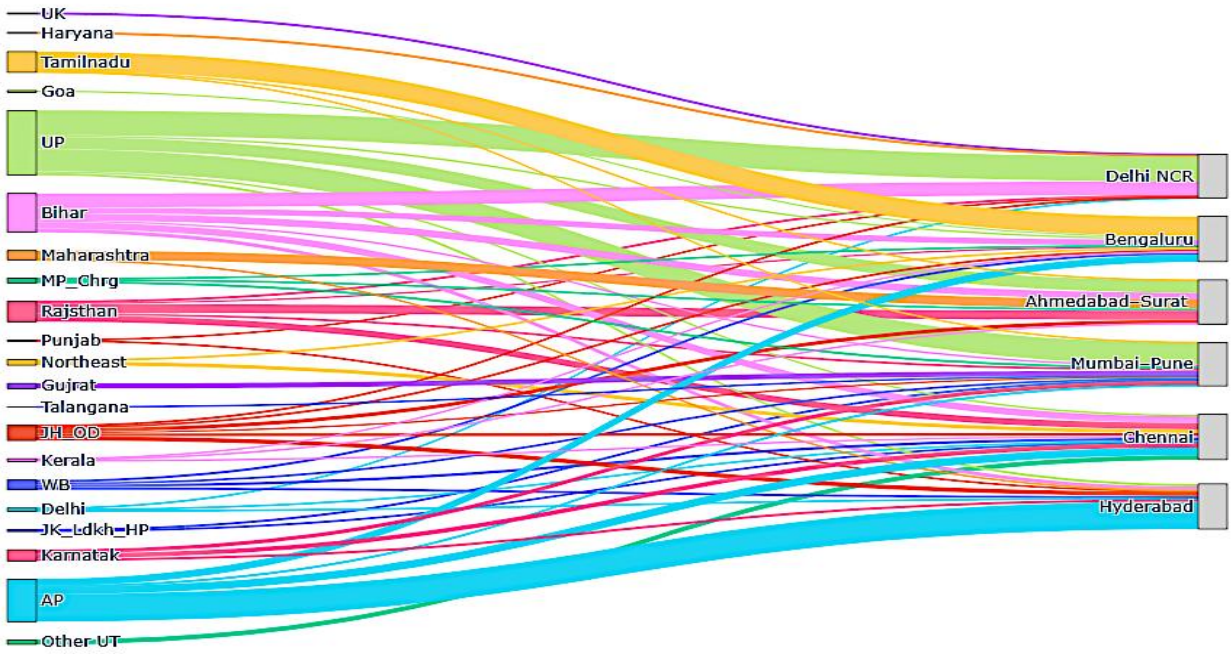

Figure 2 (b): Interstate in-migration flow in six major industrial regions of India for the medium skill

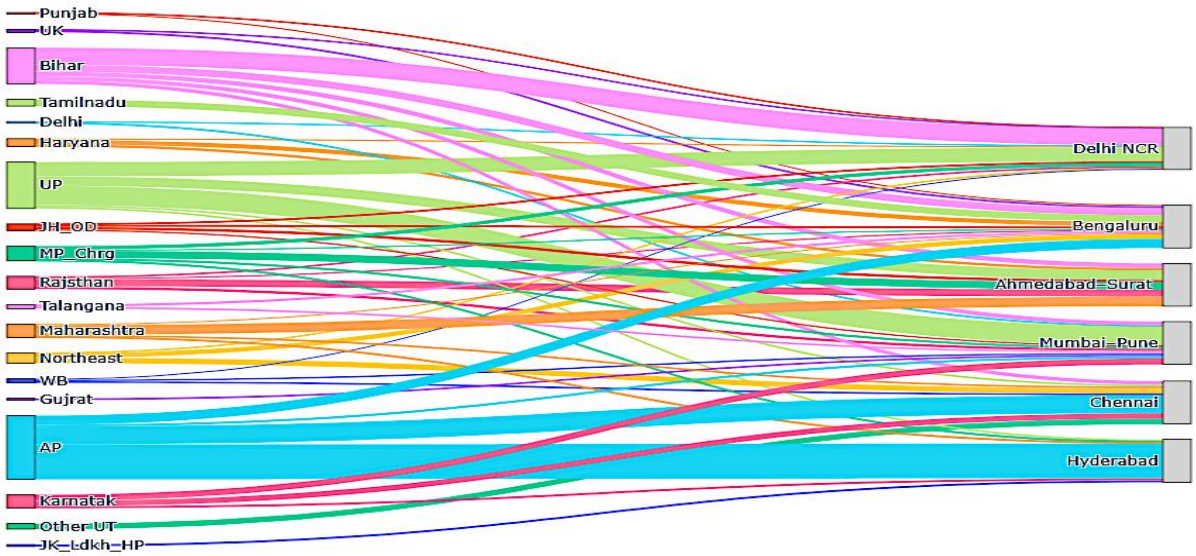

Figure 2 (c): Interstate in-migration flow in six major industrial regions of India for the low skill

For high-skilled workers, a larger share of migrants in each region originates from Andhra Pradesh, Uttar Pradesh, Rajasthan, and Tamil Nadu, followed by other states. This indicates that these states are key suppliers of skilled labour across regions, supported by better education, information access, and mobility (Figure 2a). For medium-skilled workers, the share distribution within each region is mainly dominated by Uttar Pradesh, Bihar, Andhra Pradesh, Rajasthan, Tamil Nadu, Jharkhand, and Odisha. This reflects strong migration networks and a steady labour supply from both northern and eastern states to different industrial centers (Figure 2b). In the case of low-skilled workers, the within-region share is more concentrated among Andhra Pradesh, Uttar Pradesh, Bihar, Madhya Pradesh, Chhattisgarh, Maharashtra, and the Northeast. This suggests that low-skilled migration is more dependent on established corridors, proximity, and cost considerations. Overall, by normalizing each region to 100%, the results highlight how different source states contribute to the migrant composition within each industrial region, shaped by regional disparities, labour demand, and network effects (Figure 2c)

4.1.4 Industrial employment patterns across migration status, skill levels and regions

Table 3 presents the distribution of workers across industries by migration status and industrial regions. In the full sample, migrants are predominantly employed in manufacturing, followed by TIAFF (Transport, Information, Accommodation and Food, Financial activities), agriculture and

mining. In comparison, non-migrants are more concentrated in agriculture and mining, with relatively lower participation in manufacturing, services and other industries. This pattern is consistent with the expectation that migrants are more likely to move into non-farm and urban sectors, while non-migrants remain tied to local, land-based activities. A broadly similar pattern is observed across most regions, with the notable exception of Delhi. In Delhi, both migrants and non-migrants are largely employed in manufacturing, trade, TIAFF, and basic services, which is consistent with its highly urbanised and service-oriented economic structure that offers diverse employment opportunities.

Table 3: Industry-wise distribution of workers by migration status across six major industrial regions

	Agriculture and mining	Manufacturing	Construction	Trade	TIAFF	PSPTA	Basic services	Total
Full sample								
M	17.14	20.43	9.04	14.12	16.55	7.19	15.53	100
NM	23.26	17.97	9.84	15.27	16.6	6.4	10.65	100
Total	20.98	18.88	9.54	14.85	16.58	6.69	12.47	100
Delhi NCR region								
M	5.63	30.48	10.56	14.79	14.08	9.36	15.09	100
NM	13.03	20.55	10.30	20.14	15.85	8.01	12.13	100
Total	10.75	23.61	10.38	18.49	15.30	8.43	13.04	100
Bengaluru region								
M	10.44	19.34	9.42	13.41	24.46	9.01	13.92	100
NM	26.60	15.09	9.89	14.15	20.89	4.77	8.61	100
Total	19.26	17.02	9.67	13.81	22.51	6.70	11.02	100
Chennai region								
M	22.70	13.91	13.36	13.22	17.37	4.43	15.02	100
NM	27.55	15.74	17.56	10.04	15.44	5.15	8.53	100
Total	25.50	14.97	15.79	11.38	16.25	4.84	11.26	100
Surat-Ahmedabad region								
M	17.82	35.35	4.12	18.11	9.13	6.19	9.28	100
NM	23.02	29.44	5.46	15.95	11.69	5.70	8.75	100
Total	21.52	31.15	5.07	16.57	10.95	5.84	8.90	100
Mumbai-Pune region								
M	17.86	18.35	6.41	13.80	17.47	8.66	17.47	100
NM	27.59	14.60	6.42	14.08	17.94	7.93	11.44	100
Total	23.52	16.17	6.42	13.96	17.74	8.24	13.96	100
Hyderabad region								
M	23.17	16.10	11.65	11.78	14.400	4.97	17.93	100
NM	22.12	12.15	10.36	17.68	19.24	4.52	13.94	100
Total	22.51	13.62	10.84	15.48	17.43	4.69	15.43	100

Note: Numerical figures in the tables are in percentage; TIAFF- Transport information accommodation food financial, PSTPA- Professional scientific technical and public administration, Basic services- Education, human health, social work, water sanitation, gas supply and other basic services.

However, there are clear regional variations in industrial employment. Bengaluru exhibits a higher concentration of workers in TIAFF, which reflects the region's strong service-sector orientation; migrants are additionally absorbed in manufacturing, while non-migrants retain a greater presence in agriculture and mining. In Chennai, the continued dominance of agriculture and mining alongside TIAFF suggests a mixed economic structure. In the Surat-Ahmedabad cluster, both groups are concentrated in manufacturing and trade, highlighting the region's industrial base. In the Mumbai-Pune region, migrants are more diversified across manufacturing, basic services, and TIAFF, reflecting broader labour market opportunities. Whereas non-migrants remain relatively concentrated in agriculture and mining, followed by TIAFF and manufacturing. In Hyderabad, the dominance of agriculture and mining for both groups indicates limited structural transformation, although migrants show greater engagement in basic services and manufacturing, suggesting gradual sectoral mobility (Table 3).

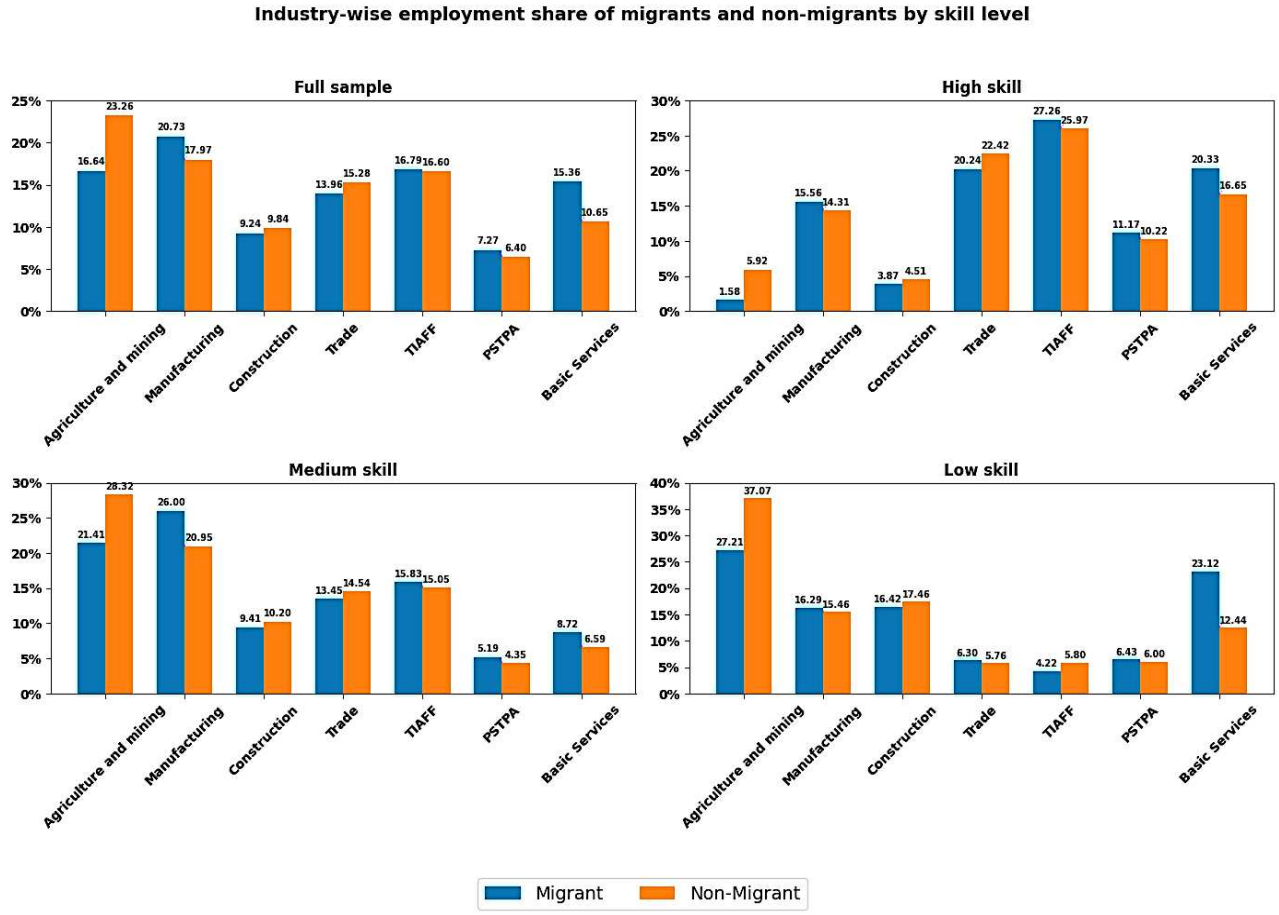

Figure 3: Industry-wise distribution of employment across skill levels

Note: TIAFF- Transport information accommodation food financial, PSTPA- Professional scientific technical and public administration, Basic services- Education, human health, social work, water sanitation, gas supply and other basic services.

Figure 3 presents the distribution of workers across industries by skill level, distinguishing between migrants and non-migrants. In the full sample, most workers are employed in agriculture & mining, manufacturing, and TIAFF, followed by other industrial clusters. Among high-skilled workers, both migrants and non-migrants are primarily employed in TIAFF, trade, and basic services. However, migrants have a higher concentration in basic services, manufacturing, and TIAFF compared to their non-migrant counterparts, reflecting their greater participation in urban and service-oriented sectors. For medium-skilled workers, employment is mainly concentrated in agriculture & mining and manufacturing, followed by TIAFF and other industries. Migrants show a higher share of employment in manufacturing, TIAFF, and basic services, whereas non-migrants are more concentrated in agriculture and mining, construction, and trade. Low-skilled workers are mainly employed in agriculture and mining. However, migrants have a lower share in this sector compared to non-migrants and a higher share in basic services. In addition, both migrant and non-migrant low-skilled workers are also significantly employed in construction and manufacturing.

4.2 Differences in skill-based migration determinants in across regions

Table 4 presents logistic regression results. Coefficients are robust across specifications with region and district fixed effects. The most striking finding is skill-based differentiation in migration propensity: medium-skilled workers are the most mobile segment, with high-skilled 1.8-2.3 percentage points less likely and low-skilled 1.9 percentage points more likely to migrate. This reflects India's labour demand structure: manufacturing, logistics, construction, and urban services create strong demand for semi-skilled workers, while high-skilled workers enjoy better local job stability in metropolitan centers. These results lend support to the theory of labour market segmentation, which posits that migration outcomes are systematically different regarding employment security and occupational structure (Piore, 1979). The evidence is also consistent with studies suggesting that low-skilled migration in India is concentrated in precarious sectors characterised by informal employment and high labour turnover (Srivastava, 2011; Tumbe, 2018). Age has a positive and significant effect on migration across all skill groups. A one-year increase in age raises the probability of migration by about 0.9–1.0 percentage points. However, the effect becomes negative at older ages. This is consistent with previous studies showing higher migration among economically active workers (Parida & Madheswaran, 2011; Tripathi & Kaur, 2017). Urban residence is also a strong determinant of migration. Urban workers are 21.3–21.6 percentage

points more likely to migrate than rural workers ($p<0.01$). The effect is stronger for low- and medium-skilled workers (20–24 percentage points) than for high-skilled workers (15–19 percentage points). These results emphasise the primacy of metropolitan and industrial areas as labour absorbing areas in the economic geography of India. Compared with rural areas, urban labour markets provide more diverse jobs, higher expected wages, greater industrial concentration, and stronger labour networks (Kundu, 2009; Chandrasekhar & Sharma, 2015). The strong urban effect for low-skilled workers reflects the growth of informal sectors such as construction, transport, domestic services, retail, and low-end manufacturing, which rely heavily on migrant labour (Breman, 1996; Srivastava, 2011). Additionally, cities such as Bengaluru, Hyderabad, and Delhi NCR attract high-skilled workers through their concentration of IT, finance, knowledge-based industries, and corporate services.

Household size is negatively associated with migration across all specifications. Compared with small households, the probability of migration falls by 8–11 percentage points for medium-small households and by 15–27 percentage points for large households ($p<0.01$). This suggests that workers from smaller households have greater flexibility to migrate and face fewer caregiving and social responsibilities (Mahapatro, 2015; Kumar & Pradhan, 2025). Scheduled Tribe workers show 7.1-7.4 percentage point lower probability ($p<0.01$), pronounced among low-skilled (-12.9pp), reflecting weaker education access and network disadvantages. Scheduled Caste workers are 2.2-2.8 percentage points less likely to migrate ($p<0.05$), while OBC workers are 2.1-3.0 percentage points more likely ($p<0.01$) from the others category. These results highlight that education, migration networks, access to labour market information and entry into formal employment systems are relatively weaker among historically marginalised caste groups (Deshingkar & Akter, 2009; Thorat & Neuman, 2012). Religion also influences migration. Hindu workers are 8.7–8.9 percentage points more likely to migrate than Muslim workers ($p<0.01$). Workers from other religious groups also show higher migration probabilities, particularly high-skilled workers, for whom the effect is 6.9–10.7 percentage points. This may reflect the greater concentration of Muslim workers in local informal employment and self-employment, which can limit interstate mobility (Sachar Committee Report, 2006). Female workers are 31.8–32.9 percentage points more likely to migrate than male workers ($p<0.01$). This reflects the continued importance of marriage-related migration. Moreover, the growing participation of women in labour migration, particularly in domestic work, garments, healthcare, hospitality, retail, and urban services (Mazumdar &

Agnihotri, 2014; Mahapatro, 2015). The stronger effect among low-skilled women suggests their increasing participation in low-paid and insecure urban employment. In India, marriage remains a major reason for female migration, while male migration is often linked to household income diversification and employment insecurity (Bhagat, 2017).

Education shows a mixed relationship with migration. Secondary and middle-level education have significant negative effects on migration, particularly among medium-skilled workers, where the probability of migration falls by about 11 percentage points ($p<0.01$). Graduate workers are also 9.2-9.4 percentage points less likely to migrate ($p<0.01$). This shows that better-educated workers may have easier access to stable local employment, public-sector jobs, or regionally anchored professional occupations that reduce the incentives to migrate (Kundu & Saraswati, 2012; Srivastava, 2011). In contrast, technical education increases migration probability by 9.0-9.2 percentage points ($p<0.01$), especially among high-skilled (9.7 pp) and medium-skilled workers (8.3 pp). This suggests that technical skills linked to manufacturing, logistics, IT, and modern services support labour mobility (Grogger & Hanson, 2011; De et al., 2025). Industrial affiliation shows segmented patterns. Manufacturing employment raises migration probability by 2.5-3.5pp overall ($p<0.01$), but 14.9-16.7pp for high-skilled workers ($p<0.01$), reflecting manufacturing hub concentration. High-skilled workers in construction, trade, TIAFF, and professional services show 9.4-16.8 percentage point increases ($p<0.05$ to $p<0.01$), concentrating in metropolitan knowledge-intensive sectors. Furthermore, to show the regional heterogeneity in migration propensity across skill levels.

Table A5 (Appendix) further shows regional differences in migration across skill groups. The results show that industrial regional migration propensity varies across skill levels. In the pooled sample, workers in Bangalore (11.1 percentage points), Mumbai–Pune (9.4 percentage points), and Chennai (7.5 percentage points) are significantly more likely to migrate than those in Hyderabad, while no significant difference is observed for Surat–Ahmedabad. Bengaluru shows the highest migration propensity across regions. The regional effect is strongest among high-skilled workers, followed by medium-skilled and low-skilled workers. These results highlight the continued importance of manufacturing and construction for migrant labour, while IT, finance, transport, and professional services increasingly attract high-skilled workers to metropolitan centres (Breman, 1996; Khadria, 2002; Narayana, 2014).

Table 4: Determinants of migration in across skill level with six major industrial regions and districts

	Full sample			High skill			Medium skill			Low skill		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Variables	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx	dy/dx
Skill level@ Medium skill												
High skill	-0.018**	-0.023***	-0.018**	-	-	-	-	-	-	-	-	-
	(0.009)	(0.009)	(0.009)									
Low skill	0.019**	0.019**	0.019**	-	-	-	-	-	-	-	-	-
	(0.009)	(0.009)	(0.009)									
Age	0.01***	0.009***	0.01***	0.014***	0.013***	0.013***	0.007***	0.007**	0.007***	0.008*	0.006	0.005
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
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)
Sectors@ Rural												
Urban	0.213***	0.216***	0.213***	0.175***	0.185***	0.153***	0.226***	0.224***	0.21***	0.241***	0.241***	0.204***
	(0.009)	(0.009)	(0.009)	(0.017)	(0.017)	(0.019)	(0.012)	(0.012)	(0.013)	(0.021)	(0.021)	(0.023)
Household size@ Small												
Medium small	-0.096***	-0.09***	-0.096***	-0.109***	-0.095***	-0.091***	-0.091***	-0.089***	-0.083***	-0.085***	-0.082***	-0.089***
	(0.008)	(0.008)	(0.008)	(0.015)	(0.014)	(0.014)	(0.011)	(0.011)	(0.011)	(0.018)	(0.018)	(0.017)
Medium	-0.148***	-0.137***	-0.148***	-0.179***	-0.155***	-0.146***	-0.146***	-0.141***	-0.132***	-0.109***	-0.102***	-0.117***
	(0.011)	(0.011)	(0.011)	(0.021)	(0.021)	(0.021)	(0.014)	(0.014)	(0.014)	(0.024)	(0.024)	(0.024)
Large	-0.213***	-0.205***	-0.213***	-0.271***	-0.247***	-0.221***	-0.198***	-0.196***	-0.163***	-0.16***	-0.159***	-0.149***
	(0.015)	(0.016)	(0.015)	(0.029)	(0.03)	(0.032)	(0.02)	(0.02)	(0.021)	(0.04)	(0.04)	(0.042)
Social groups@ Others												
ST	-0.071***	-0.074***	-0.073***	-0.064	-0.091**	-0.1***	-0.059***	-0.06***	-0.045**	-0.129***	-0.107***	-0.053*
	(0.015)	(0.015)	(0.015)	(0.039)	(0.038)	(0.037)	(0.02)	(0.02)	(0.02)	(0.029)	(0.03)	(0.031)
SC	-0.028***	-0.022**	-0.027***	-0.023	-0.036	-0.044**	-0.032***	-0.019	-0.015	-0.049**	-0.04*	-0.003
	(0.01)	(0.01)	(0.01)	(0.022)	(0.022)	(0.022)	(0.014)	(0.014)	(0.014)	(0.022)	(0.023)	(0.023)
OBC	0.021***	0.03***	0.021***	0.043***	0.027*	0.033**	0.016	0.031***	0.051***	-0.022	0.003	0.036
	(0.008)	(0.008)	(0.008)	(0.014)	(0.015)	(0.015)	(0.011)	(0.012)	(0.012)	(0.021)	(0.022)	(0.022)
Religion@ Islam												
Hindu	0.087***	0.089***	0.088***	0.112***	0.121***	0.113***	0.08***	0.077***	0.057***	0.073**	0.074**	0.037
	(0.012)	(0.012)	(0.012)	(0.021)	(0.021)	(0.021)	(0.016)	(0.016)	(0.016)	(0.031)	(0.031)	(0.032)
Others	0.076***	0.062***	0.075***	0.107***	0.087**	0.069**	0.043	0.027	-0.006	0.129**	0.123**	0.031
	(0.022)	(0.022)	(0.022)	(0.036)	(0.035)	(0.035)	(0.032)	(0.031)	(0.03)	(0.056)	(0.056)	(0.054)
Gender@ Male												
Female	0.329***	0.318***	0.327***	0.187***	0.168***	0.162***	0.4***	0.393***	0.39***	0.349***	0.344***	0.344***
	(0.008)	(0.009)	(0.008)	(0.017)	(0.017)	(0.016)	(0.012)	(0.012)	(0.012)	(0.017)	(0.017)	(0.017)
Marital status@												
Married	0.142***	0.149***	0.143***	0.134***	0.141***	0.139***	0.128***	0.132***	0.135***	0.192***	0.195***	0.201***
	(0.011)	(0.01)	(0.011)	(0.019)	(0.018)	(0.018)	(0.015)	(0.015)	(0.014)	(0.027)	(0.027)	(0.026)
Gen. education@ Up to primary												

Middle	-0.042***	-0.05***	-0.042***	-0.085***	-0.089***	-0.095***	-0.036***	-0.043***	-0.042***	-0.008	-0.016	-0.01
	(0.01)	(0.01)	(0.01)	(0.027)	(0.027)	(0.026)	(0.013)	(0.013)	(0.013)	(0.02)	(0.02)	(0.019)
Senior secondary diploma	-0.051***	-0.056***	-0.051***	-0.079***	-0.08***	-0.088***	-0.04***	-0.046***	-0.049***	-0.026	-0.032	-0.024
	(0.01)	(0.01)	(0.01)	(0.023)	(0.023)	(0.022)	(0.013)	(0.013)	(0.013)	(0.021)	(0.021)	(0.021)
Graduate and above	-0.092***	-0.094***	-0.093***	-0.095***	-0.091***	-0.098***	-0.11***	-0.112***	-0.102***	-0.044	-0.05	-0.036
	(0.012)	(0.012)	(0.012)	(0.024)	(0.024)	(0.023)	(0.017)	(0.017)	(0.017)	(0.051)	(0.05)	(0.049)
Tech. education@ Without												
With technical education	0.091***	0.09***	0.092***	0.097***	0.092***	0.066***	0.083***	0.082***	0.065**	-0.023	-0.016	-0.029
	(0.014)	(0.014)	(0.014)	(0.018)	(0.018)	(0.017)	(0.026)	(0.026)	(0.025)	(0.082)	(0.083)	(0.077)
Industry@ Agriculture and mining												
Manufacturing	0.025*	0.035***	0.027**	0.161***	0.167***	0.149***	0.003	0.014	-0.019	0.052*	0.059**	0.016
	(0.013)	(0.013)	(0.013)	(0.038)	(0.037)	(0.038)	(0.017)	(0.017)	(0.017)	(0.028)	(0.028)	(0.03)
Construction	0.012	0.012	0.014	0.108**	0.113***	0.094**	-0.005	-0.003	-0.022	0.04	0.032	0.012
	(0.015)	(0.014)	(0.015)	(0.046)	(0.045)	(0.046)	(0.02)	(0.02)	(0.02)	(0.025)	(0.025)	(0.027)
Trade	0.002	0.011	0.004	0.144***	0.157***	0.153***	-0.024	-0.014	-0.038**	0.015	0.022	-0.007
	(0.014)	(0.014)	(0.014)	(0.036)	(0.036)	(0.037)	(0.019)	(0.019)	(0.019)	(0.038)	(0.038)	(0.038)
Transport information accommodation food financial	0.02	0.018	0.021	0.141***	0.137***	0.107***	0.023	0.023	-0.006	-0.032	-0.034	-0.064
	(0.014)	(0.014)	(0.014)	(0.037)	(0.036)	(0.037)	(0.019)	(0.019)	(0.019)	(0.04)	(0.04)	(0.039)
Professional scientific technical public administration	0.025	0.027	0.026	0.162***	0.168***	0.135***	0.017	0.016	-0.019	-0.007	-0.001	-0.024
	(0.017)	(0.017)	(0.017)	(0.04)	(0.039)	(0.04)	(0.026)	(0.026)	(0.025)	(0.036)	(0.037)	(0.037)
Basic services	-0.034**	-0.028**	-0.033**	0.138***	0.149***	0.133***	-0.053**	-0.051**	-0.091***	-0.057***	-0.046	-0.098***
	(0.014)	(0.014)	(0.014)	(0.038)	(0.037)	(0.038)	(0.021)	(0.021)	(0.021)	(0.028)	(0.028)	(0.029)
Region fixed effects	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
District fixed effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
LR Test	3236.99***	3405.31***	3240.34***	630.34***	758.16***	1080.29***	1935.28***	1988.26***	2450.15***	823.48***	857.02***	1099.43***
PseudoR2	0.137	0.145	0.138	0.089	0.107	0.153	0.166	0.171	0.210	0.174	0.181	0.233
Observations	**17,824**	**17,824**	**17,824**	**5,352**	**5,352**	**5,352**	**8,979**	**8,979**	**8,979**	**3,493**	**3,493**	**3,493**

Note: TIAFF- Transport information accommodation food financial, PSTPA- Professional scientific technical and public administration, Basic services- Education, human health, social work, water sanitation, gas supply and other basic services; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.01.

5. Conclusion

This study examines skill-based labour migration across India's six major industrial regions using PLFS 2020-21 data. The findings reveal that internal migration is increasingly differentiated by occupational skill, industrial structure, and regional labour demand. Medium-skilled workers emerge as the most mobile workforce segment, while high-skilled workers concentrate in interstate and urban-oriented migration, and low-skilled workers demonstrate localised, rural-linked mobility. Delhi NCR and Mumbai-Pune regions function as principal interstate migration destinations, whereas southern regions (Bengaluru, Chennai, Hyderabad) show stronger intra-state patterns. Migrants concentrate in manufacturing, transport, trade, and service sectors. Technical education significantly promotes migration across skill levels, whereas urban residence increases migration probability across all groups. Household size, caste, religion, gender, and marital status remain critical determinants, indicating that social inequalities shape migration outcomes. The study demonstrates that contemporary Indian migration reflects economic opportunity-seeking within structurally segmented labour markets rather than distress-driven rural-urban flows alone.

These findings integrate migration theory, labour market segmentation, and industrial geography to advance understanding of India's labour market transformation. The research supports human capital theory's predictions about skill-return differentials while confirming segmentation theory's insights on divergent mobility outcomes. Policy responses must include strengthened technical and vocational education aligned with regional industrial demand; improved labour market information systems to reduce migration costs. They should also include expanded urban infrastructure, affordable housing, and social protection in industrial corridors; targeted interventions addressing caste, religion, and gender-based barriers to mobility; and regional coordination mechanisms to manage labour supply-demand mismatches. Simultaneously, policies must recognise that market-driven opportunity-seeking requires labour-market-centric rather than welfare-relief governance approaches. The cross-sectional nature of the data prevents tracing long-term trajectories or skill-matching quality. Unexplained variance in migration decisions (pseudo-R^2 0.089-0.233) suggests unmeasured factors including networks, information asymmetries, and discrimination merit investigation. Future research should employ longitudinal data to examine skill upgrading trajectories, return migration patterns, gender-differentiated mechanisms, and impacts of technological change on regional skill demands. Understanding skill dimensions of

migration is critical to effective employment, skill development, and regional development policy in an increasingly urbanised India. This study provides empirical foundation for integrated policy design recognising that migration efficiency and equity require simultaneous attention to market mechanisms and redistributive protections for disadvantaged groups.

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Data availability Data will be made available on reasonable request.

Declarations

Conflict of interest All the authors have no relevant financial or non-financial interests to disclose.

References

Ankita & Singh, I. (2025). Education and women in high-skill occupations in India. *Indian Growth and Development Review, 18* (1), 1-19.

Bhagat, R. B. (2017, September). Migration and urban transition in India: Implications for development. *In United Nations expert group meeting on sustainable cities. Human mobilities and international migration*.

Borjas, G. J. (1987). Self-selection and the earnings of immigrants (No. w2248). *National Bureau of Economic Research*.

Breman, J. (1996). Footloose labour: Working in India's informal economy (Vol. 2). *Cambridge University Press*.

Cameron, A. C., & Trivedi, P.K., (2005). Microeconometrics: methods and applications. *Cambridge University*.

Chandrasekhar, S., & Sharma, A. (2015). Urbanization and spatial patterns of internal migration in India. *Spatial demography*, *3*(2), 63-89.

Census of India, (2011). Provisional Population Totals. *New Delhi: Government of India*, 409-413.

Deshingkar, P., & Akter, S. (2009). Migration and human development in India. Human Development Research Paper 2009/13. United Nations Development Programme (UNDP), New York.

De Haas, H., Castles, S., & Miller, M. J. (2020). The age of migration: International population movements in the modern world. Guilford Publications.

De, S., Mukherjee, D., & Ray, J. (2025). Skill in Indian Labour Market: Current Trends and Estimating Future Gaps. *Arthaniti: Journal of Economic Theory and Practice*, *24*(1), 103-129.

Lee, E. S. (1966). A theory of migration. *Demography*, *3*(1), 47-57.

Government of India, (2016). India on the Move and Churning: New Evidence. *Economic Survey*.

Grogger, J., & Hanson, G. H. (2011). Income maximization and the selection and sorting of international migrants. *Journal of Development Economics*, *95*(1), 42-57.

Gujarati, D. N. (2012). Basic Econometrics 4th ed. McGraw-Hill Education.

Hanson, G. H. (2010). International migration and the developing world. In *Handbook of development economics* (Vol. 5, pp. 4363-4414). Elsevier.

Hunt, G. L., & Mueller, R. E. (2004). North American migration: returns to skill, border effects, and mobility costs. *Review of Economics and Statistics*, *86*(4), 988-1007.

Hofmann, E. T. (2015). Choosing your country: Networks, perceptions and destination selection among Georgian labour migrants. *Journal of Ethnic and Migration Studies*, *41*(5), 813-834.

Khadria, B. (2002). Skilled labour migration from developing countries: Study on India. *ILO*.

Khan, M. I. (2021). Consequences of Labour Migration on Wages and Employment: Evidence from India. *The Indian Journal of Labour Economics*, *64*(1), 23-47.

Kumar, V., & Pradhan, K. C. (2025). Regional analysis of patterns and determinants of migration in india: insights from post-pandemic period and future implications. *Journal of Population Research*, *42*(3), 27.

Kundu, A. (2009). Exclusionary urbanisation in Asia: A macro overview. *Economic and Political Weekly*, 48-58.

Kundu, A., & Saraswati, L. R. (2012). Migration and exclusionary urbanisation in India. *Economic and Political Weekly*, 219-227.

Mahapatro, S., & AN, S. (2015). Gender and intra-household migration decision in India: An Empirical Analysis. *Rev Soc Stud*, *2*.

Mazumdar, I., & Agnihotri, I. (2013). 7 Traversing Myriad Trails: Tracking Gender and Labour Migration across India. In *migration, gender and social justice: Perspectives on human insecurity* (pp. 123-151). Berlin, Heidelberg: Springer Berlin Heidelberg.

Mitra, A. (2019). Rural to urban migration and the urban labour market: The case of India. *Cities of dragons and elephants: Urbanization and urban development in China and India*, 175-218.

Mitra, A., & Shrivastav, P. K. (2024). Interstate Inequality in Consumption. *Economic & Political Weekly*, *59*(28), 17.

Narayana, M. R. (2014). Growth effects of industrial clusters: Evidence and implications for India. *South Asia Economic Journal*, *15*(1), 71-92.

Parida, J. K., & Madheswaran, S. (2011). Determinants of migration and remittance in India: Empirical evidence. *Institute for Social and Economic Change*.

Parida, J. K., & Raman, R. K. (2020). Migration and urbanization. *Handbook of internal migration in India*, 449-461.

Piore, M. J. (1979). Birds of passage. *Migrant labor and industrial societies (Cambridge 1979)*.

Rajan, S. I., & Bhagat, R. B. (2021). Internal migration in India: Integrating migration with development and urbanization policies. *Policy Brief*, *12*(59), 2021-02.

Riggi, M. R., & Maggioni, M. A. (2004, June). Labour Market Dynamics and Industrial Clusters: an Ecological Based Approach. In *XIX National Conference of Labour Economics*.

Ruhs, M., & Vargas-Silva, C. (2015). The labour market effects of immigration. *The migration observatory*.

Sachar, R. (2006). Social, economic and educational status of the Muslim community of India: A report.

Singh, J. P. (1980). Population mobility in India: studies and prospects. *Sociological Bulletin*, *29*(1), 33-62.

Sjaastad, L. A. (1962). The costs and returns of human migration. *Journal of political Economy*, *70*(5, Part 2), 80-93.

Srivastava, R. (2011). Labour migration in India: Recent trends, patterns and policy issues. *The Indian Journal of Labour Economics*, *54*(3), 411-440.

Tejada, G., & Bhattacharya, U. (2014). Indian skilled migration and development: An introduction. In *Indian skilled migration and development: To Europe and back* (pp. 3-26). New Delhi: Springer India.

Thorat, S., & Neuman, K. S. (2012). Blocked by caste: Economic discrimination in modern India. *Oxford University Press*.

Tripathi, S., & Kaur, H. (2017). Determinants of rural to urban migration in large agglomerations in India: An empirical analysis.

Tumbe, C. (2018). India moving: A history of migration. *Penguin Random House India Private Limited*.

Appendix

Table A1: Regional classification: district composition of six major industrial regions

Core region	State	District
Delhi NCR region	Delhi	Northwest, North, Northeast, East, New Delhi, Central, West, Southwest, South
	Haryana	Panipat, Sonipat, Jhajjar, Gurgaon, Faridabad
	Uttar Pradesh	Meerut, Baghpat, Ghaziabad, Gautam Buddha Nagar
Bengaluru region	Karnataka	Tumkur, Bengaluru, Mandya, Mysore, Kolar, Chikkaballapura, Bengaluru Rural, Ramanagara
Chennai region	Tamil Nadu	Thiruvallur, Chennai, Kancheepuram, Vellore, Tiruvannamalai, Viluppuram, Cuddalore
Surat-Ahmedabad region	Gujrat	Gandhinagar, Ahmadabad, Anand, Kheda, Bharuch, Navsari, Valsad, Surat
Mumbai-Pune region	Maharashtra	Nashik, Thane, Mumbai Suburban, Raigarh, Pune, Ahmadnagar, Satara
Hyderabad region	Telangana	Sangareddy, Siddipet, Yadadri, Medchal-Malkajgiri, Rangareddy, Mahbubnagar, Nalgonda

Table A2: Description of the covariates

Variables	Variable description	Unit of measurement
Age		No. of years
Age squares		Square of age
Sector	Rural, Urban	
Household size (HH size)	Small (1-3 members), medium-small (4-5 members), medium (6-7 members), large (8 and above members)	In numbers
Social groups	Scheduled castes (SC), scheduled tribe (ST), Other backward classes (OBC), Others	
Religion	Hindu, Muslim, Others (Others include the following religion: Christian Sikhism, Buddhism, Jainism, Zoroastrianism, and others)	

Marital status	Unmarried, Married	
Gender	Male, Female	
General education	Categorized the educational attributes in 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."	
Occupations	Based NCO-2004 classification we have categorized it into ten broader occupations categories and then as per skill level we have categories' it three categories: High skill, medium skill, low skill	National Occupation Code 2004
Industry	Based on NIC-2008 classification we have categorized 7 major industrial group: Agriculture and mining, manufacturing, construction, trade, transport information accommodation food financial (TIAFF), professional scientific technical public administration (PSTPA), basic services (gas, water, electricity, sanitation, education, human health, social work and household employer activities.)	National Industrial Classification 2008
Six major industrial Regions	Based on literature and Indian geographical structure we have divided India into six major regions: Delhi NCR, Bengaluru region, Chennai region, Surat-Ahmedabad, Mumbai-Pune, Hyderabad region	

Table A3: Assigned skill level based on broader national code of occupation (NCO) 2004 categories

NCO code-2004	broader occupation category	Require education attainments	NCO based skill level	Skill basis broader category (Ankita & Singh, 2025)
111/130	Legislators, senior officials and managers	Not defined	Skill not defined*	
211/246	Professionals	Postgraduate university degree and above	IV	High skill
311/348	Technicians and associate professionals	First university degree	III	
411/422	Clerks	Secondary education	II	
511/523	Service workers and shop & market sales workers	Secondary education	II	
611/620	Skilled agricultural and fishery workers	Secondary education	II	Medium skill
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 (2024); NCO (2004); *The concept of skill level has not been applied in the case of legislators, senior officials & managers as skills for executing task 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 A4: Classification of Major Industrial Divisions for Analytical Purposes based on National Industrial Classification (NIC)-2008 categories

NIC 3-Digit Group	Division	Subsectors	Industrial clusters
011-032	A	Agriculture, Forestry and Fishing	Agriculture & mining
051-099	B	Mining and Quarrying	
101-332	C	Manufacturing	Manufacturing
351-353	D	Electricity, Gas, Steam and Air conditioning Activities	Basic services
360-390	E	Water supply, Sewerage, Waste Management and Remediation Activities	
410-439	F	Construction	Construction
451-439	G	Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles	Trade
491-532	H	Transport and Storage	Transport information accommodation food financial
551-563	I	Accommodation and Food Service Activities	
581-639	J	Information and Communication	
641-663	K	Financial and Insurance Activities	
681-682	L	Real Estate Activities	
691-750	M	Professional, Scientific and Technical Activities	professional scientific technical
771-829	N	Administrative and Support Service Activities	
841-843	O	Public administration and defence; compulsory social security	public administration
851-855	P	Education	Basic services
861-889	Q	Human health and social work activities	
900-932	R	Arts, entertainment and recreation	
941-960	S	Other service activities	
970-982	T	Activities of households as employers; undifferentiated goods- and services producing activities of households for own use	
990	U	Activities of extraterritorial organizations and bodies	

Table A5: Determinants of migration across six major industrial regions and skill level

	Full sample		High skill		Medium skill		Low skill	
Variables	**Odds ratio**	**dy/dx**	**Odds ratio**	**dy/dx**	**Odds ratio**	**dy/dx**	**Odds ratio**	**dy/dx**
Other socio-demographic and economic variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Core region@ Hyderabad region								
Delhi NCR region	1.040 (.071)	0.007 (0.012)	.825 (.108)	-0.035 (0.024)	1.077 (.104)	0.013 (0.017)	1.511*** (.242)	0.076*** (0.029)
Bangalore region	1.774*** (.127)	0.111*** (0.014)	2.210*** (.278)	0.163*** (0.025)	1.611*** (.170)	0.086*** (0.019)	2.017*** (.373)	0.132*** (0.034)
Chennai	1.484*** (.097)	0.075*** (0.012)	2.050*** (.258)	0.147*** (0.025)	1.258** (.114)	0.041** (0.016)	1.598*** (.249)	0.087*** * (0.028)
Surat-Ahmedabad	1.045 (.076)	0.008 (0.013)	1.403** (.187)	0.066*** (0.026)	1.003 (.105)	0.001 (0.018)	.948 (.169)	-0.009 (0.032)

region								
Mumbai-Pune	1.634***	0.094***	1.791***	0.118***	1.554***	0.080***	1.725***	0.101***
region	(.104)	(0.012)	(.214)	(0.023)	(.141)	(0.016)	(.253)	(0.026)
Constant	.038***		.013***		.043***		.030***	
	(.008)		(.006)		(.014)		(.014)	
Observations	**17,824**	**17,824**	**5,352**	**5,352**	**8,979**	**8,979**	**3,493**	**3,493**

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

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