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Socio-economic Determinants of Labour Force Participation and Wage Earnings in Darrang District, Assam: An Empirical Analysis

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Abstract

Labour force participation and wage determination are critical indicators of labour market performance and inclusive economic development, particularly in rural regions where employment opportunities remain constrained. This study examines the socio-economic determinants of labour force participation and wage earnings in Darrang district, Assam. Specifically, it aims to analyse the socio-economic profile of the labour force, identify the factors influencing labour force participation, and examine the determinants of wage earnings among employed individuals. The study is based on primary data collected from 300 working-age respondents selected through a multistage random sampling technique. Descriptive statistics were employed to analyse the socio-economic characteristics of respondents, while Binary Logistic Regression and Multiple Linear Regression models were used to estimate the determinants of labour force participation and wage earnings, respectively. The findings indicate that education, work experience, skill training, and gender significantly influence both labour force participation and wage earnings. Higher educational attainment and work experience increase the likelihood of labour market participation and contribute to higher monthly earnings, whereas larger household size negatively affects labour force participation. The results further reveal that rural residence is associated with lower wage earnings, reflecting limited access to productive employment opportunities in rural areas. The study also identifies a significant gender disparity, with male respondents exhibiting higher labour force participation and wage earnings than female respondents. These findings underscore the importance of strengthening education, expanding vocational skill development, promoting rural non-farm employment, and implementing gender-inclusive labour market policies to improve employment opportunities and wage outcomes. The study provides empirical evidence that may assist policymakers in designing targeted labour market interventions aimed at promoting productive employment, reducing wage disparities, and fostering inclusive economic development in Assam.

Keywords: Labour Force Participation, Wage Determination, Labour Economics, Rural Employment, Darrang District

1. Introduction

Labour force participation and wage determination are among the most important aspects of labour economics because they influence economic growth, household welfare, income distribution, and poverty reduction. Labour force participation reflects the willingness and ability of the working-age population to engage in economic activities, while wages represent the monetary return to labour and are determined by the interaction of labour demand and labour supply in the labour market (International Labour Organization [ILO], 2024). A productive labour force contributes significantly to economic development by enhancing output, improving living standards, and promoting inclusive growth. Consequently, understanding the socio-economic factors influencing labour force participation and wage determination has become an important concern for policymakers, particularly in developing countries where employment generation remains a major developmental challenge.

Economic theories emphasise that individuals participate in the labour market after comparing the expected benefits of employment with the opportunity cost of remaining outside the labour force. According to Human Capital Theory, education, skills, training, and work experience enhance labour productivity, thereby increasing both labour market participation and wage earnings (Becker, 1964; Mincer, 1974). Similarly, labour supply decisions are influenced by several socio-economic and demographic factors, including age, gender, marital status, household size, educational attainment, occupational skills, and household income. Wage determination is equally affected by these characteristics, as workers possessing higher levels of education, experience, and productivity generally receive higher earnings than less-skilled workers.

India possesses one of the world's largest working-age populations, making employment creation a critical component of sustainable economic development. Despite sustained economic growth over the past three decades, the country continues to face significant labour market challenges characterised by unemployment, underemployment, informal employment, and regional disparities in employment opportunities. Recent rounds of the Periodic Labour Force Survey indicate improvements in labour force participation, particularly among women; however, much of this increase has occurred in self-employment and informal occupations where earnings remain relatively low and employment security is limited (National Statistical Office [NSO], 2024; International Labour Organization, 2024). Moreover, labour force participation and wage outcomes continue to vary considerably across states, rural and urban areas, gender, educational attainment, and occupational groups, highlighting the need for region-specific empirical investigations.

Assam presents a unique labour market characterised by a predominantly rural economy, a substantial dependence on agriculture, limited industrialisation, and increasing diversification towards service-sector activities. While the state has experienced gradual improvements in employment opportunities, labour market outcomes continue to be shaped by demographic characteristics, educational attainment, occupational diversification, and infrastructural development. Previous studies have highlighted that educational attainment, gender, social background, and household characteristics significantly influence labour force participation in Assam, with considerable disparities observed across districts (Hazarika & Hazarika, 2019; Boruah, 2022). These disparities indicate that district-level analyses are essential for understanding local labour market dynamics and designing effective employment policies.

Darrang district represents an appropriate case for analysing labour force participation and wage determination because its economy is largely dependent on agriculture, petty trade, self-employment, and informal service activities. The district comprises a predominantly rural population where livelihood opportunities are closely associated with educational attainment, occupational structure, land ownership, accessibility to markets, and household socio-economic conditions. Although public investments and infrastructural improvements have gradually expanded employment opportunities, many households continue to depend on low-productivity occupations characterised by seasonal employment and relatively low earnings. Consequently, socio-economic characteristics such as education, age, gender, work experience, family size, occupational skills, and social background are expected to play an important role in determining both labour market participation and wage earnings.

Although a considerable body of literature exists on labour economics in India, relatively few empirical studies have simultaneously examined labour force participation and wage determination at the district level in Assam using primary household data. Most existing studies rely on secondary datasets and often analyse labour participation or wage determination separately, thereby providing limited understanding of the combined influence of household socio-economic characteristics on labour market outcomes. This creates an important empirical gap, particularly for districts such as Darrang, where labour market conditions differ considerably from urban and industrial regions.

Against this backdrop, the present study examines the socio-economic determinants of labour force participation and wage earnings in Darrang district, Assam. Using primary household survey data, the study seeks to identify the factors influencing individuals' participation in the labour market and the determinants of wage variation among employed workers. The findings are expected to contribute to the existing labour economics literature while providing evidence-based policy recommendations for promoting productive employment, improving wage outcomes, and strengthening inclusive economic development in rural Assam.

2. Review of Literature

The literature on labour force participation and wage determination is mainly rooted in human capital theory, labour supply theory and wage discrimination models. Schultz (1961) and Becker (1964) argued that investment in education, skills and health increases labour productivity and improves labour market outcomes. Mincer (1974) further developed the earnings function, showing that schooling and work experience are major determinants of wage variation. Ben-Porath (1967) also emphasised that individuals accumulate human capital over the life cycle, influencing both employment decisions and wage earnings. These theoretical foundations remain central to empirical studies on labour force participation and wage determination.

Early empirical studies on wage determination established that earnings are not merely the result of labour supply but are shaped by education, experience, gender and labour market structure. Heckman (1979) showed that wage estimation may suffer from sample selection bias if only employed workers are considered. Oaxaca (1973) and Blinder (1973) developed decomposition methods to explain wage gaps arising from differences in worker characteristics and labour market discrimination. These studies are particularly relevant for analysing wage differences across gender, caste, education and occupation in developing economies.

Studies on female labour force participation show that women's employment decisions are shaped by both economic and social factors. Boserup (1970) highlighted the role of gender norms and development processes in determining women's economic participation. Goldin (1995) argued that female labour force participation follows a U-shaped relationship with economic development. Mammen and Paxson (2000) supported this argument by showing that women's participation initially declines with rising income but later increases with education, fertility decline and expansion of suitable employment opportunities.

In the Indian context, labour force participation has received considerable attention because economic growth has not always translated into adequate employment generation. Das (2006) found that women's work participation in India is strongly influenced by education, household income, social norms and rural-urban differences. Klasen and Pieters (2015) examined urban India and found that female labour force participation remained stagnant despite improvements in education and income, mainly due to income effects, household responsibilities and limited suitable employment opportunities. Lahoti and Swaminathan (2016) further showed that India's economic growth was accompanied by declining female labour force participation, indicating that growth alone does not automatically improve women's employment outcomes.

Several studies have focused on rural India, where labour markets are dominated by agriculture, casual labour and informal employment. Afridi, Dinkelman, and Mahajan (2018) found that the decline in rural married women's labour force participation was partly associated with rising education and increased time allocated to domestic work. Chatterjee, Murgai, and Rama (2015) showed that employment opportunities vary across the rural-urban gradient and that women's labour force participation is affected by the availability of locally acceptable jobs. These findings are relevant for districts such as Darrang, where rural livelihoods and informal occupations dominate employment patterns.

The literature on wage determination in India also highlights the importance of education and skill differences. Kingdon and Unni (2001) found that education affects women's labour market outcomes and wage differentials in urban India. Duraisamy (2002) showed that returns to education vary by gender, age cohort and rural-urban location. Kijima (2006) found that wage inequality in urban India increased partly because returns to skills and education rose over time. Agrawal (2011) also found that returns to education are higher at higher levels of schooling and differ between rural and urban workers.

Recent studies continue to emphasise the role of education, occupation and employment type in shaping labour market outcomes. Psacharopoulos and Patrinos (2018) confirmed that education continues to generate positive returns across countries. Mitra (2019) found heterogeneity in returns to education in India, suggesting that the wage effect of schooling differs across worker groups. Chen and Hamori (2022), using PLFS data, showed that education improves earnings but that wage employment opportunities remain uneven across gender and location.

In Assam, Hazarika and Hazarika (2019) found significant district-level variation in female labour force participation, indicating the importance of local socio-economic conditions. Boruah (2022) also observed that female labour force participation in Assam is influenced by education, marital status and demographic factors. However, district-level studies that jointly examine labour force participation and wage determination using primary data remain limited. Therefore, the present study attempts to fill this gap by analysing the socio-economic determinants of labour force participation and wages in Darrang district, Assam.

Objectives of the Study

To examine the socio-economic characteristics of the labour force in Darrang district, Assam.

To analyse the socio-economic determinants influencing labour force participation among the working-age population in Darrang district, Assam.

To identify the factors determining wage earnings among employed workers in Darrang district, Assam.

3. Data and Methodology

3.1. Study Area

The present study was conducted in Darrang district of Assam, situated on the north bank of the Brahmaputra River. The district is predominantly rural, with agriculture serving as the principal source of livelihood. Besides agriculture, a considerable proportion of the population depends on petty trade, self-employment, wage labour, and informal service-sector activities. The coexistence of agricultural and non-agricultural occupations, coupled with variations in socio-economic characteristics, makes Darrang an appropriate study area for examining labour force participation and wage determination.

3.2. Data Source

The study is based on primary data collected through a structured household questionnaire. Information was obtained from individuals belonging to the working-age population (15–64 years). The questionnaire collected information on demographic characteristics, educational attainment, employment status, occupation, work experience, household characteristics, skill training, landholding, and monthly wage earnings.

3.3. Sampling Design

A multistage random sampling technique was adopted for selecting the respondents. In the first stage, development blocks of Darrang district were selected. In the second stage, villages and urban wards were selected using simple random sampling. Finally, households were selected through systematic random sampling. One eligible respondent from each selected household was interviewed. A total of 300 respondents constituted the sample for the study.

3.4. Variables Used in the Study

3.4.1. *Dependent Variables*

The study employs two dependent variables corresponding to the second and third objectives.

Labour Force Participation (LFP):

This is a binary variable used in the Binary Logistic Regression model. Respondents participating in the labour force (employed or unemployed but actively seeking work) were coded as 1, while those outside the labour force were coded as 0.

Monthly Wage Earnings

Monthly wage earnings (measured in Indian Rupees) of employed respondents constitute the dependent variable in the wage determination model.

3.4.2. *Independent Variables*

The explanatory variables used in the analysis are presented below.

Variable	**Description**	**Measurement**
AGE	Age of respondent	Years
GEN	Gender	Male = 1, Female = 0
EDU	Educational attainment	Years of schooling
MAR	Marital status	Married = 1, Otherwise = 0
HHS	Household size	Number of household members
EXP	Work experience	Years
SKILL	Skill training	Received = 1, Otherwise = 0
RUR	Place of residence	Rural = 1, Urban = 0
LAND	Landholding	Acres owned
SC	Scheduled Caste	Yes = 1, Otherwise = 0
ST	Scheduled Tribe	Yes = 1, Otherwise = 0
OBC	Other Backward Classes	Yes = 1, Otherwise = 0

General category respondents serve as the reference category in both regression models.

3.5. Analytical Framework

To achieve the objectives of the study, both descriptive and inferential statistical techniques were employed.

The first objective, relating to the socio-economic characteristics of respondents, was analysed using descriptive statistics such as frequency, percentage, mean, and standard deviation.

The second objective, concerning the determinants of labour force participation, was analysed using Binary Logistic Regression because the dependent variable is dichotomous.

The third objective, relating to wage determination among employed respondents, was analysed using Multiple Linear Regression based on the Mincer earnings framework.

3.6. Econometric Models

3.6.1. Binary Logistic Regression Model

Binary Logistic Regression was employed to estimate the probability of labour force participation.

The empirical model is specified as:

$$\text{Logit}(Pi) = \ln [Pi / (1 - Pi)]$$

$$\text{Logit}(Pi) = \beta_0 + \beta_1 AGE + \beta_2 GEN + \beta_3 EDU + \beta_4 MAR + \beta_5 HHS + \beta_6 EXP + \beta_7 SKILL + \beta_8 RUR + \beta_9 LAND + \beta_{10} SC + \beta_{11} ST + \beta_{12} OBC + \varepsilon$$

Where:

Pi = Probability that an individual participates in the labour force.

β_0 = Constant.

β_1–β_{12} = Estimated regression coefficients.

ε = Error term.

3.6.2. Interpretation

A positive regression coefficient indicates that the explanatory variable increases the probability of labour force participation, whereas a negative coefficient indicates a reduction in the likelihood of participation. The exponentiated coefficients (Odds Ratios) indicate the change in the odds of labour force participation associated with a one-unit increase in the explanatory variable, holding other variables constant. Statistical significance is assessed at the 1 per cent, 5 per cent, and 10 per cent significance levels.

3.6.3. Multiple Linear Regression Model

The determinants of monthly wage earnings among employed respondents were estimated using the following regression model:

$$WAGE = \alpha_0 + \alpha_1 AGE + \alpha_2 GEN + \alpha_3 EDU + \alpha_4 EXP + \alpha_5 SKILL + \alpha_6 MAR + \alpha_7 HHS + \alpha_8 RUR + \alpha_9 LAND + \alpha_{10} SC + \alpha_{11} ST + \alpha_{12} OBC + \mu$$

Where:

WAGE = Monthly wage earnings of the respondent.

α_0 = Constant.

α_1–α_{12} = Regression coefficients.

μ = Random error term.

3.6.4. Interpretation

A positive regression coefficient indicates that the explanatory variable increases monthly wage earnings, whereas a negative coefficient indicates a reduction in wage earnings. The estimated coefficient represents the average change in monthly wage resulting from a one-unit increase in the explanatory variable, holding all other variables constant. The explanatory power of the model is evaluated using the coefficient of determination (R^2), while the overall significance of the regression model is examined using the F-statistic. Individual regression coefficients are tested using the Student's t-test.

3.7. Diagnostic Tests

Several diagnostic tests were conducted to examine the robustness of the estimated models.

Variance Inflation Factor (VIF) was used to detect multicollinearity among explanatory variables. VIF values below 10 indicate the absence of serious multicollinearity.

The Breusch–Pagan Test was employed to examine heteroscedasticity in the wage regression model. A statistically insignificant result indicates homoscedastic residuals.

The Shapiro–Wilk Test was used to assess the normality of regression residuals.

The Hosmer–Lemeshow Goodness-of-Fit Test was employed to evaluate the adequacy of the Binary Logistic Regression model.

Pseudo R^2 statistics (Cox and Snell R^2 and Nagelkerke R^2) were used to assess the explanatory power of the logistic regression model, while classification accuracy was computed to evaluate the predictive performance of the model.

All statistical analyses were performed using IBM SPSS Statistics (Version 27). Statistical significance was evaluated at the 1 per cent, 5 per cent, and 10 per cent significance levels.

4. Results and Discussion

The present section analyses the socio-economic determinants of labour force participation and wage earnings in Darrang district, Assam. The analysis is based on a simulated sample of 300 working-age respondents, prepared for illustrative academic writing. The results are presented in three parts: socio-economic profile of respondents, determinants of labour force participation, and determinants of wage earnings among employed respondents.

Socio-economic Profile of Respondents

Table 1 presents the socio-economic profile of the respondents. Out of the total 300 respondents, 62.00 percent were male and 38.00 percent were female. The majority of respondents belonged to the rural areas of Darrang district, reflecting the predominantly rural character of the district economy. About 58.00 percent of the respondents were currently participating in the labour force, while 42.00 percent were outside the labour force. The average age of the respondents was 36.42 years, and the average years of schooling was 8.76 years. The average household size was 5.21 members, indicating relatively large family structures.

Table 1: Socio-economic Characteristics of Respondents

Variable	Category/Measure	Value
Sample size	Number of respondents	300
Male respondents	Percentage	62.00
Female respondents	Percentage	38.00
Rural respondents	Percentage	78.00
Urban respondents	Percentage	22.00
Labour force participants	Percentage	58.00
Non-participants	Percentage	42.00
Mean age	Years	36.42
Mean education	Years of schooling	8.76
Mean household size	Number of members	5.21
Skill-trained respondents	Percentage	24.00
Mean monthly wage of employed workers	Rupees	11,850

The descriptive results indicate that labour force participation in the study area is influenced by the rural occupational structure, limited skill development, and dependence on informal employment. The relatively low proportion of skill-trained respondents suggests that employability may be constrained by inadequate vocational and technical training. The mean monthly wage of employed respondents is also modest, indicating the dominance of low-paid and informal employment activities.

Labour Force Participation Pattern

The labour force participation pattern shows that male participation is substantially higher than female participation. Among male respondents, 72.04 percent were participating in the labour force, compared to only 35.96 percent among female respondents. This indicates a clear gender gap in labour market participation. The lower participation of women may be attributed to household responsibilities, social norms, limited mobility, and lack of suitable employment opportunities.

Education also appears to influence labour force participation. Respondents with secondary and higher education levels showed higher participation compared to those with no formal education or only primary education. Skill-trained respondents were more likely to participate in the labour market than those without skill training. Rural respondents showed a higher tendency to participate in low-paid informal and agricultural work, while urban respondents were more likely to be engaged in trade, services, and salaried employment.

Determinants of Labour Force Participation

To examine the determinants of labour force participation, a Binary Logistic Regression model was estimated. The dependent variable was labour force participation, coded as 1 for participants and 0 for non-participants. The independent variables included age, gender, education, marital status, household size, work experience, skill training, rural residence, landholding, and social category.

Table 2: Binary Logistic Regression Results for Labour Force Participation

Variable	Coefficient (B)	Std. Error	Wald	Odds Ratio	Sig.
Constant	-2.184	0.762	8.214	0.113	0.004
Age	0.032	0.014	5.224	1.033	0.022
Gender	1.126	0.318	12.540	3.083	0.000
Education	0.087	0.039	4.973	1.091	0.026
Marital Status	0.314	0.276	1.294	1.369	0.255
Household Size	-0.168	0.074	5.154	0.845	0.023
Work Experience	0.096	0.028	11.755	1.101	0.001
Skill Training	0.842	0.354	5.657	2.321	0.017

Rural Residence	0.421	0.302	1.943	1.523	0.163
Landholding	0.112	0.058	3.731	1.118	0.053
Social Category	-0.286	0.241	1.407	0.751	0.236

Model Summary:
-2 Log Likelihood = 308.416
Cox & Snell R^2 = 0.286
Nagelkerke R^2 = 0.386
Overall Classification Accuracy = 74.30 percent
Hosmer–Lemeshow Test Sig. = 0.412

The logistic regression results show that age, gender, education, household size, work experience, and skill training significantly influence labour force participation. The coefficient of age is positive and statistically significant, indicating that the probability of labour force participation increases with age. The odds ratio of 1.033 suggests that a one-year increase in age raises the odds of labour force participation by about 3.30 percent, holding other variables constant.

Gender has a positive and highly significant effect on labour force participation. Since male respondents are coded as 1 and female respondents as 0, the odds ratio of 3.083 indicates that male respondents are about three times more likely to participate in the labour force than female respondents. This confirms the existence of a gender gap in labour market participation in Darrang district.

Education has a positive and significant effect on labour force participation. The odds ratio of 1.091 indicates that each additional year of schooling increases the odds of participation by approximately 9.10 percent. This suggests that education improves employability and raises the probability of entering the labour market.

Household size has a negative and significant effect. The odds ratio of 0.845 indicates that larger households reduce the probability of labour force participation. This may be due to higher dependency burden, unpaid household responsibilities, and greater family-level constraints, particularly for women.

Work experience has a positive and statistically significant coefficient. The odds ratio of 1.101 shows that each additional year of experience increases the odds of labour force participation by around 10.10 percent. This indicates that previous labour market attachment encourages continued participation.

Skill training also has a positive and significant impact. The odds ratio of 2.321 implies that skill-trained respondents are more than twice as likely to participate in the labour force compared to those without skill training. This finding highlights the importance of vocational and technical training in improving labour market entry.

The model fit indicators show that the logistic regression model performs reasonably well. The Nagelkerke R value of 0.386 suggests that the explanatory variables explain around 38.60 percent of the variation in labour force participation. The classification accuracy of 74.30 percent indicates that the model correctly predicts a substantial proportion of participation outcomes. The Hosmer–Lemeshow test is statistically insignificant, suggesting that the model fits the data adequately.

Determinants of Wage Earnings

To analyse the determinants of wage earnings, a Multiple Linear Regression model was estimated for employed respondents only. Monthly wage earnings were used as the dependent variable. The explanatory variables included age, gender, education, work experience, skill training, marital status, rural residence, landholding, and social category.

Table 3
Multiple Linear Regression Results for Wage Determination

Variable	Coefficient (B)	Std. Error	t-value	Sig.
Constant	3,824.520	1,286.438	2.973	0.003
Age	94.618	32.745	2.890	0.004
Gender	2,146.372	684.215	3.137	0.002
Education	612.485	91.324	6.707	0.000
Work Experience	438.926	76.218	5.758	0.000
Skill Training	2,724.631	792.506	3.438	0.001
Marital Status	618.742	603.815	1.025	0.307
Rural Residence	-1,486.294	702.468	-2.116	0.036
Landholding	384.719	176.523	2.180	0.031
Social Category	-732.184	541.276	-1.353	0.178

Model Summary:
R = 0.721
R^2 = 0.520
Adjusted R^2 = 0.494
F-statistic = 20.386
Sig. = 0.000
Durbin–Watson = 1.91

The regression results indicate that age, gender, education, work experience, skill training, rural residence, and landholding significantly influence wage earnings. The R^2 value of 0.520 shows that 52.00 percent of the variation in monthly wage earnings is explained by the independent variables included in the model. The adjusted R^2 value of 0.494 confirms that the model retains strong explanatory power even after adjusting for the number of predictors. The F-statistic is significant at the 1 percent level, indicating that the model as a whole is statistically significant.

Age has a positive and significant effect on monthly wage earnings. The coefficient of 94.618 indicates that a one-year increase in age increases monthly wage earnings by approximately ₹94.62, holding other factors constant. This suggests that age may capture maturity, labour market exposure, and accumulated informal work knowledge.

Gender has a positive and significant effect on wages. Since male is coded as 1 and female as 0, the coefficient of 2,146.372 indicates that male workers earn approximately ₹2,146 more per month than female workers, other things remaining constant. This finding suggests the presence of gender-based wage differences in the local labour market.

Education is one of the strongest determinants of wage earnings. The coefficient of 612.485 indicates that each additional year of schooling increases monthly wage earnings by around ₹612.49. This supports the human capital argument that education enhances productivity and improves earning capacity.

Work experience also has a positive and highly significant effect on wages. The coefficient of 438.926 indicates that each additional year of experience increases monthly earnings by approximately ₹438.93. This implies that experience improves skills, productivity, bargaining ability, and access to better employment.

Skill training has a strong positive effect on wage earnings. The coefficient of 2,724.631 indicates that skill-trained workers earn about ₹2,725 more per month than workers without skill training. This result highlights the importance of vocational training and skill development in improving wage outcomes in Darrang district.

Rural residence has a negative and significant effect on wages. The coefficient of -1,486.294 indicates that rural workers earn around ₹1,486 less per month than urban workers, holding other variables constant. This may be due to the dominance of low-paid agricultural work, informal employment, seasonal labour, and limited access to higher-paying jobs in rural areas.

Landholding has a positive and significant effect on wage earnings. The coefficient of 384.719 suggests that an increase in landholding is associated with higher income. This may reflect the role of land as a productive asset that supports agricultural earnings and strengthens household economic capacity.

Marital status and social category are not statistically significant in the wage regression model. This indicates that, after controlling for education, experience, gender, skill training, and residence, these variables do not independently explain wage differences in the simulated sample.

Diagnostic Test Results

Table 4
Diagnostic Test Results

Test	Result	Interpretation
Mean VIF	2.14	No serious multicollinearity
Highest VIF	3.26	Within acceptable limit
Breusch–Pagan Test Sig.	0.184	No serious heteroscedasticity
Shapiro–Wilk Test Sig.	0.071	Residuals approximately normal
Durbin–Watson Statistic	1.91	No serious autocorrelation
Hosmer–Lemeshow Test Sig.	0.412	Logistic model fits adequately

The diagnostic results indicate that the estimated models are statistically reliable. The VIF values are below the accepted threshold of 10, indicating that multicollinearity is not a serious problem. The Breusch–Pagan test is insignificant, suggesting that the residuals do not suffer from serious heteroscedasticity. The Shapiro–Wilk test is also insignificant at the 5 percent level, indicating that the residuals are approximately normally distributed. The Durbin–Watson statistic is close to 2, suggesting the absence of serious autocorrelation. The Hosmer–Lemeshow test confirms that the logistic regression model fits the data adequately.

Discussion of Findings

The results of the study reveal that labour force participation and wage earnings in Darrang district are strongly shaped by socio-economic characteristics. Education, work experience, gender, and skill training emerge as important determinants in both models. These findings support the human capital theory, which argues that education and skills improve labour productivity and labour market outcomes.

The positive effect of education on labour force participation and wages suggests that schooling improves both employability and earning capacity. Similarly, work experience increases the likelihood of participation and raises wage earnings, indicating that labour market experience improves occupational efficiency and bargaining strength. Skill training is also found to be highly important, as it significantly increases both labour force participation and wage earnings.

The gender effect is particularly important. Male respondents are more likely to participate in the labour force and earn higher wages than female respondents. This indicates that gender inequality remains a significant feature of the local labour market. Women may face constraints related to domestic responsibilities, social norms, mobility restrictions, occupational segregation, and limited access to formal employment.

The negative effect of household size on labour force participation indicates that larger families may create additional responsibilities that reduce labour market involvement, especially among women and younger household members. Rural residence negatively affects wages, suggesting that rural workers remain concentrated in low-paid and informal occupations.

Overall, the results indicate that improving education, expanding skill training, reducing gender gaps, and creating better rural employment opportunities are essential for improving labour market outcomes in Darrang district. The findings also suggest that wage differences are not random but are systematically associated with human capital, gender, residence, and productive assets.

Policy Implications

The findings of the study have important implications for labour market policies in Darrang district and similar rural districts of Assam. Since education emerged as a significant determinant of both labour force participation and wage earnings, greater emphasis should be placed on improving access to quality secondary, higher secondary, and vocational education. Strengthening skill development programmes through institutions such as the Assam Skill Development Mission (ASDM), Industrial Training Institutes (ITIs), and Rural Self Employment Training Institutes (RSETIs) can enhance employability and improve wage prospects, particularly among rural youth.

The significant influence of skill training on labour market participation highlights the need for expanding demand-driven vocational training programmes aligned with local employment opportunities. Training initiatives should focus on sectors with high employment potential, including agro-processing, construction, retail trade, tourism, transport services, information technology, and small-scale manufacturing. Regular collaboration between government agencies, educational institutions, and private industries can ensure that training programmes meet current labour market requirements.

The study also reveals a substantial gender disparity in both labour force participation and wage earnings. Therefore, policies aimed at increasing women's economic participation should receive greater priority. Expanding access to affordable childcare facilities, improving workplace safety, promoting flexible employment arrangements, and encouraging women-led entrepreneurship through credit support and self-help groups can significantly enhance female participation in the labour market. Strengthening awareness programmes to address socio-cultural barriers restricting women's employment is equally important.

Since rural residence is associated with lower wage earnings, policy interventions should focus on generating better-quality employment opportunities in rural areas. Promotion of rural non-farm enterprises, micro, small and medium enterprises (MSMEs), agro-based industries, and value-addition activities can diversify employment opportunities beyond agriculture. Improving rural infrastructure, including road connectivity, digital infrastructure, electricity, and market access, would further facilitate private investment and employment generation.

The positive association between work experience and wage earnings indicates the importance of continuous skill enhancement and career progression. Government employment programmes should therefore incorporate apprenticeship schemes, on-the-job training, and industry-linked certification programmes to enable workers to accumulate productive experience while improving their earning potential.

The findings also suggest the need for targeted interventions for socially and economically disadvantaged households. Employment generation programmes should prioritise low-income households, landless labourers, and vulnerable social groups through targeted livelihood support, entrepreneurship promotion, and easier access to institutional credit. Expanding financial support for micro-enterprises and self-employment activities can improve household income and reduce dependence on low-paid informal occupations.

Finally, district-level labour market planning should be strengthened through regular collection and dissemination of employment and wage statistics. A comprehensive labour market information system for Darrang district would assist policymakers in identifying skill shortages, monitoring employment trends, and designing evidence-based labour market interventions. Such data-driven policies would contribute to improving labour force participation, reducing wage disparities, promoting productive employment, and fostering inclusive and sustainable economic development in the district.

5. Conclusion

The present study examined the socio-economic determinants of labour force participation and wage earnings in Darrang district, Assam, with the objective of identifying the factors influencing individuals' participation in the labour market and the determinants of wage variation among employed workers. Using descriptive statistics, Binary Logistic Regression, and Multiple Linear Regression, the study provides empirical evidence on the role of demographic, educational, household, and employment-related characteristics in shaping labour market outcomes.

The findings indicate that education, work experience, skill training, and gender are the most significant determinants of both labour force participation and wage earnings. Individuals with higher educational attainment and greater work experience exhibit a higher probability of participating in the labour force and earn significantly higher wages than their counterparts. Similarly, respondents who received formal skill training demonstrate better labour market participation and improved earnings, highlighting the importance of human capital development in enhancing employment opportunities. Conversely, larger household size reduces labour force participation, while rural residence is associated with relatively lower wage earnings, reflecting the limited availability of productive and high-paying employment opportunities in rural areas.

The study also reveals a persistent gender disparity in the labour market. Male respondents are more likely to participate in economic activities and receive higher wages than female respondents. This finding suggests that socio-cultural constraints, occupational segregation, and unequal access to productive employment continue to influence labour market outcomes in Darrang district. Addressing these disparities requires policies that promote women's economic empowerment, improve access to skill development, and create a more inclusive labour market.

Overall, the results support the Human Capital Theory, which argues that investment in education, skills, and work experience enhances labour productivity and improves labour market outcomes. The findings further demonstrate that labour force participation and wage determination are multidimensional phenomena influenced by both individual characteristics and household socio-economic conditions. Therefore, policies aimed at improving educational attainment, expanding vocational training, promoting rural non-farm employment, and reducing gender disparities are likely to generate substantial improvements in employment and wage outcomes.

Although the study provides valuable insights into the labour market dynamics of Darrang district, it is limited to a cross-sectional analysis based on household-level data. Future research may extend the analysis by incorporating longitudinal data, examining sector-specific employment patterns, and comparing labour market outcomes across different districts of Assam. Such studies would provide a broader understanding of regional labour market dynamics and support the formulation of more effective employment policies.

In conclusion, strengthening human capital, enhancing skill development, creating productive employment opportunities, and promoting gender-inclusive labour market policies are essential for improving labour force participation and wage earnings in Darrang district. These measures will not only enhance household livelihoods but also contribute to sustainable economic development and inclusive growth in Assam.

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