
DECOMPOSING THE RURAL–URBAN YOUTH UNEMPLOYMENT GAP IN TANZANIA: EVIDENCE FROM THE 2024 INTEGRATED LABOUR FORCE SURVEY

 Charles Fumbo¹ and  France A. Shayo²

¹Eastern Africa Statistical Training Centre, P.O.Box 35103, Dar es Salaam, Tanzania

²Eastern Africa Statistical Training Centre, P.O.Box 35103, Dar es Salaam, Tanzania

<http://doi.org/10.35409/IJBMER.2026.3810>

Received: 20 July 2026/ Published: 2 Sept 2026

ABSTRACT

This study examines the rural–urban youth unemployment differential in Tanzania and assesses the extent to which it is associated with differences in observable characteristics. Using data from the 2024 Integrated Labour Force Survey, the study analyses youth aged 15–35 years in Mainland Tanzania. Descriptive statistics, binary logistic regression, and Fairlie decomposition are used to examine the associations of education, vocational training, and gender with unemployment across rural and urban settings. The results show that youth unemployment is higher in urban areas than in rural areas. Education is not significantly associated with unemployment in either setting. Vocational training exhibits a pronounced spatial difference as it is not significantly associated with rural youth unemployment but is strongly and positively associated with urban youth unemployment. Male youth have lower estimated odds of unemployment than female youth in both settings. The Fairlie decomposition shows that observable characteristics account for only 7.7% of the rural–urban unemployment differential, leaving 92.3% unexplained by the characteristics included in the analysis. The findings suggest that individual human capital characteristics alone provide a limited explanation for the spatial unemployment gap. Understanding youth unemployment therefore requires greater attention to labour-market contexts, skills–demand alignment, place-sensitive employment policies, and gender-responsive interventions.

Keywords: Youth unemployment; rural–urban inequality; Fairlie decomposition; vocational training; labour-market context; Tanzania.

1. INTRODUCTION

Youth unemployment remains a major labour-market and development challenge because young people often face greater difficulty securing productive, decent employment than adults do. Although global youth unemployment declined to a 15-year low in 2023, young people continue to experience difficulties transitioning from education to work, particularly in developing economies (International Labour Organisation, 2024). The challenge is particularly important in Africa, where the rapid growth of the working-age population is increasing the number of young people entering the labour market. Woldegiorgis (2023) argues that Africa’s demographic transition can contribute to inclusive development only when countries create the economic and institutional conditions necessary to harness the potential of a growing working-age population. However, the creation of productive and remunerative employment has not kept pace with the growth of the labour force in many African economies. Baah-Boateng (2016) identifies weak

labour demand, structural economic conditions, and demographic pressures as important drivers of youth unemployment in Africa. More recently, Sumberg et al. (2021) argue that Africa's youth employment challenge is not simply a skills crisis but also a "missing jobs" crisis, reflecting the inadequate supply of productive employment opportunities. Thus, addressing youth unemployment requires attention to both the characteristics of young jobseekers and the broader economic and institutional conditions that shape employment opportunities. Recent research similarly emphasises that youth unemployment is influenced by multiple interacting factors rather than by a single individual characteristic (Guan et al., 2025).

The relationship between human capital and employment is particularly important in this context. Human Capital Theory posits that education, knowledge, and skills increase individual productivity and should improve employment prospects (Becker, 1964). From this perspective, differences in youth unemployment may arise from differences in educational attainment and vocational skills. However, the employment benefits of human capital are not automatic. Where labour demand is weak or acquired skills do not correspond to available jobs, education and training may not translate into employment. Evidence from African labour markets supports this qualification. Morsy and Mukasa (2021) document substantial educational and skills mismatches among African youth, while Habiyaremye et al. (2022) show that skills mismatch can constrain youth employment even where demand for skilled labour exists. These findings suggest that the employment value of human capital depends partly on the conditions under which it is deployed. Labour Market Segmentation Theory provides a complementary perspective. Doeringer and Piore (1971) argue that labour markets consist of segments characterised by different employment conditions, opportunities, rules, and barriers to mobility. From this perspective, individuals with similar characteristics may experience different employment outcomes because they operate in different labour-market environments. Geographic location is therefore potentially important because rural and urban areas may differ in economic structure, labour demand, infrastructure, access to information, employer networks, and opportunities to acquire and utilise skills. Sumberg et al. (2021) emphasise the importance of productive job creation in shaping youth employment outcomes, while Morsy and Mukasa (2021) demonstrate that the relationship between education, skills, and employment can be affected by the degree of mismatch between workers' capabilities and available jobs. Location may therefore influence not only the availability of employment but also the extent to which individual characteristics are converted into employment.

These considerations are particularly relevant to rural–urban comparisons. Rural youth are more concentrated in agricultural activities, although movement between farm and non-farm employment reflects changing livelihood opportunities (Kafle et al., 2025). Urban labour markets generally provide greater opportunities for non-agricultural employment but may also attract large numbers of jobseekers competing for a limited supply of formal and productive jobs (Mligo, 2021; Sumberg et al., 2021). Spatial differences may also affect access to labour-market information, infrastructure, employer networks, and opportunities to apply acquired skills. Consequently, geographical location should not be treated merely as a demographic characteristic. It may represent exposure to different labour-market structures that shape employment opportunities and the returns to individual characteristics.

The Tanzanian context provides an important setting in which to examine these relationships. Employment creation and skills development remain important priorities in East Africa (East African Community [EAC], 2022), while Tanzania continues to experience substantial spatial

disparities in economic activity and labour market opportunities. National labour force data document differences in labour market outcomes between rural and urban populations (National Bureau of Statistics [NBS], 2023). Recent studies also indicate that youth unemployment in Tanzania is associated with broader economic conditions, including economic growth, income inequality, and investment in education (Mpojota et al., 2025). These conditions raise an important question about whether rural–urban differences in youth unemployment primarily reflect differences in the characteristics of young people or differences in the labour-market environments in which they seek employment.

Existing empirical evidence does not provide a consistent answer. In Tanzania, Chacha and Junjuan (2023) found that being skilled and living in an urban area were associated with higher youth unemployment. Setonga and Omary (2025), however, reported that higher education was associated with greater employability among youth graduates and that rural youth were more vulnerable to unemployment than their urban counterparts. The apparent contradiction may partly reflect differences in study populations, measures of unemployment, educational levels, and labour-market settings. It may also indicate that the employment value of education and skills depends on whether the acquired competencies align with available employment opportunities. Recent evidence strengthens this interpretation. Massia et al. (2026) identified shortcomings in the alignment of vocational education curricula with labour market requirements in Tanzania, highlighting the importance of curriculum relevance and employer engagement.

Evidence from other countries similarly demonstrates that the relationship between individual characteristics and youth unemployment is context-dependent. Yoana et al. (2024) found that vocational education was associated with lower unemployment in Indonesia, whereas Prieto et al. (2023) reported positive associations between urban residence, education, and youth unemployment in Ecuador. Duguma and Tolcha (2019) identified education as an important predictor of urban youth unemployment in Ethiopia. Gender differences have also been documented, with Aprilia and Anas (2024) finding higher unemployment among female youth in Indonesia. At the regional level, Njifen and Meungwe (2024) found that higher enrolment in primary and tertiary schools was associated with lower youth unemployment in the long run across sub-Saharan African countries, although the effects varied by educational level and time horizon. Taken together, these findings indicate that education, vocational training, gender, and location do not have uniform relationships with youth unemployment across labour markets.

Despite this growing literature, an important empirical gap remains. Much of the existing research has examined determinants or correlates of youth unemployment within particular populations or labour-market settings (Baah-Boateng, 2016; Chacha & Junjuan, 2023; Setonga & Omary, 2025), while comparatively less attention has been given to decomposing the rural–urban unemployment differential into differences in observable characteristics and differences that remain unexplained. Such analyses are useful for identifying characteristics associated with unemployment, but they do not establish how much of the rural–urban unemployment differential is attributable to differences in young people’s characteristics and how much remains after those characteristics are accounted for. This distinction is important both theoretically and for policy. If the spatial differential is primarily compositional, interventions aimed at improving education, skills, or other individual characteristics may substantially reduce the gap. If, however, most of the differential persists after observable characteristics are accounted for, a purely human-capital-based explanation would be insufficient.

The present study addresses this gap by examining the rural–urban youth unemployment differential in Tanzania using data from the 2024 Integrated Labour Force Survey (ILFS) conducted by the National Bureau of Statistics. The analysis focuses on youth aged 15–35 years and considers three theoretically relevant observable characteristics: education level, vocational training/skills, and gender. Education represents formal human capital, vocational training reflects occupation-oriented capabilities relevant to labour-market entry, and gender captures potential differences in labour-market opportunities and outcomes. Binary logistic regression is first used to examine the association between these characteristics and youth unemployment and to assess whether these relationships differ across rural and urban settings. The study then applies the Fairlie (2005) decomposition, an extension of the Blinder–Oaxaca decomposition for nonlinear binary outcomes, to determine the extent to which the rural–urban unemployment differential is associated with differences in observable characteristics and the extent that remains unexplained by those characteristics.

Accordingly, the study pursues four objectives: (a) to examine the association between education level and youth unemployment among rural and urban youth in Tanzania; (b) to examine the association between vocational training/skills and youth unemployment across the two settings; (c) to examine gender differences in youth unemployment between rural and urban youth; and (d) to decompose the rural–urban youth unemployment differential into components associated with differences in observable characteristics and differences in estimated coefficients.

The study contributes to the literature in two main ways. First, it provides recent evidence on the rural–urban distribution of youth unemployment using the 2024 ILFS. Second, it extends conventional regression analysis by applying the Fairlie decomposition to distinguish the portion of the spatial unemployment differential attributable to observable characteristics from the portion that remains unexplained by them (Fairlie, 2005). This approach provides a more direct assessment of whether the rural–urban youth unemployment differential is primarily associated with differences in young people’s characteristics or with differences that persist across the labour-market settings in which those characteristics operate.

2. METHODOLOGY

2.1 Research Design and Data

The study employed a quantitative cross-sectional design using secondary data from the 2024 Integrated Labour Force Survey (ILFS) conducted by Tanzania’s National Bureau of Statistics (NBS). The ILFS was designed to generate information on employment, unemployment, labour force participation, and related labour market characteristics. The survey employed a stratified two-stage cluster sampling design and was conducted between January and December 2024. It targeted 14,232 households across Mainland Tanzania and Zanzibar and successfully enumerated 61,588 individuals, achieving an overall response rate of 98.6% (NBS, 2025).

The present study was restricted to youth aged 15–35 years in Mainland Tanzania. After applying the study’s sample-selection criteria and data-cleaning procedures, the final analytical sample comprised 10,106 youth, including 4,420 rural and 5,686 urban respondents. The individual youth respondent was the unit of analysis.

The study used rural–urban location as the grouping variable and youth unemployment status as the outcome variable. The analytical strategy combined descriptive statistics, binary logistic regression, and Fairlie decomposition. This combination was appropriate because logistic

regression permits examination of associations between individual characteristics and a binary unemployment outcome, while Fairlie decomposition enables the observed rural–urban difference to be partitioned into a component associated with differences in observable characteristics and a residual component (Fairlie, 2005).

Although the ILFS employed a stratified two-stage cluster sampling design, the original analysis does not document the application of survey weights, strata, or cluster-adjusted variance estimation in the reported regression and decomposition analyses. Accordingly, the present study does not claim that the reported inferential estimates are survey-weighted or adjusted for the complex survey design. The methodology is reported according to the analytical procedure documented in the original study.

2.2 Variables and Measurement

The dependent variable was youth unemployment status, coded 1 for unemployed and 0 for employed respondents. Three observable individual characteristics were included as explanatory variables: education level, vocational training/skills, and gender. Their selection was guided by the study’s theoretical framework and empirical literature. Education represents formal human capital and reflects knowledge and qualifications that may influence employment prospects (Becker, 1964). Vocational training/skills represent occupation-oriented human capital relevant to labour-market entry, while gender captures potential differences in labour-market opportunities and outcomes. Together, these variables provide a parsimonious representation of observable individual characteristics relevant to the study’s examination of the rural–urban unemployment differential.

Education level was classified into four categories: no formal education, primary education, secondary education, and tertiary education. Secondary education was used as the reference category in the logistic regression models. Vocational training/skills was represented by a binary variable, coded 1 for respondents with vocational training/skills and 0 for those without. Gender was coded 1 for males and 0 for females, with females serving as the reference category. Location was coded 0 for rural and 1 for urban. It was included in the full-sample logistic regression model but excluded from the separate rural and urban models because location defines the respective subsamples.

2.3 Analytical Strategy

Data analysis was conducted using Stata and proceeded in three stages: descriptive analysis, binary logistic regression, and Fairlie decomposition.

Descriptive analysis

Frequencies and percentages were used to describe the distribution of unemployment status, education, vocational training/skills, and gender across rural and urban youth. The unemployment rate for each location was calculated as:

$$UR_g = (U_g / N_g) \times 100$$

where UR_g is the unemployment rate for location g , U_g is the number of unemployed youths in location g , and N_g is the total number of youths in location g . The rural–urban difference in unemployment status was assessed using the Pearson chi-square test.

Binary logistic regression

Binary logistic regression was employed because the dependent variable was dichotomous. The full-sample model was specified as:

$$\ln[P_i / (1 - P_i)] = \beta_0 + \beta_1 \text{Education}_i + \beta_2 \text{Training}_i + \beta_3 \text{Gender}_i + \beta_4 \text{Urban}_i + \varepsilon_i$$

where P_i is the probability that youth respondent i is unemployed.

Separate models were estimated for rural and urban youth:

$$\ln[P_i^R / (1 - P_i^R)] = \beta_0^R + \beta_1^R \text{Education}_i + \beta_2^R \text{Training}_i + \beta_3^R \text{Gender}_i + \varepsilon_i^R$$

$$\ln[P_i^U / (1 - P_i^U)] = \beta_0^U + \beta_1^U \text{Education}_i + \beta_2^U \text{Training}_i + \beta_3^U \text{Gender}_i + \varepsilon_i^U$$

where the superscripts R and U denote rural and urban youth, respectively.

The regression results were reported as odds ratios (ORs) together with standard errors, z-statistics, p-values, and 95% confidence intervals. An odds ratio greater than 1 indicates higher estimated odds of unemployment relative to the reference category, whereas an odds ratio below 1 indicates lower estimated odds.

The percentage change in estimated odds was calculated as:

$$\text{Percentage change in odds} = (OR - 1) \times 100$$

Fairlie decomposition

The principal analytical technique was the Fairlie (2005) decomposition, which extends the Blinder–Oaxaca decomposition framework to nonlinear binary outcome models. The approach has also been applied to examine rural–urban differences in Tanzania using nationally representative survey data (Ndifwa et al., 2025). The observed difference in predicted unemployment probabilities between urban and rural youth can be expressed as:

$$\Delta = \bar{P}_U - \bar{P}_R$$

where Δ represents the rural–urban unemployment differential, $\bar{P}_U$ is the mean predicted unemployment probability for urban youth, and $\bar{P}_R$ is the corresponding probability for rural youth.

For the nonlinear logistic model, the predicted probability is expressed as:

$$P(Y_i = 1 | X_i) = F(X_i \beta)$$

where $F(\cdot)$ is the logistic cumulative distribution function, X_i is the vector of explanatory characteristics, and β is the vector of estimated coefficients.

Following Fairlie (2005), the observed difference can be decomposed as:

$$\Delta = \Delta_X + \Delta_\beta$$

where:

Δ_X represents the explained component associated with differences in observable characteristics; and

Δ_β represents the unexplained component associated with differences in estimated coefficients and factors not captured by the model.

The characteristics component included education level, vocational training/skills, and gender. The decomposition therefore assessed the extent to which differences in the composition of these characteristics were associated with the rural–urban unemployment differential and the extent of the differential that remained unexplained by them.

The explained component was interpreted as reflecting differences in observable characteristics rather than causal effects. Similarly, the unexplained component was not interpreted as a direct

measure of structural labour-market effects. It may reflect differences in coefficients, omitted variables, unobserved characteristics, measurement differences, and other residual sources of heterogeneity. Statistical significance was assessed at the 5% level. Logistic regression models were evaluated using the likelihood-ratio chi-square statistic and pseudo- R^2 , while individual associations were assessed using odds ratios, confidence intervals, and p -values.

2.4 Ethical Considerations and Methodological Limitations

The study used secondary data from the 2024 ILFS and did not involve direct recruitment or interaction with research participants. The dataset was obtained from the NBS under the applicable data-access arrangements. The cross-sectional design limits causal inference. In particular, the strong association between vocational training and urban unemployment cannot establish that vocational training causes unemployment. Selection into training, previous unemployment, differences in training fields, work experience, and other unobserved characteristics may contribute to the observed association.

The analysis also uses a deliberately parsimonious set of observable characteristics. Variables such as household socioeconomic circumstances, previous work experience, migration, local economic structure, access to labour-market information, infrastructure, social networks, and employer demand were not included. Consequently, the unexplained component of the Fairlie decomposition should not be attributed exclusively to labour-market segmentation or other structural factors. The Fairlie decomposition is also dependent on the variables and specification used in the model. The explained and unexplained components should therefore be interpreted specifically in relation to the observable characteristics included in this study.

Finally, because the original analysis does not document the application of survey weights or complex-survey variance adjustments, the reported regression and decomposition estimates should not be described as survey-weighted or complex-survey adjusted. This limitation is acknowledged to ensure that the statistical procedures reported in this study correspond accurately to those used in the underlying analysis.

3. RESULTS

The results are presented in five stages. First, the characteristics of the study population are described. Second, the rural–urban difference in youth unemployment is examined. Third, logistic regression results are presented for the full sample and separately for rural and urban youth. Fourth, the rural–urban unemployment differential is decomposed using the Fairlie technique. The results are interpreted strictly as associations, given the cross-sectional nature of the data.

3.1 Characteristics of the Study Sample

The final analytical sample comprised 10,106 youth aged 15–35 years, of whom 4,420 (43.74%) were from rural areas, and 5,686 (56.26%) were from urban areas. Overall, 9,246 respondents (91.49%) were employed, and 860 (8.51%) were unemployed. Secondary education was the predominant educational category in both locations, accounting for 93.67% of rural youth and 97.87% of urban youth. Tertiary education accounted for 3.69% of rural youth compared with 1.25% of urban youth. Thus, the rural sample contained a somewhat higher proportion of youth with tertiary education, although secondary education overwhelmingly dominated both groups. Vocational training was more prevalent among rural youth. Approximately 78.48% of rural

respondents reported vocational training/skills compared with 65.53% of urban respondents. Gender composition also differed between the two locations. Males constituted 53.30% of rural youth and 47.94% of urban youth, while females constituted 46.70% and 52.06%, respectively.

Table 1. Characteristics of youth respondents by location

Variable	Rural (n=4,420)	Urban	Total (N=10,106)
Unemployment			
Employed	4,079 (92.29%)	5,167 (90.87%)	9,246 (91.49%)
Unemployed	341 (7.71%)	519 (9.13%)	860 (8.51%)
Education Level			
No formal	24 (0.54%)	11 (0.19%)	35 (0.35%)
Primary	93 (2.10%)	39 (0.69%)	132 (1.31%)
Secondary	4,140 (93.67%)	5,565 (97.87%)	9,705 (96.03%)
Tertiary	163 (3.69%)	71 (1.25%)	234 (2.32%)
Vocational Training/Skills			
No training	951 (21.53%)	1,960 (34.47%)	2,911 (28.80%)
Has training	3,469 (78.48%)	3,726 (65.53%)	7,195 (71.20%)
Gender			
Female	2,064 (46.70%)	2,960 (52.06%)	5,024 (49.71%)
Male	2,356 (53.30%)	2,726 (47.94%)	5,082 (50.29%)

Source: Author's compilation from ILFS 2024 (2026)

3.2 Rural–Urban Youth Unemployment Differential

Youth unemployment was 7.71% in rural areas compared with 9.13% in urban areas. The resulting difference was 1.42 percentage points, with urban youth experiencing the higher unemployment rate. The Pearson chi-square test indicated that the difference in unemployment status between rural and urban youth was statistically significant ($\chi^2(1) = 6.3751$, $p = .012$).

Table 2. Youth unemployment by location

Location	Employed	Unemployed	Total	Unemployment Rate
Rural	4,079	341	4,420	7.71%
Urban	5,167	519	5,686	9.13%
Total	9,246	860	10,106	8.51%

Source: ILFS 2024, author's calculations (2026)

The finding is noteworthy because the descriptive evidence indicates higher measured unemployment among urban youth despite the higher prevalence of vocational training among rural youth. This pattern reinforces the need to distinguish between differences in individual characteristics and differences in the labour-market environments within which those characteristics operate.

3.3 Logistic Regression Results

3.3.1 Full-Sample Model

The full-sample logistic regression model was statistically significant, LR ($\chi^2(5) = 279.31$), $p < .001$. The model's pseudo- R^2 was 0.0475. Vocational training/skills, gender, and location were significantly associated with youth unemployment, whereas education level was not. Youth with vocational training/skills had 3.829 times the odds of unemployment compared with those without training (OR = 3.829, $p < .001$, 95% CI [3.056, 4.798]). This corresponds to approximately 282.9% higher odds.

Male youth had lower estimated odds of unemployment than female youth (OR = 0.539, $p < .001$, 95% CI [0.465, 0.624]), corresponding to approximately 46.1% lower odds. Urban youth had higher estimated odds of unemployment than rural youth (OR = 1.303, $p < .001$, 95% CI [1.126, 1.508]), equivalent to approximately 30.3% higher odds. None of the education categories differed significantly from the secondary-education reference category.

Table 3. Full-sample logistic regression results

Variable	Odds Ratio	Std. Error	Z	P> z	95% CI
No education	0.330	0.337	-1.09	0.278	[0.045, 2.438]
Primary education	0.836	0.293	-0.51	0.609	[0.420, 1.663]
Tertiary education	0.776	0.211	-0.93	0.351	[0.455, 1.323]
Vocational training/skills	3.829	0.441	11.67	0.000	[3.056, 4.798]
Male	0.539	0.041	-8.22	0.000	[0.465, 0.624]
urban	1.303	0.097	3.56	0.000	[1.126, 1.508]
Constant	0.036	0.004	-26.58	0.000	[0.028, 0.045]

Note. Reference categories are secondary education, no vocational training/skills, female, and rural location.

Source: Author's construction based on ILFS 2024 data with Stata (2026)

The full-sample model therefore provides three important results: education was not significantly associated with unemployment; vocational training was positively associated with unemployment; and male and rural youth had lower estimated odds of unemployment.

3.3.2 Rural Youth Model

The rural-specific logistic regression model was not statistically significant overall (LR ($\chi^2(5) = 8.22$), $p = .1445$), with a pseudo- R^2 of 0.0034.

None of the education categories was significantly associated with unemployment. Relative to secondary education, the odds ratios were 0.531 for no formal education, 1.135 for primary education, and 0.819 for tertiary education, but none were statistically significant.

Vocational training/skills was also not significantly associated with rural youth unemployment (OR = 1.038, $p = .787$, 95% CI [0.791, 1.363]). The point estimate indicates 3.8% higher odds among trained youth, but the wide confidence interval and p -value indicate that the evidence is

insufficient to conclude that the association differs from zero.

Gender was the only statistically significant predictor. Rural males had 25.7% lower estimated odds of unemployment than rural females (OR = 0.743, $p = .009$, 95% CI [0.595, 0.928]).

Table 4. Rural youth logistic regression results

Variable	OR	SE	<i>z</i>	<i>p</i>	95% CI
No formal education	0.531	0.544	-0.62	.537	[0.071, 3.953]
Primary education	1.135	0.425	0.34	.735	[0.545, 3.366]
Tertiary education	0.819	0.272	-0.60	.548	[0.427, 1.571]
Vocational training/skills	1.038	0.144	0.27	.787	[0.791, 1.363]
Male	0.743	0.843	-2.62	.009	[0.595, 0.928]

Source: Author's calculations based on ILFS 2024.

The rural model, therefore, provides limited evidence of systematic associations between the included human capital characteristics and unemployment. Gender is the only characteristic that demonstrates a statistically significant association.

3.3.3 Urban Youth Model

The urban-specific model was statistically significant, LR ($\chi^2(4) = 404.53$), $p < .001$, with a pseudo- (R^2) of 0.1165. Education was not significantly associated with unemployment. Relative to secondary education, the estimated odds ratios were 0.248 for primary education and 0.649 for tertiary education, but neither association was statistically significant. In contrast, vocational training/skills showed a very strong positive association with urban youth unemployment. Urban youth with vocational training had 15.690 times the estimated odds of unemployment compared with those without training (OR = 15.690, $p < .001$, 95% CI [9.765, 25.212]). This corresponds to approximately 1,469% higher odds. Male youth had substantially lower estimated odds of unemployment than female youth (OR = 0.426, $p < .001$, 95% CI [0.347, 0.522]), corresponding to approximately a 57.4% reduction in odds.

Table 5. Urban youth logistic regression results

Variable	OR	SE	<i>z</i>	<i>p</i>	95% CI
Primary education	0.248	0.254	-0.36	.173	[0.033, 1.843]
Tertiary education	0.649	0.308	-0.91	.363	[0.256, 1.645]
Vocational training/skills	15.690	3.797	11.38	<.001	[9.765, 25.212]
Male	0.426	0.044	-8.20	<.001	[0.347, 0.522]

Source: Author's calculations based on ILFS 2024.

The urban model therefore differs substantially from the rural model, particularly in relation to vocational training. While vocational training is not statistically significant in rural areas, it has a very large positive association with unemployment in urban areas. However, this result should not be interpreted as evidence that vocational training causes unemployment. The cross-sectional design cannot distinguish between causal effects, selection into training, skills mismatch, prior unemployment, or other unobserved factors.

3.4 Comparison of Rural and Urban Associations

The location-specific models reveal three central patterns. First, education is not statistically significant in either setting. There is therefore no evidence from these models that the included education categories are associated with youth unemployment relative to the secondary-education reference category. Second, vocational training displays a pronounced location-specific association. Its estimated association is essentially null in rural areas ($OR = 1.038$, $p = .787$) but extremely large and positive in urban areas ($OR = 15.690$, $p < .001$). This difference is substantively important, although the separate regression coefficients alone do not constitute a formal statistical test that they differ significantly from one another. Third, gender is consistently associated with unemployment in both locations, with male youth exhibiting lower estimated odds than female youth. The association is stronger in urban areas than in rural areas.

These results indicate that individual characteristics do not have uniform associations with unemployment across geographical settings. In particular, the urban labour-market context appears to be associated with a substantially different relationship between vocational training and unemployment than the rural context.

3.5 Fairlie Decomposition of the Rural–Urban Unemployment Differential

The Fairlie decomposition provides the central result of the study. The predicted unemployment probability was 0.0771 for rural youth and 0.0913 for urban youth, corresponding to an observed rural–urban difference of -0.0142 , or -1.42 percentage points, when calculated as rural minus urban. Thus, urban youth experienced a higher probability of unemployment. The decomposition indicates that the explained component was -0.0011 , corresponding to 7.7% of the observed differential, while the remaining -0.0131 , corresponding to 92.3%, was unexplained by the characteristics included in the decomposition.

Table 6. Fairlie decomposition of the rural–urban youth unemployment differential

Component	Value	Share of gap
Rural predicted probability	0.0771	7.71%
Urban predicted probability	0.0913	9.13%
Rural – Urban differential	-0.0142	100.0%
Explained component	-0.0011	7.7%
Unexplained component	-0.0131	92.3%

Source: Author's calculations based on ILFS 2024.

The result indicates that differences in education, vocational training/skills, and gender account for only a small share of the observed rural–urban unemployment differential. The contribution of individual characteristics was heterogeneous. Gender (male) made a statistically significant contribution to the explained component ($p = .012$). The contributions associated with the education categories and vocational training were not statistically significant at the 5% level.

The decomposition therefore provides an important qualification to the regression results. Although vocational training is strongly associated with unemployment among urban youth, differences in vocational training prevalence between rural and urban youth do not, on their own, account for a large share of the overall unemployment differential.

4. DISCUSSION

The study examined the rural–urban youth unemployment differential in Tanzania by combining binary logistic regression with Fairlie decomposition. The results reveal a relatively small but statistically significant rural–urban unemployment gap, substantial differences in the association between vocational training and unemployment across locations, persistent gender differences, and, most importantly, a large proportion of the unemployment differential that is not explained by the observable characteristics included in the model. These findings have implications for how youth unemployment is conceptualised and addressed in Tanzania.

4.1 Rural–Urban Differences in Youth Unemployment

The study found that youth unemployment was higher in urban areas than in rural areas, with unemployment rates of 9.13% and 7.71%, respectively. Although the absolute difference was modest at 1.42 percentage points, it was statistically significant. This finding is consistent with the results reported by Chacha and Junjuan (2023), who found urban residence to be positively associated with youth unemployment in Tanzania, but contrasts with those of Setonga and Omary (2025), who reported lower unemployment among urban youth graduates.

The higher measured unemployment rate in urban areas should not, however, be interpreted as evidence that rural youth necessarily experience better labour-market conditions. The unemployment indicator captures whether individuals satisfy the statistical criteria for being unemployed; it does not measure employment quality, earnings, productivity, job security, underemployment, or vulnerability. Rural youth may therefore be more likely to engage in agricultural, informal, family-based, or other economic activities that keep them classified as employed even when the employment provides limited income or economic security.

The finding can also be understood from a labour-market perspective. Urban areas tend to attract young people seeking non-agricultural and formal employment opportunities. This may increase the number of job seekers competing for a limited number of vacancies. Consequently, urban labour markets can simultaneously feature more employment opportunities and higher unemployment among young people seeking access to them.

The result therefore reinforces the need to distinguish between employment availability and employment accessibility. A location may contain more jobs overall while still generating greater competition for those jobs among young entrants.

4.2 Education and Youth Unemployment

Education level was not statistically associated with youth unemployment in either the rural or urban model. This finding is important because Human Capital Theory predicts that greater investment in education should enhance productivity and improve labour-market outcomes (Becker, 1964).

The result is broadly consistent with Chacha and Junjuan (2023), who found no statistically significant association between education and youth unemployment in Tanzania. However, it differs from Setonga and Omary (2025), who found that higher education reduced unemployment among youth graduates. International evidence is also mixed. Prieto et al. (2023) found that education was associated with higher youth unemployment in Ecuador, while Duguma and Tolcha (2019) identified education as an important predictor of urban youth unemployment in Ethiopia.

The differences across studies suggest that the labour-market value of education cannot be assumed to be uniform across countries, locations, or groups of young people. One possible explanation is that educational attainment increases the supply of qualified labour without necessarily generating a corresponding increase in demand for workers with those qualifications. Under such circumstances, educated youth may remain unemployed while waiting for jobs that match their qualifications and expectations.

This interpretation does not invalidate Human Capital Theory. Rather, it suggests that the employment return to human capital depends partly on the labour-market environment in which that human capital is deployed. Education may increase individual productivity while failing to reduce measured unemployment when suitable employment opportunities are insufficient. The absence of a statistically significant education effect in the present study should therefore not be interpreted as evidence that education has no economic value. It indicates only that, conditional on the variables and specification used in this analysis, education does not provide sufficient statistical evidence for explaining differences in youth unemployment.

4.3 Vocational Training and Urban Youth Unemployment

The strongest individual-level result was the association between vocational training and unemployment among urban youth. Urban youth with vocational training had estimated unemployment odds 15.69 times those of youth without training. By contrast, vocational training was not statistically associated with unemployment among rural youth.

This finding is counterintuitive from a conventional human-capital perspective. Vocational training is generally intended to provide practical skills that facilitate entry into employment. The result nevertheless has some empirical precedent. Chacha and Junjuan (2023) similarly reported a positive association between being skilled and youth unemployment in Tanzania. In contrast, Yoana et al. (2024) found that vocational education reduced unemployment in Indonesia. The divergence suggests that the effectiveness of vocational training may depend heavily on the context in which training is provided and the labour market into which graduates enter. Several explanations are plausible, although they cannot be distinguished using the present cross-sectional data.

First, selection into training may be important. Youth experiencing difficulties entering employment may be more likely to acquire vocational skills in an attempt to improve their employment prospects. In this case, the observed positive association would partly reflect characteristics of those entering training rather than an adverse effect of training.

Second, the result may reflect skills mismatch. Training institutions may produce graduates in occupational fields for which demand is insufficient. In such circumstances, increasing the number of trained youths does not necessarily increase employment if labour demand remains constrained. Third, urban labour markets may involve stronger competition among educated and trained job seekers. Young people may migrate or otherwise move toward urban centres precisely because they expect better employment opportunities. The resulting concentration of job seekers can increase competition for available positions.

Fourth, the category “vocational training/skills” is relatively broad. It does not distinguish among fields of training, training quality, duration, certification, practical experience, or employer recognition. Consequently, the observed association may conceal substantial heterogeneity between different forms of vocational education.

These explanations should be treated as hypotheses for further research rather than established mechanisms. The present study demonstrates an association, not causation. The policy implication is nevertheless significant. Expanding vocational-training enrolment should not be treated automatically as an employment-generation strategy. Training policy should be accompanied by systematic assessment of employer demand, graduate employment outcomes, occupational saturation, work-based learning, and the alignment of curricula with local labour market requirements.

4.4 Gender Differences in Youth Unemployment

Gender was consistently associated with youth unemployment. Male youth had lower estimated odds of unemployment than female youth in both rural and urban settings. The association was stronger in urban areas, where males had approximately 57.4% lower estimated odds of unemployment than females, compared with approximately 25.7% lower odds in rural areas. This finding is consistent with Aprilia and Anas (2024), who reported higher unemployment among female youth in Indonesia. It also corresponds with evidence from Tanzania reported by Chacha and Junjuan (2023). However, differences across studies indicate that the magnitude and direction of gender disparities can vary according to context and population.

The persistence of the gender differential suggests that youth employment policies should not assume that young men and women face identical barriers. Factors such as occupational segregation, differences in labour-market networks, social expectations, employer preferences, care responsibilities, and access to employment opportunities may contribute to gender disparities. However, these mechanisms were not directly measured in the present study and should therefore not be presented as established explanations. The finding nevertheless provides a clear policy signal: gender should remain an explicit dimension of youth employment policy, rather than being treated simply as a control variable.

4.5 What Does the Fairlie Decomposition Tell Us?

The most important contribution of the study is the decomposition of the rural–urban unemployment differential. Only 7.7% of the observed differential was associated with differences in the observable characteristics included in the model, while 92.3% remained unexplained by those characteristics. This finding substantially changes the interpretation of the rural–urban unemployment gap.

If differences in education, vocational training, and gender composition were the principal drivers of the gap, the explained component would be expected to account for a much larger proportion of the observed difference. Instead, the decomposition suggests that these characteristics explain only a small share. This finding is difficult to reconcile with a purely compositional human-capital explanation. Rural and urban youth have broadly similar educational profiles, and rural youth report a higher prevalence of vocational training. Yet urban youth have the higher unemployment rate.

The result is therefore more consistent with an explanation in which the labour-market context matters substantially. This interpretation is compatible with Labour Market Segmentation Theory, which emphasises that employment opportunities and returns to individual characteristics may differ across labour-market segments (Doeringer & Piore, 1971). The characteristics included in the model explain only a small proportion of the rural–urban youth unemployment differential,

suggesting that other factors beyond the model are likely important.

5. CONCLUSION AND IMPLICATIONS

5.1 Conclusion

This study examined the rural–urban youth unemployment differential in Tanzania using data from the 2024 Integrated Labour Force Survey and combining binary logistic regression with Fairlie decomposition. The analysis focused on education, vocational training/skills, gender, and location as observable characteristics that may be associated with youth unemployment.

The results show that youth unemployment was significantly higher in urban areas than in rural areas, at 9.13% and 7.71%, respectively. However, the observed difference was relatively modest, amounting to 1.42 percentage points. The logistic regression results further indicate that education level was not statistically associated with youth unemployment in either rural or urban settings.

Vocational training produced the most striking result. It was not statistically associated with unemployment among rural youth but was strongly positively associated with unemployment among urban youth. This finding should not be interpreted as evidence that vocational training causes unemployment because the cross-sectional design cannot establish causality. Rather, it suggests that the relationship between vocational training and employment may depend substantially on the labour market context in which trained youth seek work.

Gender was consistently associated with unemployment. Male youth had lower estimated odds of unemployment than female youth in both rural and urban settings, with the association being stronger in urban areas.

The Fairlie decomposition provides the central contribution of the study. Differences in the observable characteristics included in the analysis—education, vocational training/skills, and gender—accounted for only 7.7% of the rural–urban unemployment differential, with 92.3% remaining unexplained by these characteristics. The result indicates that individual characteristics alone provide a limited explanation of the observed spatial difference in youth unemployment.

The study therefore concludes that understanding youth unemployment in Tanzania requires attention not only to the characteristics of young people but also to the economic and labour-market environments within which those characteristics operate. The large unexplained component is consistent with the potential importance of spatial labour-market conditions, although the study does not establish which specific structural or unobserved factors account for the residual difference.

5.2 Contribution to the Literature

This study contributes to the literature on youth unemployment in Tanzania in three main respects. First, it provides updated evidence on the rural–urban unemployment differential using the 2024 Integrated Labour Force Survey (ILFS), thereby extending the empirical evidence base with more recent nationally representative data.

Second, the study reveals substantial spatial heterogeneity in the relationship between individual characteristics and youth unemployment. In particular, the association between vocational training and unemployment differs markedly between rural and urban youth. This finding suggests that the labour-market outcomes associated with skills and training are contingent on the context in which those skills are deployed, an issue that may be obscured when rural and urban labour markets are analysed as a single setting.

Third, the Fairlie decomposition provides evidence on the extent to which observable characteristics account for the rural–urban unemployment differential. The results indicate that the characteristics included in the decomposition explain only 7.7% of the observed gap, leaving 92.3% unexplained. This does not establish the causes of the unexplained component; rather, it demonstrates the limited explanatory power of the observed characteristics considered in the present analysis. In this respect, the study extends a literature that has largely examined the determinants or correlates of youth unemployment within population groups by applying a between-group decomposition framework to the rural–urban divide.

5.3 Theoretical Implications

The findings have implications for how youth unemployment is theoretically understood. Human Capital Theory provides an important starting point because education, skills, and training represent investments intended to enhance individuals' productivity and employment prospects. However, the limited explanatory contribution of the observed human-capital characteristics suggests that their relationship with employment cannot be assumed to operate uniformly across spatial contexts.

The findings are therefore consistent with a more contextual interpretation of labour-market outcomes, in which the returns to individual characteristics depend in part on the opportunities available in the surrounding economic environment. Labour Market Segmentation Theory provides a useful complementary lens in this regard. The theory suggests that structurally different labour markets may generate different employment opportunities for individuals with otherwise similar characteristics (Doeringer & Piore, 1971). The observed rural–urban differences, particularly in the association between vocational training and unemployment, are compatible with this perspective.

Nevertheless, the study does not directly measure segmentation, job quality, labour demand, or the institutional barriers that separate labour-market segments. Labour Market Segmentation Theory should therefore be regarded as a plausible interpretive framework rather than a mechanism established by the empirical analysis. The theoretical implication is consequently not that segmentation has been demonstrated, but that explanations of youth unemployment should account for the interaction between individual capabilities and the structural context in which employment opportunities are generated.

5.4 Policy Implications

The policy implications follow from the observed spatial differences and the limited explanatory power of the characteristics included in the analysis. Tanzania's youth employment strategy should therefore complement interventions aimed at improving individual employability with measures that expand productive employment opportunities, particularly in locations where such opportunities are limited. This requires greater attention to private-sector development, enterprise growth, investment, and employment-intensive activities.

The findings concerning vocational training warrant particular attention. Rather than expanding training provision solely on the basis of enrolment or completion, policymakers should strengthen its connection with actual labour-market demand. Employer involvement in curriculum design, systematic labour-market assessments, apprenticeships, work-based learning, career guidance, and graduate tracer studies can help ensure that training responds to market requirements. Training

institutions should consequently be assessed partly on the employment outcomes of their graduates.

The rural–urban differential also points to the importance of place-based employment policies. Strengthening local enterprise development, infrastructure, market connectivity, and non-agricultural economic activities could broaden employment opportunities beyond major urban centres. Such interventions should, however, be viewed as policy responses suggested by the findings rather than as measures demonstrated by this study to account for the unexplained 92.3% of the differential.

Finally, the observed gender disparity calls for employment interventions that explicitly address the barriers faced by young women. Skills development, entrepreneurship support, employment services, and job-matching mechanisms should be designed and evaluated with attention to gender differences in access, participation, and employment outcomes.

5.6 Limitations

The study has several limitations that should be considered when interpreting its findings.

First, the cross-sectional nature of the ILFS data limits causal inference. In particular, the strong association between vocational training and urban unemployment cannot establish that vocational training causes unemployment. Selection into training, previous unemployment, differences in training fields, work experience, and other unobserved factors may contribute to the observed association.

Second, the analysis is based on a relatively limited set of explanatory characteristics. Variables such as household socioeconomic status, previous work experience, migration, local economic structure, access to labour-market information, transportation, employer demand, and social networks were not included in the reported models. Their omission may partly account for the large unexplained component of the Fairlie decomposition.

Third, the unexplained component should not be interpreted as a direct measure of labour-market segmentation or structural disadvantage. It represents the portion of the rural–urban differential not explained by the characteristics included in the model and may include omitted variables, unobserved heterogeneity, coefficient differences, and other sources of residual variation.

Fourth, although the 2024 ILFS employed a stratified two-stage cluster sampling design, the original analytical procedure did not document the application of sampling weights or complex-survey variance adjustments to the regression and Fairlie decomposition. Consequently, the reported inferential results should not be described as survey-weighted or complex-survey adjusted.

5.7 Recommendations for Future Research

The findings identify several areas that warrant further investigation, particularly the mechanisms underlying the large unexplained component of the rural–urban unemployment differential. Future research should move beyond individual-level characteristics by incorporating labour-demand variables and local economic structure, including sectoral employment opportunities, enterprise density, infrastructure, access to markets, labour-market information, migration, and work experience. Such variables could help establish whether differences in employment opportunities and local economic conditions account for a substantial proportion of the observed spatial gap.

The strong positive association between vocational training and urban unemployment also requires

more nuanced investigation. Future studies should disaggregate vocational training by training field, level, institution, certification, quality, and work experience, rather than treating it as a homogeneous characteristic. This would help determine whether the observed association reflects differences in the quality or type of training and whether particular forms of vocational education generate better employment outcomes.

Longitudinal research is particularly important for distinguishing selection effects from actual training effects. Tracking individuals over time would establish whether youth who enter vocational training differ systematically from those who do not and whether training subsequently improves their employment prospects.

Future studies should also formally test whether the coefficients estimated for rural and urban youth differ statistically, rather than relying solely on comparisons of separate regression estimates. Finally, researchers could extend the Fairlie decomposition by incorporating household, geographic, economic, and labour-market variables. This would reveal whether the currently unexplained component declines substantially after accounting for broader dimensions of spatial inequality, thereby providing stronger evidence on the sources of Tanzania's rural–urban youth unemployment differential.

REFERENCES

- Aprilia, C., & Anas, Y. (2024). Characteristics of youth unemployment: Before and during the COVID-19 pandemic in Indonesia. *EKOMBIS Review: Jurnal Ilmiah Ekonomi dan Bisnis*, 12(2), 1917–1930. <https://doi.org/10.37676/ekombis.v12i2.5521>
- Prieto, A. B. T., Báez Salazar, P. A., & Aguilar-Rodríguez, I. E. (2023). Determinants of youth unemployment in Ecuador in 2019. *Economies*, 11(2), Article 59. <https://doi.org/10.3390/economies11020059>
- Baah-Boateng, W. (2016). The youth unemployment challenge in Africa: What are the drivers? *The Economic and Labour Relations Review*, 27(4), 413–431. <https://doi.org/10.1177/1035304616645030>
- Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press.
- Chacha, V. E., & Junjuan, D. H. (2023). A study of youth unemployment in Tanzania and statistical analysis. *International Journal for Research in Applied Science and Engineering Technology*, 11(4), 3128–3135. <https://doi.org/10.22214/ijraset.2023.50691>
- Doeringer, P. B., & Piore, M. J. (1971). *Internal labour markets and manpower analysis*. D. C. Heath.
- Duguma, A. L., & Tolcha, F. T. (2019). Determinants of urban youth unemployment: The case of Guder Town, Western Shoa Zone, Ethiopia. *International Journal of Research - Granthaalayah*, 7(8), 318–327. <https://doi.org/10.29121/granthaalayah.v7.i8.2019.674>
- East African Community. (2022). *EAC regional employment policy*. East African Community.
- Fairlie, R. W. (2005). An extension of the Blinder–Oaxaca decomposition technique to logit and probit models. *Journal of Economic and Social Measurement*, 30(4), 305–316. <https://doi.org/10.3233/JEM-2005-0259>
- Guan, P. T. H., Ng, K. M., Tan, R. H., & Kushnarevych, A. (2025). The hidden drivers of youth unemployment: A modern-day crisis. *International Journal of Asian Business and Information Management*, 16(1). <https://doi.org/10.4018/IJABIM.388564>

-
- Habiyaremye, A., Habanabakize, T., & Nwosu, C. (2022). Bridging the labour market skills gap to tackle youth unemployment in South Africa. *The Economic and Labour Relations Review*, 33(4), 786–805. <https://doi.org/10.1177/10353046221138400>
- International Labour Organisation. (2024). *Global employment trends for youth 2024: Decent work, brighter futures*. International Labour Office. <https://doi.org/10.54394/ZUUI5430>
- Kafle, K., Paliwal, N., & Benfica, R. (2025). Do youth work in agriculture? Short-term dynamics of on-farm rural youth employment in Tanzania and Malawi. *The Journal of Development Studies*, 61(5), 748–775. <https://doi.org/10.1080/00220388.2024.2420019>
- Massia, J. W., Anangisye, W. A. L., & Sarakikya, A. M. (2026). Examining the alignment of vocational education curricula with labour market demands for youth employability in Tanzania: Bridging the skills gap. *Cogent Education*, 13(1), Article 2626623. <https://doi.org/10.1080/2331186X.2026.2626623>
- Mligo, I. (2021). Youth rural-urban migration and change in livelihoods: A case of informal traders in Njombe Town, Tanzania. *Journal of the Geographical Association of Tanzania*, 38(1). <https://doi.org/10.56279/jgat.v38i1.126>
- Morsy, H., & Mukasa, A. N. (2021). ‘Mind the mismatch?’ Incidence, drivers, and persistence of African youths’ skill and educational mismatches. *African Development Review*, 32(S1), S5–S19. <https://doi.org/10.1111/1467-8268.12478>
- Mpojota, A. S., Minga, N., & Joseph, E. S. (2025). Youth unemployment and income inequality: Exploring the linkages in Tanzania. *Eastern Africa Journal of Official Statistics*, 1(1). <https://doi.org/10.63933/eajos.1.1.2025.6>
- National Bureau of Statistics. (2023). *Tanzania labour force survey 2022: Analytical report*. National Bureau of Statistics.
- National Bureau of Statistics. (2025). *Integrated Labour Force Survey 2024: Analytical report*. National Bureau of Statistics.
- Ndifwa, N. J., Katunzi, T., & Kengela, B. (2025). Decomposing rural-urban variations in maternal healthcare utilization among women of reproductive age in Tanzania: Evidence from the 2022 Tanzania Demographic and Health Survey. *Rural Planning Journal*, 26(2), 49–67. <https://doi.org/10.59557/rpj.26.2.2024.90>
- Njifen, I., & Meungwe, C. N. (2024). African youth and unemployment: Does human capital investment still matter? *Journal of Contemporary African Studies*, 42(3), 347–370. <https://doi.org/10.1080/02589001.2024.2341620>
- Setonga, J. A., & Omary, P. S. (2025). Unveiling the determinants of unemployment among youth graduates in Tanzania. *Eminent Journal of Social Sciences*, 1(2), 67–81. <https://doi.org/10.70582/bkmm9p62>
- Sumberg, J., Flynn, J., Mader, P., Oosterom, M., & Barnett, C. (2021). Africa’s “youth employment” crisis is actually a “missing jobs” crisis. *Development Policy Review*, 39(4), 601–614. <https://doi.org/10.1111/dpr.12528>
- Woldegiorgis, M. M. (2023). Towards inclusive development through harnessing demographic dividend? Empirics for Africa. *Journal of Social and Economic Development*, 25(2), 380–402. <https://doi.org/10.1007/s40847-023-00243-2>
- Yoana, Y., Auwalin, I., & Rumayya. (2024). The role of vocational education on unemployment in Indonesia. *Cogent Education*, 11(1), Article 2340858. <https://doi.org/10.1080/2331186X.2024.2340858>
-

