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Exploring The Impact Of Migration Duration On Expected Urban Income: A Quantile Regression Analysis Of Rural Migrants In Guwahati

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Abstract:
Rural-to-urban migration plays a critical role in shaping urban economies, particularly in developing countries. Guwahati, the largest city in northeastern India, has witnessed a significant influx of rural migrants in recent decades. This paper investigates the relationship between migration duration and expected urban income among rural migrants in Guwahati, with skill level and formal training status as control variables. While most studies rely on traditional Ordinary Least Squares (OLS) regression to model income trajectories, this paper employs quantile regression, providing a more nuanced analysis of income disparities across various percentiles. The findings reveal that the duration of migration significantly affects expected income, with varying impacts across different income groups. This heterogeneity, often masked in OLS models, suggests that policymakers need to consider differentiated strategies to address the unique challenges faced by migrants at different income levels. The paper concludes that the relationship between migration duration and income is strongest in the lower-income groups, while formal training enhances income prospects across all levels.

Keywords: Rural-urban migration, Harris-Todaro Model, Expected income, Quantile Regression,

1. Introduction:

Rural-to-urban migration has become a central feature of urbanization in developing countries, contributing significantly to the demographic and socio-economic transformation of cities. Migrants, driven by the promise of better economic opportunities, access to services, and improved living conditions, often leave their rural homes for the challenges and opportunities presented by urban environments. However, the journey from rural livelihoods to urban prosperity is rarely smooth. Migrants face numerous challenges, including a lack of social networks, limited access to resources, skill underutilization, and barriers to employment in their new surroundings.

Guwahati, the largest and most rapidly growing urban centre in the northeastern region of India, has become a prime destination for rural migrants from surrounding areas. The city's expanding service sector, construction boom, and transport network offer various livelihood opportunities for migrants. Yet, this influx of rural migrants places significant pressure on the city's infrastructure and labour market, resulting in overcrowding, underemployment, and income inequality. The dynamic nature of urban migration patterns in Guwahati, coupled with the diverse profiles of migrants, calls for a deeper investigation into the factors that shape their economic outcomes in the city.

While the literature on rural-urban migration is extensive, much of it focuses on the broad determinants of migration, such as wage differentials, employment prospects, and living conditions. Classical models, such as the Harris-Todaro (1970) two-sector model, suggest that migration decisions are driven by expected wage differentials between rural and urban areas, where individuals move in search of higher earnings in cities. However, the simplistic assumption that all migrants benefit equally from urban opportunities is increasingly being challenged. Recent studies highlight the heterogeneity of migrant experiences, particularly in relation to income dynamics, skills, and duration of stay in urban environments.

In this regard, human capital theory (Becker, 1964) provides a useful framework for understanding how education, skills, and work experience—key forms of human capital—affect migrants' economic outcomes. According to this theory, individuals invest in their human capital through education and training to increase their productivity and, consequently, their income. However, for many rural migrants, the urban labour market presents complexities that may hinder their ability to fully utilize their skills, leading to underemployment or skill mismatches. This highlights the importance of factors such as formal training and skill development in shaping migrants' income trajectories.

Most empirical studies on migrant income employ traditional Ordinary Least Squares (OLS) regression techniques to explore the relationship between migrants' characteristics—such as education, experience, and duration of stay—and their income outcomes. While these studies provide valuable insights, OLS assumes a uniform effect of independent variables across the entire income distribution. This limitation overlooks the variations in income growth among different groups of migrants, particularly those at the lower and upper ends of the income spectrum. For instance, lower-income migrants may experience slower wage growth despite longer durations of stay, while higher-income migrants may benefit disproportionately from additional skills or training.

To address this gap, this paper employs **quantile regression** as a more robust analytical tool to examine how the duration of stay, skill levels, and formal training influence the income of rural migrants in Guwahati. Unlike OLS, quantile regression allows us to explore how the effects of these factors vary across different income percentiles, providing a more nuanced understanding of income disparities among migrants. This approach is particularly valuable in understanding the income trajectories of rural migrants, as it accounts for the heterogeneity within the migrant population—capturing the unique challenges faced by lower-income groups as well as the wage advantages that may accrue to higher-income migrants.

The context of Guwahati, with its rapid urban growth and influx of rural migrants, provides an ideal setting for studying the complex relationship between migration duration and income. Migrants from nearby districts and rural regions move into the city's burgeoning construction, transport, and services sectors, where they navigate the urban labour market with varying degrees of success. Some benefit from formal vocational training, while others rely on informal skills acquired through experience. Additionally, the varying skill levels of migrants—from unskilled labourers to those with specialized skills—pose unique challenges in terms of employment and wage growth.

The primary contribution of this paper lies in its application of quantile regression to study rural-urban migrants in Guwahati, a method that has not been widely used in the migration literature. By focusing on different quantiles of the income distribution, this study provides critical insights into how migration duration, skills, and formal training influence income in ways that go beyond the average effects captured by OLS models. This study is novel in its use of quantile regression in the context of rural-urban migration, addressing a gap in the literature by focusing on income heterogeneity and how different migrant subgroups experience wage growth over time. The key objective of this study is:

To analyse the relationship between migration duration and expected income among rural migrants in Guwahati.

2. Literature Review:

The dynamics of rural-to-urban migration have been widely studied across disciplines, with human capital theory serving as a cornerstone in understanding wage growth and employment transitions. Becker's (1964) theory of human capital posits that individuals can enhance their productivity through investments in education, training, and work experience, which eventually translates into higher income. Migrants, in particular, often undergo substantial human capital development as they adapt to new urban environments, acquiring new skills and work experience that contribute to their income growth.

The Harris-Todaro model (1970) also emphasizes the role of wage differentials in driving rural-urban migration, arguing that individuals make migration decisions based on the expected wage differentials between rural and urban areas. While these models provide a foundation for understanding the motivations behind migration, they often fail to capture the heterogeneity within migrant populations, particularly in terms of income distribution.

Recent research has looked on the relationship between education, skill development, and income among migrants. Mahato and Paudel (2023) discovered a substantial link between educational attainment, skilled training, and better monthly salaries for labor migrants. Similarly, Roman and Popescu (2014) found that training programs resulted in higher salaries for Romanian migrants. Messinis and Olekalns (2007, 2008) evaluated the influence of firm-provided job training on labor income in Australia, finding that training increased earnings and helped alleviate skill-job mismatches. Their findings also revealed that training was especially beneficial for undereducated and young workers, aiding in the

rehabilitation and replenishment of human capital. These studies jointly suggest that formal education and skill training play critical roles in increasing migrants' economic potential and addressing skill mismatches in various labour market.
Quantile regression has emerged as a valuable tool for analysing income disparities that traditional OLS models cannot capture. Quantile regression has emerged as a valuable tool for analyzing income disparities and wage structures across different points of the distribution, offering insights beyond traditional OLS models (Porter, 2015). This technique has been applied to examine various economic phenomena, including income inequality's impact on growth (Sbaouelgi, 2018) and changes in the U.S. wage structure (Buchinsky, 1994). While OLS focuses on the mean of the dependent variable, quantile regression provides a more comprehensive analysis by estimating effects at different points along the income distribution. This is particularly relevant for migration studies, where different income groups may experience distinct wage dynamics. In this paper, we build on this literature by applying quantile regression to examine how the duration of migration affects income growth across different income groups in Guwahati.

3. Study Area and Methodology

3.1 Study Area

Location:

The study is conducted in Guwahati, the largest city in Assam and a key economic and cultural hub in northeastern India. The city has experienced significant urbanization and growth, making it a major destination for rural-urban migrants seeking employment and better living standards.

Rationale for Selection

Guwahati, known as the "Gateway to the Northeast," has seen rapid development in the construction, transportation, and hospitality sectors. Its growing economy and expanding infrastructure make it an ideal location for examining livelihood transitions among rural-urban migrants. According to Macro Trends (2020), the city’s population has reached approximately 1.13 million, further highlighting its role as a magnet for migration in the region.

Characteristics of the Study Area

Guwahati features a diverse urban landscape, with bustling commercial centres, informal settlements, and peri-urban areas. Key sectors driving the city's economy include trade, services, transportation, and construction, with a growing influence from industries such as hospitality and retail. Its strategic location as a gateway to the northeastern states facilitates trade and migration from neighbouring regions.

Population Profile

The city's population consists of a mix of indigenous communities and migrants from across Assam, as well as other parts of India and neighbouring countries. Migration to Guwahati is largely driven by limited economic opportunities in rural areas, alongside the city's expanding infrastructure and employment prospects.

Significance of the Study Area

Analysing the livelihood transitions of migrants in Guwahati is essential for shaping policies and development strategies aimed at managing urbanization and addressing the socio-economic challenges migrants face. This study aims to generate insights that can support livelihood enhancement initiatives, improve urban planning, and inform policy interventions tailored to migrant populations.

3.2 Methodology

Sampling Design

The study employs a multi-stage sampling design, drawing data from the Guwahati Municipal Corporation (GMC). Given the large migrant population, 10 wards out of 60 in the GMC were purposively selected based on migrant density in key sectors.

Sampling Size and Sector Selection

A total sample of 450 rural-urban migrants was selected to explore livelihood transitions across three sectors: Construction, Transportation, and Hotels & Restaurants. An equal allocation method was used to ensure balanced representation of the sectors, given the lack of specific population data for each sector. This method helps facilitate sectoral comparisons on equal footing (Cochran, 1977; Creswell, 2014).

- **Construction Sector:** 150 respondents

- **Transportation Sector:** 150 respondents
- **Hotels & Restaurants Sector:** 150 respondents

This allocation allows for a comprehensive analysis of the socio-economic and cultural impacts of migration in these sectors.

Data Collection:
In the final stage, structured interviews and surveys were conducted with selected migrants to gather data on their migration experiences, livelihood activities, income sources, housing conditions, and social integration. This approach provides detailed insights into the factors influencing migrants' livelihood transitions.

4. Line of Analysis

The Harris-Todaro model, introduced by John R. Harris and Michael P. Todaro in 1970, is a seminal theoretical framework for understanding rural-urban migration. This model is grounded in the economic principle that migration decisions are influenced by differences in expected income between rural and urban areas. It provides a nuanced explanation of why individuals may choose to migrate despite the potential risks of urban unemployment.

Key Concepts of the Model

a) **Expected Income Calculation:** The Harris-Todaro model posits that individuals migrate from rural to urban areas based on the comparison of expected income in these regions. Expected income in an urban area is calculated as:

Expected Urban Income= Urban Wage × Probability of Employment

This formula reflects the potential earnings adjusted for the likelihood of unemployment. In contrast, rural income is typically lower but associated with lower unemployment risk.

b) **Urban Unemployment and Migration Decisions:** The model accounts for urban unemployment, which can affect the migration decision. High unemployment rates in urban areas may reduce the attractiveness of the city despite higher wages. The probability of securing employment thus becomes a critical factor in the migration decision.
c) **Rural-Urban Migration Dynamics:** According to the model, migration occurs when the expected urban income surpasses the rural income. Individuals weigh the potential benefits of higher wages against the risk of unemployment, leading to a migration decision based on the net expected gain.

Application to this Objective

a) **Relevance:** The Harris-Todaro model is central to this objective of this research, which aims to determine the change in expected urban income of rural migrants over their duration of residence in Guwahati. By analysing wage differentials and unemployment rates in the Construction, Hotels & Restaurant, and Transportation sectors, this study applies the model to assess how these factors influence income expectations and migration decisions.
b) **Model Variables:** The key variables in the Harris-Todaro model—urban wage rates, rural wage rates, probability of urban employment, and urban unemployment rates—are directly relevant to this study. Data collected from surveys and interviews will be used to estimate these variables and analyze their impact on the migration and livelihood patterns of rural migrants.

Todaro model is mainly based on-

- Rural urban Wage Differential
- Scope to look at different sectors

Livelihood transition exhibits vertical mobility with increasing years of residence in urban areas of the rural migrants. This research will mainly focus on the scope to trace the livelihood path over the years of the migrant (Espíndola et al., 2006).

Vertical mobility is associated with increasing expected urban wage. So, one of the focuses of the research is to determine how urban expected income of the migrant changes as his period of migration (Barbosa et al., 2018).

In order to analyse this objective, as we know that

Expected Urban wage [E (Y)] = P. W_U

where, P = $\frac{UWF}{ULF}$ = Ratio of urban workforce and urban labour force

W_U = Wage in Urban Area (Harris & Todaro, 1970)

Here we will mainly consider the number of years of a migrated labour, his presently drawing income in the consecutive years, and the change in his expected income. This will be studied separately for migrants in construction sector, hotels and restaurant sector and transportation sector.

Livelihood Path	**Wage (W_U)**	**P_W (WF/LF)**	**E(Y)**
0-5 years	X_0	P_0	X_0P_0
5-10 years	X_1	P_1	X_1P_1
10-15 years	X_2	P_2	X_2P_2
15 & more	X_3	P_3	X_3P_3

Here, wages ($W=_U$) in each span of years is calculated at an average rate.
And so on. Here with increasing years of the migrants in the destination area, we can observe the change in expected income over their livelihood and it will be analysed with the help of regression model.
$E(Y)t=\alpha+\beta_1 t_1 + \beta_2 SL_2 + \beta_3 TS_3 + \epsilon$
Where,
$E(Y)_t$ = Expected Income of the migrants (P. W_U)
t_1 = Number of Years of the Migrants
SL_2 = Skill Level of the Migrants
TS_3 = Training Status of the Migrants

Table 1: Representation of the Probability of Finding Job in the Three Sectors

NO. OF YEARS	WORKFORCE	LABOUR FORCE		P
0-5	46	8 (54)	46 in workforce, 8 irregularly employed. Current Daily Status Unemployment: 8 workers with daily employment gap	0.9
5-10	346	5 (351)	Weekly Status Unemployment: Some workers lack full weekly employment	1
10-15	26	8 (34)	8 work 2-3 days a week. Usual Status Unemployment: Intermittent employment over the year.	0.8
15 & MORE	11	11	All are in the workforce.	1

Source: Author's Own Calculation, Field Survey, 2022-23

Table 2: Representation of E(Y) of the migrants in the different spans of time

Period of Stay	**Wage (WU) (In Rs.)**	**PW (WF/LF)**	**E(Y) (In Rs.)**
0-5 years	820 (44300/54)	0.9	738
6-10 years	615 (216130/351)	1	615
11-15 years	742 (25250/34)	0.8	577
16 & more	1145 (12595/11)	1	1145

Source: Author's Own Calculation, Field Survey, 2022-23

The table above highlights key indicators of migrant earnings based on their period of stay in Guwahati. The variable "Wage (WU)" represents the prevailing wage rate for each period, while "PW" is the probability of finding work in the urban environment. The probability is calculated by dividing the urban workforce by the urban labour force. The "Expected Income (E(Y))" is then derived by multiplying the wage (WU) by the probability of finding work (PW).

The periods of stay for the migrants are categorized into four groups: 0-5 years, 6-10 years, 11-15 years, and 16 years or more. This categorization is adopted due to the technical difficulty of calculating individual probabilities for each migrant. Therefore, a grouped approach has been applied to simplify the analysis, which allows for regression analysis to be conducted with all 450 migrants based on their years of stay, using the expected wage values for each category.

For example:

- Migrants who have stayed in Guwahati for 0-5 years have a prevailing wage of Rs. 820, with a probability of finding work at 0.9. This results in an expected income of Rs. 738.
- Migrants in the 6–10-year range have a wage of Rs. 615 and a probability of 1, making their expected income Rs. 615.

This method enables the study to generalize expected wage growth over time, reflecting how both the probability of finding work and the wages change as migrants stay longer in the city. It provides a clearer picture of the income transition of rural-urban migrants across different time spans.

Let us perform a Regression analysis to explore the relationship between the number of years of the migrants in Guwahati and the expected wage. We can use skill level and formal training status as control variables in our regression model. Control variables are used in regression analysis to account for their potential impact on the dependent variable, allowing you to isolate the effect of your key independent variable (in this example, the number of years) on expected income.

Table 3: Representation of the Model Summary

Model	R	R Square	Adjusted R Square	R Square Change	F Change	Sig. F Change
	.313[a]	.098	.092	.098	16.190	.000

Source: Author's Own Calculation, Field Survey, 2022-23

The model above discusses about how the number of years in Guwahati (t_1) is the sole independent factor affecting the change in expected wages.

Since R square is 0.100, this means that only 9.8 % of the change in expected wages is explained by the predictors (t_1, SL_2, FT_3). Adjusted R square is similar to R square which is 9.2%. F-statistic compares the ratio of explained variation (SSR) to unexplained variation (SSE). The F Change statistic of 16.190 indicates the improvement in model fit achieved by adding the predictor variable which is the number of years in Guwahati (t_1)", Skill level of the migrants (SL_2) and Formal Training Status of the Migrants (FT_3) to the regression model. Specifically:

The null hypothesis assumes that the model without the predictor variables is sufficient.

The alternative hypothesis suggests that the model with the predictor variables (the more complex model) provides a better fit. In this case, a larger F Change suggests that the predictor variables significantly contribute to explaining the outcome (i.e. expected wage). Sig. F Change (0.000) indicates this improvement is statistically significant.

Table 5.4: Regression Coefficients for Factors Affecting the Expected Urban Income of Rural-Urban Migrants

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
	(Constant)	610.423	37.818		16.141	.000

(Number Of Years of Migration) t_1	32.985	5.497	.345	6.000	.000
(Skilled Level) SL_2	-221.312	42.075	-.302	-5.260	.000
(Formal Training) FT_3	95.762	33.105	.130	2.893	.004

Dependent Variable: P x W

Source: Author's Own Calculations, Field Survey, 2022-23

In the above table, B = 610.423 is the expected income when the number of years of migration (t_1), Skill Level (SL_2), and Formal Training (FT_3) all equal zero. While 0 years of migration, skill level, or no formal training may not be realistic, it does provide a baseline for the regression equation.

For the predictor variable t_1, controlling for skill level and formal training status, every additional year of migration raises expected income by 32.985 units. The standardized coefficient (Beta) of 0.345 reveals how important t_1 is in the model. The t-value and significance level ($p < 0.001$) show a statistically significant effect.

Having formal training is associated with an increase in expected income by 95.762 units, controlling for the number of years of migration and skill level of the migrants. The standardized coefficient (Beta) of 0.130 indicates the relative importance of formal training in the model. The positive sign suggests that formal training is associated with higher expected income. This result is statistically significant ($p < 0.01$).

Higher skill levels are related with a 221.312 unit fall in expected income, after controlling for years of migration and formal training status. The standardized beta (Beta) of -.302 illustrates how important skill level is in the model. The negative sign indicates that as skill level grows expected income drops. The finding is statistically significant ($p < 0.001$).

The regression analysis was conducted to determine the change in expected urban income of rural migrants over their livelihood path, with the number of years of migration as the primary independent variable. Skill level and formal training status were included as control variables to account for their potential influence on income.

The regression model was statistically significant, explaining a significant portion of the variance in expected income. The number of years of migration (t_1) had a significant positive effect on expected income (B = 32.985, $p < 0.001$), indicating that each additional year of migration increased expected income by 32.985 units, controlling for skill level and formal training status.

Skill level (SL) and formal training status (FT) were included as control variables in the model. Higher skill levels were associated with a decrease in expected income (B = -221.312, $p < 0.001$), which suggested that migrants with higher skill levels might be in sectors with lower pay or face other challenges affecting their income. Conversely, having formal training was associated with an increase in expected income (B = 95.762, $p < 0.01$), which indicated that formal training can be considered beneficial for income growth among migrants."

Regression Equation with Control Variables

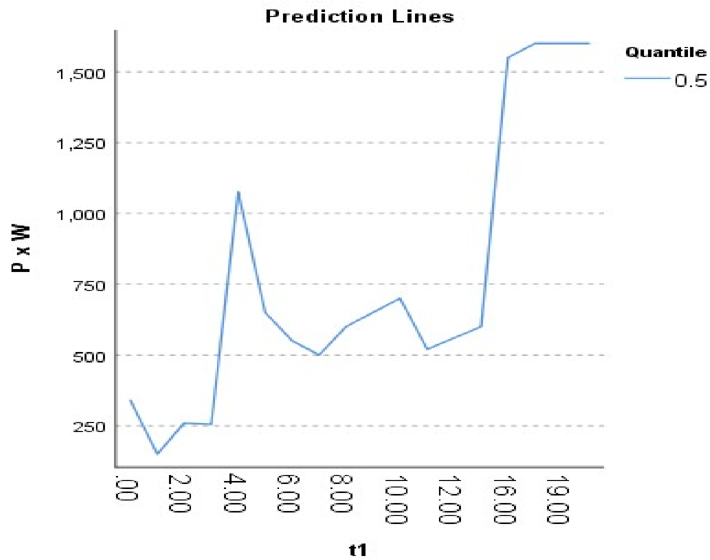
$E(Y)t = 610.423 + 32.985 \cdot t_1 - 221.312 \cdot SL_2 + 95.762 \cdot FT_3$

Thus, by including skill level and formal training status as control variables, it helps to isolate the effect of the number of years of migration on expected income, providing a clearer understanding of this relationship.

5. Quantile Regression Analysis

Since this study is made in different scales of experience, we have considered using quantile regression which allows us to analyse wage differences at various percentiles (e.g., median, 25th percentile, 75th percentile).

Quantile regression provides insights into how wages change across the wage distribution, accounting for potential heterogeneity. Unlike OLS (Ordinary Least Squares) method, which estimates the mean of the dependent variable conditional on the independent variable, the quantile regression studies the effect of independent variable on the dependent variable on various quantiles i.e. lower, median and upper quantiles. Here in this study quantile regression is used to study the comprehensive effect of the independent variable, i.e. Number of years of the migrant (t_1), on the dependent variable expected income of the migrants in the lower income group (Lower quantile), in the medium income group (Median quantile) and the higher income group (Upper Quantile).



In the above figure, the vertical axis measures the expected income of the migrants which has been indicated by P x W [E(Y)]. And the horizontal axis measures the number of years of the migrants denoted by t_1.

The figure depicts that in the initial years of the migrant from, 0 to 5 years of his stay in Guwahati, a sharp increase can be seen in the expected income which signifies that there is increase in income in the initial years of migration. This is because some migrants benefitted from higher-paying prospects or quick wage growth as they adjust to the urban environment.

However, in the middle years, i.e. from 6 to 15 years of his migration, a fluctuation and decrease in the expected income can be observed where the expected income rises and falls but generally remains lower compared to the initial spike. Income decreases and fluctuations may represent issues such as job insecurity, adjusting to new job roles, or competition in the labour market.

Again, in the later years i.e. from 16- 20 years it can be seen that the expected income experiences a steep rise which suggests that migrants who have stayed for a longer time in Guwahati, have significantly higher expected incomes. The significant gain in income in later years could be attributed to increased experience, greater work opportunities, or higher compensation for long-term residents.

The patterns observed in migrant income growth in this study can be effectively explained through the lens of **Human Capital Theory**. This theory, developed by economists such as Gary Becker (1964), posits that individuals invest in their own education, training, and work experience to enhance their productivity and, consequently, their earnings over time. According to Becker, human capital investment is similar to other forms of capital investment, as it involves an upfront cost (in terms of time, effort, and money) that yields future returns in the form of higher income.

In the early years of migration, the sharp increase in income can be attributed to the immediate returns on the human capital that migrants bring with them to the urban labour market. These initial returns are likely due to migrants utilizing their existing skills and experience in a new, potentially more lucrative, environment. As migrants adapt to the urban context, they may further invest in their human capital by acquiring new skills or knowledge, which helps them to increase their productivity.

The middle years of migration, where income fluctuates or decreases, may represent a period of adjustment and further investment in human capital. During this time, migrants might be learning new skills, transitioning between jobs, or facing competition that requires them to adapt and refine their capabilities. This period of fluctuation is consistent with Human Capital Theory, which suggests that the returns on investment are not always immediate and may require a longer time horizon to fully materialize.

Finally, the significant increase in income observed in the later years of migration aligns with the theory's prediction that long-term investment in human capital leads to higher wages. Over time, migrants accumulate more experience, build stronger social networks, and gain a deeper understanding of the labour market, all of which contribute to higher earnings. The sustained investment in human capital, as described by Becker, results in a substantial payoff, particularly for those who remain in the urban environment for a longer period.

This interpretation of the findings through the lens of Human Capital Theory provides a robust theoretical foundation for understanding the wage trajectories of rural-urban migrants. It emphasizes the importance of both initial human capital and continued investment in skills and experience as key drivers of income growth.

4. Results & Discussion:

The results from the quantile regression analysis underscore the importance of considering income heterogeneity when studying the effects of migration duration on income. While OLS regression provides a useful overview, it fails to capture the variations in how migration duration, skill level, and formal training affect different income groups. Quantile regression offers a more detailed understanding by showing that the relationship between migration duration and income is strongest among lower-income migrants, while formal training benefits migrants across all income levels.

The contradictory finding that skilled migrants earn less than unskilled migrants may be explained by the structure of the urban labour market in Guwahati, where skilled workers may face limited opportunities to fully utilize their skills. This underemployment may result from a mismatch between the skills possessed by migrants and the demands of the local labour market. In contrast, formal training appears to offer migrants a more direct path to higher incomes, possibly because it equips them with job-specific skills that are immediately applicable in the urban labour market.

The quantile regression analysis also reveals that the impact of migration duration on income diminishes as migrants move up the income distribution. This suggests that while longer stays in the city benefit lower-income migrants, higher-income migrants may rely on other factors, such as social networks or entrepreneurial opportunities, to increase their earnings.

6. Conclusion:

This paper contributes to the literature on rural-urban migration by using quantile regression to analyse the relationship between migration duration and expected income. The findings show that the effect of migration duration on income is not uniform across the income distribution. Migrants in lower-income groups benefit the most from longer stays in Guwahati, while the impact of migration duration diminishes in the middle time period from 6 to 15 years whereas from time period of 16-20 years and more expected income of the migrants steeps up. Formal training emerges as a key factor in enhancing income prospects across all income levels.

7. Policy Implications:

The study's findings have important policy implications. First, policymakers should prioritize the provision of formal training programs for rural migrants, particularly those in lower-income groups. These programs can help migrants acquire job-specific skills that increase their employability and earning potential. Second, efforts should be made to address skill mismatches in the urban labour market by improving the alignment between training programs and the demands of local industries. Finally, policies aimed at supporting longer stays in the city, such as providing affordable housing and access to social services, can help lower-income migrants achieve greater income gains over time.

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