

Beyond Labour-Force Participation: Gender Differences in Employment and Earnings in Assam, India

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Beyond Labour-Force Participation: Gender Differences in Employment and Earnings in Assam, India

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Abstract: Gender disparities in labour markets extend beyond participation to the type of work women obtain and the earnings they receive. This study examines these dimensions in Assam using 2025 Periodic Labour Force Survey (PLFS) public-use microdata comprising 42,465 persons from 10,154 households. Weighted descriptive estimates are combined with logistic models of labour-force participation and regular salaried employment, a weighted log-earnings model for regular salaried/wage workers under Current Weekly Status (CWS), and a male-reference Oaxaca–Blinder decomposition. Regression models use FSU-clustered standard errors and district fixed effects. Women’s labour-force participation rate (LFPR) is 42.75 per cent, compared with 81.72 per cent among men, a 38.97-percentage-point gap that is wider in urban Assam. Women are disproportionately concentrated in self-employment and agriculture, whereas men are more represented in construction, trade and transport. Among regular salaried CWS workers with positive earnings, women’s weighted mean monthly earnings are ₹14,046, compared with ₹21,002 for men. The adjusted female earnings association remains negative, although the differential is smaller in urban areas. The Oaxaca–Blinder decomposition indicates that observed characteristics account for 14.39 per cent of the mean log-earnings gap under the male-reference counterfactual. The findings show that gender inequality in Assam operates across participation, employment structure, sectoral allocation and remuneration. The study, therefore, supports attention to access to suitable non-farm and regular employment alongside participation itself.

Keywords: female labour-force participation; gender earnings gap; Assam; employment quality; PLFS 2025

JEL Classification: J16; J21; J22; J31; C25

1. Introduction

Women's access to productive, remunerative, and secure employment is crucial for inclusive development. Labour market participation affects household resources and economic autonomy, while the nature of the employment determines earnings, security and opportunities for advancement. In India, women's labour-market outcomes continue to differ markedly from men's, and the disadvantage extends beyond whether women work to where they work and what they earn. Evidence suggests that female labour-force participation is shaped by the interaction of household resources, education, labour demand and the availability of suitable jobs rather than by economic development alone (Klasen & Pieters, 2015; Desai & Joshi, 2019).

Research on the feminisation U-curve also cautions against assuming that development automatically raises women's participation. Gaddis and Klasen (2014) question the robustness of a simple U-shaped relationship, while Lahoti and Swaminathan (2016) show that the composition of growth and the sectors generating employment matter greatly. Klasen and Pieters (2015) identify both household-level influences and weak expansion of suitable employment for women in urban India. Desai and Joshi (2019) likewise focus on employment opportunities and measurement aspects rather than on increasing prosperity alone.

A second dimension concerns employment quality and composition. Women may participate in economic activity without obtaining comparable access as men to regular salaried work, non-farm employment or higher-paying occupations. Occupational and sectoral segregation can narrow women's employment opportunities even as education and skills improve (Chatterjee et al., 2018). Unpaid domestic and caregiving responsibilities are another constraint on the allocation of women's time and employment choices (Srija & Vijay, 2020; Gupta & Pattanaik, 2025).

The earnings dimension moves the focus from the extensive to the intensive margin. The gender earnings differentials in India persist even after controlling for observable characteristics, though their magnitude differs across periods, locations and the wage distribution (Azam & Shariff, 2011; Desai et al., 2016). Recent work based on PLFS continues to reveal large gaps within regular workers and also establishes the merit of counterfactual approaches (Soni & Pattanaik, 2025). Hence, participation and earnings should be viewed together, instead of participation being the sole indicator of gender disadvantage.

The state of Assam provides an important subnational setting in which to examine these issues. The state has a large rural population, substantial agricultural employment, and pronounced differences between rural and urban areas, as well as significant heterogeneity across social groups. Assam-specific studies document persistent gender differences in participation and identify education, age, marital status and social-group characteristics as important correlates (Boruah & Das, 2022; Roy & Barua, 2022). Earlier work also points to women's strong concentration in agriculture (Saikia & Goswami, 2013). National mechanisms should therefore not be assumed to operate uniformly within the state.

The 2025 PLFS is particularly relevant because the survey design was revamped from January 2025. The revised framework changed the stratification and selection of first-stage sampling units (FSU) and increased the annual sample size; districts became the basic geographical unit for most state/UT coverage, while NSS regions remained basic strata for the remaining coverage. The 2025 annual estimates should consequently be treated as the first benchmark under the revised framework, and comparisons with earlier rounds should be made cautiously (MoSPI, 2026a, 2026b). The PLFS 2025 microdata filtered for Assam nevertheless allow a more detailed examination of gender differences than headline state-level indicators alone.

Against this backdrop, this study looks at four inter-related but distinct aspects: labour-force participation and employment; variations by place of residence, age and social group; employment status and industrial concentration; and adjusted earnings among regular salaried/wage workers. The study poses the following questions: (i) what is the magnitude of gender differences in participation, employment, and unemployment in Assam; (ii) how do these differences vary based on residence, age, and social group; (iii) are women disproportionately represented in specific employment statuses and industries; and (iv) what is the extent of the adjusted gender earnings differential among regular salaried/wage workers?

The contribution is empirical and analytical rather than causal. The study uses PLFS 2025 microdata (filtered for Assam) to examine participation, employment structure and earnings within one framework; distinguishes rural and urban gender associations through interaction terms; links participation to employment quality and earnings; and uses a male-reference Oaxaca–Blinder decomposition to quantify the share of the mean log-earnings gap associated with observed characteristics. Because the data are cross-sectional, all regression and decomposition results are interpreted as conditional associations or accounting terms, not causal effects.

2. Review of Literature

The literature on women's labour-market participation has moved from explanations centred mainly on human capital and household specialisation toward frameworks incorporating labour demand, structural change, household resources, social norms and unpaid work. Becker's (1985) household-specialisation framework highlights the opportunity cost of market work relative to household production, while Goldin's (1995) development framework proposes a U-shaped relationship. Subsequent evidence shows that this relationship is context dependent: Gaddis and Klasen (2014) demonstrate limited support for a universal U-shape, and Lahoti and Swaminathan (2016) emphasise the composition of growth and employment.

India-specific research assigns particular weight to the interaction between labour supply and demand. Klasen and Pieters (2015) show that women's participation in urban India remained low despite rising education and growth, with household-income effects and weak expansion of suitable employment both relevant. Mehrotra and Parida (2017) associate changes in participation with structural transformation and insufficient non-farm employment, while Desai and Joshi (2019) conclude that supply-side improvements alone cannot explain the observed pattern. Andres et al. (2018) also warn against reading changes in participation as simply a function of rising prosperity.

The education–employment relationship provides another important aspect. Education does not translate automatically into employment. Chatterjee et al. (2018) demonstrate a non-linear relationship between education and women's participation, emphasising occupational availability and segregation alongside household resources. This is important for the present study because sectoral concentration can affect both the probability of working and the returns from work.

Another important aspect is the unpaid domestic and care work. Time use research has pointed out that women's over-representation in household and care work limits their time for paid work (Srija & Vijay, 2020; Gupta & Pattanaik, 2025). Non-participation should, therefore, not be equated with economic inactivity.

Labour-market outcomes also vary across social groups and locations. Deshpande (2011) and Thorat and Newman (2010) show that social identity can shape access to economic opportunities, while Assam-specific studies document socioeconomic variation in women's

participation (Boruah & Das, 2022; Roy & Barua, 2022). Women in Assam should therefore not be treated as a homogeneous labour-market population.

Employment status deserves separate attention because self-employment, regular salaried work and casual wage work differ in earnings, security and access to employer-linked protection. A change in the female worker-population rate may therefore coexist with limited improvement in job quality, especially where agriculture and household enterprises are important sources of work. The earnings literature shifts attention from the extensive to the intensive margin. Azam and Shariff (2011) report substantial gender wage differentials in India with a rural–urban dimension, while Desai et al. (2016) demonstrate persistent differences even after accounting for observed characteristics. Further, using NSS and PLFS data and several counterfactual methods, Soni and Pattanaik (2025) find that gender wage gaps remain substantial in regular employment. These findings support the inclusion of earnings in a multidimensional assessment of gender inequality.

The Oaxaca–Blinder framework provides an accounting tool for mean wage differences. Oaxaca (1973) and Blinder (1973) decomposed observed gaps into components associated with differences in characteristics and differences in estimated coefficients. Methodological work stresses that the decomposition is counterfactual and depends on the reference coefficient vector and included covariates (Jann, 2008; Fortin et al., 2011). The residual component should therefore not be interpreted mechanically as discrimination, particularly when occupation, tenure, employer characteristics and selection into employment are not fully observed.

Taken together, the literature suggests three gaps that motivate the present study. First, national evidence shows that female participation depends jointly on labour supply and the availability and composition of jobs, but the relative importance of these mechanisms can differ across local labour markets. Second, participation does not imply comparable employment quality because women may remain concentrated in agriculture, self-employment or other lower-return activities. Third, evidence on gender earnings differentials is more developed nationally than for Assam. The present study addresses these gaps by examining participation, employment structure, industrial concentration and regular salaried earnings in Assam using the PLFS 2025 microdata, while distinguishing descriptive, conditional and decomposition-based evidence.

3. Objectives of the Study

The specific objectives of the present study are –

- i) To estimate gender-specific labour-force participation, worker-population ratio and unemployment rate in Assam in 2025, with separate rural and urban and social-group estimates.
- ii) To quantify gender differences in employment status, particularly self-employment, regular salaried employment and casual wage work.
- iii) To document gender concentration across broad industries and identify the sectors in which male and female employment differ most strongly.
- iv) To estimate the adjusted gender earnings differential among regular salaried workers and decompose the observed log earnings gap into components associated with observed characteristics and residual differences.

4. Data and Methodology

4.1 Data source, analytical sample and data linkage

The analysis uses the officially released PLFS 2025 public-use microdata for January–December 2025 and is restricted to Assam (State Code 18). The person-level file contains 42,465 records and 153 variables; the household file contains 10,154 records and 48 variables. The analytical sample comprises 26,068 rural and 16,397 urban persons, including 21,191 men and 21,274 women. These are unweighted sample counts and are reported to document sample construction.

Person and household records were linked using the common survey identifiers, including quarter, month, visit, sector, state, district, NSS region, stratum, FSU, second-stage stratum and sample household number. The linkage produced no unmatched person records. Household size, social group and monthly household consumer expenditure (HHCE) were appended to the person-level file. Because PLFS assigns the household head's social group to household members, social group is treated as a household-level survey characteristic rather than an individually observed caste attribute (MoSPI, 2026b).

4.2 Survey weighting and estimation framework

The PLFS sampling multiplier is used as the expansion weight and is divided by 100 for computational convenience; this rescaling does not affect weighted estimates or regression coefficients. Population rates, employment shares, and earnings statistics are weighted, whereas sample counts are unweighted. As an internal validation, weighted Assam LFPR

estimates reproduce the corresponding published 2025 benchmarks after rounding (MoSPI, 2026a).

Regression models use the sampling multiplier, FSU-clustered sandwich standard errors and district fixed effects. FSU clustering allows for within-PSU dependence, while district fixed effects account for systematic district differences. Because the public-use files do not provide replicate weights, the standard errors are design-informed cluster-robust estimates rather than exact replicate-weight or fully linearised survey-variance estimates.

The empirical strategy proceeds from the extensive to the intensive margin. Weighted descriptive estimates first characterise participation, worker-population ratios, unemployment, employment status and broad industry. Logistic models estimate conditional associations with labour-force participation and, among employed persons, regular salaried employment. Weighted linear regression estimates log monthly earnings among regular salaried/wage workers observed under CWS. Finally, a male-reference Oaxaca–Blinder decomposition separates the mean log-earnings gap into components associated with observed characteristics and coefficients (Jann, 2008; Fortin et al., 2011).

4.3 Variable construction

Usual-status labour-force measures are constructed from principal usual activity status (PAS) and subsidiary usual activity status (SAS), following PLFS definitions. Employment comprises codes 11, 12, 21, 31, 41 and 51; code 81 denotes unemployment. A person is employed if either PAS or SAS is an employment code and is in the labour force if employed or unemployed. LFPR is the labour force divided by population; WPR is employed persons divided by population; and the unemployment rate is unemployed persons divided by the labour force. The principal analytical population is aged 15 years and above.

Employment status is defined from the usual-status employment code: self-employment comprises codes 11, 12 and 21; regular wage/salaried employment is code 31; and casual wage labour comprises codes 41 and 51. Industry is assigned from the principal usual-status industry where principal employment exists and from the subsidiary industry otherwise. Five-digit NIC-2008 codes are aggregated by the first two digits into broad sectors to capture structural concentration rather than detailed occupational segregation.

CWS is taken directly from the PLFS-derived ACWS variable. For earnings, regular salaried/wage employment comprises CWS codes 31, 71 and 72, and the sample is restricted to persons reporting positive regular monthly earnings. The earnings sample is therefore

distinct from the usual-status sample used for participation and employment-status analyses; this distinction avoids conflating different reference periods and labour-status concepts (MoSPI, 2026b).

4.4 Econometric strategy and model specification

The econometric analysis covers four linked outcomes: labour-force participation, regular salaried employment conditional on observed employment, monthly earnings among regular salaried/wage workers, and the mean log-earnings decomposition. Binary outcomes are estimated by logistic regression and earnings by weighted linear regression in logarithmic form. Logistic results are reported as odds ratios, but interpretation of gender–residence interactions is based on the joint terms because individual odds ratios cannot simply be combined in nonlinear models (Long & Freese, 2014; Wooldridge, 2010).

All models estimate conditional associations rather than causal effects. The cross-sectional design does not establish temporal ordering, and household expenditure and household size may be jointly determined with labour-market outcomes. Important factors such as childcare, unpaid care, mobility constraints, social norms and local job availability are incompletely measured.

Model 1: Labour-force participation

Let $LFP_i=1$ when person i is in the labour force under usual status and 0 otherwise. The logistic specification is:

$$Pr (LFP_i = 1 | X_i) = \Lambda (\beta_0 + \beta_1 Female_i + \beta_2 Urban_i + \beta_3 Female_i \times Urban_i + \beta_4 Age_i + \beta_5 Age_i^2 + \beta_6 Married_i + \beta_7 Education_i + \beta_8 SocialGroup_i + \beta_9 HouseholdSize_i + \beta_{10} \ln (HHCE_i) + \delta_d)$$

Where $\Lambda(z) = \exp(z) / [1 + \exp(z)]$ and δ_d denotes district fixed effects. Rural men form the reference category. Thus, β_1 captures the conditional female–male association in rural Assam, while β_3 captures the additional female–urban association. The quadratic age term permits a nonlinear age profile; its turning point is $-\beta_4 / (2\beta_5)$.

Model 2: Regular salaried employment

Among persons employed under usual status, let $RSE_i=1$ denotes regular wage/salaried employment and 0 denotes self-employment or casual wage work:

$$Pr(RSE_i = 1 | E_i = 1, X_i) = A(\gamma_0 + \gamma_1 Female_i + \gamma_2 Urban_i + \gamma_3 Female_i \times Urban_i + \gamma_4 Age_i + \gamma_5 Age_i^2 + \gamma_6 Married_i + \gamma_7 Education_i + \gamma_8 SocialGroup_i + \gamma_9 HouseholdSize_i + \gamma_{10} \ln(HHCE_i) + \delta_d).$$

Here, γ_1 is the conditional female–male difference in the rural reference category, while γ_3 indicates how that association differs in urban Assam. Conditioning on employment is intentional: the model describes employment type among observed workers rather than the probability of entering employment. Because employment is itself gendered, the coefficient is subject to selection into the worker sample. A Heckman type correction is not implemented because the data do not provide a credible exclusion restriction or the additional information needed for a convincing selection model (Heckman, 1979; Wooldridge, 2010).

Model 3: Monthly earnings

For persons aged 15 years and above who are classified as regular wage/salaried under CWS (codes 31, 71 or 72) and report positive regular monthly earnings:

$$\ln(Earnings_i) = \alpha_0 + \alpha_1 Female_i + \alpha_2 Urban_i + \alpha_3 Female_i \times Urban_i + \alpha_4 Age_i + \alpha_5 Age_i^2 + \alpha_6 Married_i + \alpha_7 Education_i + \alpha_8 SocialGroup_i + \alpha_9 Hours_i + \delta_d + \varepsilon_i.$$

The logarithmic dependent variable reduces the influence of highly skewed earnings and permits percentage interpretation of coefficients. The exact percentage association corresponding to coefficient **b** is $100 \times [\exp(b) - 1]$. The female coefficient represents the rural female–male earnings association, while the urban female association is obtained by jointly evaluating $\alpha_1 + \alpha_3$. Weekly hours actually worked are included as a labour-input covariate. The hours coefficient is an association with monthly earnings rather than a causal return to an additional hour. The model does not observe occupation, tenure, employer characteristics or bargaining conditions, which may also contribute to earnings differences.

Model 4: Male-reference Oaxaca–Blinder decomposition

The mean log-earnings gap among regular salaried workers is decomposed as:

$$\Delta = E[\ln(W_m)] - E[\ln(W_f)] = (\bar{X}_m - \bar{X}_f)' \beta_m + \bar{X}_f' (\beta_m - \beta_f)$$

The first term is the component associated with differences in observed characteristics, and the second is the coefficient/residual component under the male-reference counterfactual. The decomposition uses the same observed covariates as the earnings model, excluding the sex indicator, and follows the standard Blinder–Oaxaca framework (Blinder, 1973; Oaxaca, 1973)

and subsequent methodological guidance on reference-group dependence and interpretation (Jann, 2008; Fortin et al., 2011). The coefficient/residual component is an accounting term and is not interpreted as discrimination; it may reflect unequal returns, omitted variables, tenure and employer characteristics, selection into regular salaried employment, and other unobserved factors (Jann, 2008; Fortin et al., 2011).

5. Results and Discussion

The results are organised from the extensive margin of labour-market participation to the employment structure and then to the intensive margin of earnings. This sequence highlights how gender inequality accumulates across participation, employment type, sectoral allocation and remuneration.

5.1 The gender participation gap is large, with a pronounced rural–urban divide

Table 1 shows a pronounced gender asymmetry in Assam. Overall LFPR is 61.94 per cent, but female LFPR is 42.75 per cent, compared with 81.72 per cent for men, a 38.97-percentage-point gap. The WPR gap is similarly large (40.93 per cent for women versus 78.96 per cent for men), while female unemployment is only modestly higher (4.26 per cent versus 3.39 per cent). The principal gender disadvantage therefore lies in labour-force attachment rather than unemployment alone. This is consistent with Indian evidence emphasising household constraints, labour demand and the structure of available employment (Klasen & Pieters, 2015; Lahoti & Swaminathan, 2016; Desai & Joshi, 2019).

Table 1. Labour-market indicators among persons aged 15 years and above, Assam, 2025

Group	LFPR (%)	WPR (%)	UR (%)
All persons	61.94	59.65	3.70
Male	81.72	78.96	3.39
Female	42.75	40.93	4.26
Rural male	82.26	79.65	3.17
Rural female	44.87	43.23	3.64
Urban male	78.14	74.32	4.89
Urban female	29.22	26.19	10.36

Source: Authors' calculations from PLFS 2025 Assam microdata; estimates weighted by the supplied PLFS multiplier. Usual status (principal status plus subsidiary status) is used.

The rural–urban contrast is especially marked. Female LFPR falls from 44.87 per cent in rural Assam to 29.22 per cent in urban Assam, whereas male LFPR changes much less, from 82.26 per cent to 78.14 per cent. Female unemployment also rises from 3.64 per cent in rural areas to 10.36 per cent in urban areas. Urbanisation therefore does not automatically translate

into stronger female labour-market integration, consistent with evidence that suitable female employment has not expanded sufficiently in urban India (Klasen & Pieters, 2015).

As a national benchmark, the all-India usual-status LFPR for persons aged 15 years and above was 59.3 per cent in 2025, with male and female rates of 79.1 per cent and 40.0 per cent, respectively (MoSPI, 2026a). Assam shows the same broad gender asymmetry, but its particularly low urban female participation and higher urban female unemployment warrant attention to local employment structure. The comparison is descriptive rather than causal, and differences in economic structure and survey context should be kept in view.

5.2 The gender gap emerges early and persists through prime working age

Table 2 shows that gender inequality is already pronounced among younger people and persists through prime working age. Among 15–29-year-olds, female LFPR is 30.76 per cent, compared with 66.93 per cent for men, and female unemployment is 15.91 per cent, compared with 11.03 per cent for men. Among those aged 30–59, participation reaches 98.00 per cent for men but only 56.18 per cent for women. The pattern indicates both an entry problem for young women and a persistent participation deficit during prime working age.

Table 2. Labour-market indicators by age group and gender, Assam, 2025

Age group	Sex	LFPR	WPR	UR
15–29	Male	66.93	59.54	11.03
15–29	Female	30.76	25.86	15.91
30–59	Male	98.00	97.37	0.64
30–59	Female	56.18	55.84	0.61
60+	Male	50.31	50.30	0.03
60+	Female	16.90	16.90	0.00

Source: Authors' calculations from PLFS 2025 Assam microdata; estimates weighted by the supplied PLFS multiplier.

The relatively high unemployment of young women indicates that disadvantage does not operate solely through non-participation. Among women who seek or undertake work, access to employment is also constrained. Conversely, the very low unemployment rate among older women should not be read as favourable because it coexists with very low participation. These results are compatible with evidence on weak demand for suitable female employment and occupational segmentation (Klasen & Pieters, 2015; Mehrotra & Parida, 2017).

5.3 Social-group differences show that gender disadvantage is heterogeneous

Table 3 shows substantial variation in female participation across social groups. Female LFPR is highest among ST women (55.30 per cent), followed by OBC women (51.44 per cent),

and lowest among women in the ‘Others’ category (32.84 per cent). Male LFPR varies less across groups. Female unemployment is highest among SC women (5.60 per cent) and lowest among ST women (3.37 per cent). The pattern indicates that gender disadvantage is heterogeneous rather than uniform.

Table 3. Labour-market indicators by social group and gender, Assam, 2025

Social group	Male LFPR	Female LFPR	Male WPR	Female WPR	Male UR	Female UR
ST	81.05	55.30	78.26	53.44	3.45	3.37
SC	80.53	40.48	78.58	38.21	2.42	5.60
OBC	81.23	51.44	78.47	49.54	3.40	3.68
Others	82.53	32.84	79.59	31.18	3.56	5.05

Source: Authors’ calculations from PLFS 2025 Assam microdata; estimates weighted by the supplied PLFS multiplier. Social group is a household-level PLFS characteristic.

Higher participation among ST women should not be interpreted as evidence of uniformly better labour-market opportunities. In Assam, as in other parts of India, higher participation can reflect greater engagement in agriculture, household enterprises and other forms of work with limited earnings security. The social-group results therefore reinforce the value of examining employment type and sector alongside participation.

5.4 Participation does not imply comparable employment quality

Table 4 shows marked differences in employment status. Self-employment accounts for 75.02 per cent of female usual-status workers, compared with 51.68 per cent of male workers. Regular salaried employment accounts for 16.16 per cent of female workers and 18.78 per cent of male workers, while casual wage work is much more common among men (29.54 per cent) than women (8.82 per cent). The central result is therefore not simply lower female participation but a different composition of observed employment.

Table 4. Employment-status composition of usual-status workers by gender, Assam, 2025

Employment status	Female (%)	Male (%)	Female–male difference (pp)
Self-employed	75.02	51.68	+23.34
Regular salaried	16.16	18.78	–2.62
Casual wage	8.82	29.54	–20.72

Source: Authors’ calculations from PLFS 2025 Assam microdata; shares weighted by the supplied PLFS multiplier and calculated among usual-status workers aged 15 years and above.

Self-employment includes diverse own-account and household-enterprise activities and should not automatically be labelled precarious. Nevertheless, the strong female concentration

matters because self-employment does not provide the same employment-based protections as regular salaried work. The result is consistent with evidence that gains in women's employment can be concentrated in self-employment and other informal forms (UNFPA India, 2026).

5.5 Sectoral concentration provides a structural counterpart to the participation gap

Table 5 shows pronounced gender concentration across industries. Agriculture accounts for 67.33 per cent of female employment compared with 31.04 per cent of male employment, a 36.29-percentage-point difference. Women also have greater shares in education, health/social work and household services, whereas men are more concentrated in construction, trade and transport.

Table 5. Gender concentration across major industries, Assam, 2025

Broad industry	Female (%)	Male (%)	Gender concentration gap (pp)
Agriculture	67.33	31.04	+36.29
Manufacturing	9.70	8.01	+1.69
Trade	6.59	16.53	−9.94
Education	6.05	2.74	+3.31
Health/social work	2.19	0.60	+1.59
Accommodation/food	1.88	1.92	−0.04
Household services	1.66	0.41	+1.25
Transport	0.87	8.83	−7.96
Construction	0.68	22.20	−21.52

Source: Authors' calculations from PLFS 2025 Assam microdata; shares weighted by the supplied PLFS multiplier and calculated among usual-status workers aged 15 years and above. Broad industries are aggregated from PLFS NIC-2008 codes.

The sectoral pattern is consistent with evidence that the composition of economic activity influences women's employment opportunities. Lahoti and Swaminathan (2016) find that the composition of economic activity, rather than economic growth alone, is central to explaining changes in female participation. Klasen and Pieters (2015) similarly show that sectors attractive to women expanded relatively slowly in urban India. The Assam results therefore point to limited diversification of women's employment as an important structural feature of the gender gap.

5.6 The participation gap remains large after multivariate adjustment

Table 6 confirms that the participation gap remains large after adjustment for age, residence, marital status, education, social group, household size, household expenditure and district fixed effects. The female coefficient is -2.77 ($p < 0.001$), implying substantially lower participation odds for women in the rural reference category. Urban residence is negatively

associated with participation, and the Female $\times$ Urban interaction is also negative and significant, indicating a larger female disadvantage in urban Assam.

Table 6. Weighted logistic model of labour-force participation, persons aged 15+, Assam

Variable	Coefficient	SE	Odds ratio	95% CI (odds ratio)	p-value
Female	−2.77	0.10	0.06	[0.05, 0.08]	<0.001
Urban	−0.54	0.10	0.58	[0.48, 0.71]	<0.001
Female $\times$ Urban	−0.46	0.13	0.63	[0.49, 0.81]	<0.001
Age	0.48	0.02	1.62	[1.55, 1.68]	<0.001
Age ²	−0.0057	0.0002	0.994	[0.994, 0.995]	<0.001
Household size	−0.06	0.02	0.94	[0.90, 0.98]	0.004
Log household expenditure	0.21	0.10	1.24	[1.02, 1.51]	0.035

Notes: $N = 42,465$. Coefficients are log-odds and odds ratios are $\exp(\text{coefficient})$. Rural men are the reference category for the gender–residence interaction. Education and social-group controls and district fixed effects are included but not displayed. Standard errors are FSU-clustered.

Source: Authors' estimates from PLFS 2025 Assam microdata.

The age coefficients indicate a non-linear association: the positive age coefficient (0.48) and negative age-squared coefficient (−0.0057) imply an inverted-U profile with an implied turning point of approximately 42 years. Household size is negatively associated with participation, while household expenditure is positively associated. These associations are compatible with the literature's emphasis on household resources, care responsibilities, social norms and labour demand as interconnected determinants of women's participation (Klasen & Pieters, 2015; Desai & Joshi, 2019).

The participation model is associational rather than causal. Household expenditure and household size may be endogenous, and several relevant factors are incompletely measured. The estimates should therefore be read as conditional differences rather than structural causal effects.

5.7 Regular salaried employment is less likely for women in rural Assam, but the gender difference is attenuated in urban areas

Table 7 examines regular salaried employment conditional on being employed. The female coefficient is negative in the rural reference category (−0.29; $p = 0.004$), while urban residence is positively associated with regular salaried employment (0.59; $p < 0.001$). The positive Female $\times$ Urban interaction (0.54; $p < 0.001$) indicates that the female disadvantage is substantially smaller in urban Assam.

Table 7. Weighted logistic model of regular salaried employment among workers

Variable	Coefficient	SE	Odds ratio	95% CI (odds ratio)	p-value
Female	-0.29	0.10	0.75	[0.61, 0.91]	0.004
Urban	0.59	0.11	1.80	[1.47, 2.22]	<0.001
Female × Urban	0.54	0.16	1.71	[1.25, 2.33]	<0.001
Age	0.13	0.03	1.14	[1.09, 1.20]	<0.001
Age ²	-0.0017	0.0003	0.998	[0.998, 0.999]	<0.001
Married	-0.39	0.09	0.68	[0.56, 0.82]	<0.001
Household size	-0.06	0.03	0.94	[0.89, 0.99]	0.018
Log household expenditure	0.15	0.11	1.17	[0.94, 1.45]	0.166

Notes: $N = 18,503$. Regular salaried employment is defined from the usual-status employment status, conditional on being employed. Rural men are the reference category. Education and social-group controls and district fixed effects are included but not displayed. Standard errors are FSU-clustered.

Source: Author's calculations from PLFS 2025 microdata (filtered for Assam).

The result should be read jointly with the participation model. Urban women have much lower overall participation, yet among observed workers the gender difference in regular salaried employment is less adverse than in rural areas. This pattern is compatible with selection into observed employment, but the cross-sectional design cannot establish that urbanisation causes better employment quality. The result nevertheless corroborates the finding that urban labour markets can offer better-paid opportunities while simultaneously excluding many women from participation (Klasen & Pieters, 2015).

5.8 A substantial gender earnings gap persists within regular salaried employment

Table 8 shows a sizeable descriptive earnings gap among regular salaried/wage workers under CWS. Women's weighted mean monthly earnings are ₹14,046, compared with ₹21,002 for men; medians are ₹6,800 and ₹15,000, respectively. The gap appears in both rural and urban areas: rural women earn ₹10,773 on average versus ₹18,150 for rural men, while urban women earn ₹23,189 versus ₹29,228 for urban men.

Table 8. Weighted monthly earnings by residence and gender among regular salaried CWS workers

Residence	Sex	N	Mean monthly earnings (₹)	Median monthly earnings (₹)
Rural	Male	1,435	18,150	13,000
Rural	Female	694	10,773	6,500
Urban	Male	1,783	29,228	18,500
Urban	Female	709	23,189	12,000

Source: Author's calculations from PLFS 2025 microdata (filtered for Assam); current 2025 rupees; CWS regular salaried/wage codes 31, 71 and 72; positive earnings only.

The residence gradient is pronounced for both sexes, and the female earnings disadvantage is smaller in urban areas. Nevertheless, the descriptive gap remains substantial. This pattern is consistent with evidence of persistent gender wage differences among regular workers in India (Deshpande et al., 2018; Soni & Pattanaik, 2025).

Table 9 provides the adjusted earnings estimates. The Female coefficient is -0.5680 ($p < 0.001$), corresponding to approximately 43.3 per cent lower monthly earnings for women in the rural reference category, conditional on observed covariates and district fixed effects. Urban residence is positively associated with earnings (0.1291 ; about 13.8 per cent higher for the reference group), while the Female $\times$ Urban interaction is positive and significant (0.1713 ; $p = 0.004$). The combined urban female association is -0.3967 log points, or approximately 32.8 per cent lower earnings relative to the rural male reference category.

Table 9. Weighted log monthly earnings model among regular salaried CWS workers

Variable	Coefficient	SE	Effect	95% CI	p-value
Female	-0.5680	0.0485	-43.3%	[-48.5%, -37.7%]	<0.001
Urban	0.1291	0.0368	+13.8%	[+5.9%, +22.3%]	<0.001
Female $\times$ Urban	0.1713	0.0591	+18.7% interaction	[+5.7%, +33.3%]	0.004
Age	0.0332	0.0078	—	[0.0180, 0.0485]	<0.001
Age ²	-0.000265	0.000095	—	[-0.000450, -0.000079]	0.005
Married	0.2229	0.0345	+25.0%	[+16.8%, +33.7%]	<0.001
Weekly hours	0.00927	0.00179	+0.93% per hour	[+0.58%, +1.29%]	<0.001

Notes: N = 4,621. Dependent variable is log monthly earnings. Weekly hours are total hours actually worked during the reference week. Education and social-group controls and district fixed effects are included but not displayed. Standard errors are FSU-clustered. Percentage effects and their intervals are obtained by exponentiating the unrounded coefficients. The Female $\times$ Urban effect is an interaction coefficient; the combined urban female association must be evaluated as $\beta_{\text{Female}} + \beta_{\text{Female} \times \text{Urban}}$.

Source: Authors' estimates from the supplied PLFS 2025 Assam microdata.

The age terms indicate a concave age-earnings profile. Marriage is positively associated with monthly earnings, and weekly hours are also positively associated. The hours coefficient is an association with monthly earnings rather than a causal return to an additional hour because hours are part of the earnings-generating process. The large negative female coefficient is consistent with national evidence of persistent gender earnings gaps (Deshpande

et al., 2018; Soni & Pattanaik, 2025), but it is not a direct measure of discrimination because occupation, tenure, employer characteristics and other relevant factors are not observed.

5.9 The decomposition indicates that observed characteristics explain only a minority of the earnings gap

Table 10 decomposes the mean log-earnings gap using the male-reference Oaxaca–Blinder framework. The total gap is 0.611 log points. Differences in observed characteristics account for 0.088 log points, or 14.39 per cent of the total, while the residual component accounts for 0.523 log points, or 85.61 per cent.

Table 10. Male-reference Oaxaca–Blinder decomposition of the gender log-earnings gap

Component	Log points	Share of total gap (%)
Total log earnings gap	0.611	100.00
Explained by observed characteristics	0.088	14.39
Residual component	0.523	85.61

Notes: $N = 4,621$. The decomposition uses the same observed covariates as the earnings model, excluding the sex indicator, and applies the male-reference coefficient structure. The residual component is a counterfactual accounting term and is not a measure of discrimination.

Source: Authors' calculations from PLFS 2025 Assam microdata.

The residual component should not be equated with discrimination. Oaxaca–Blinder decomposition allocates the observed gap between differences in characteristics and differences in coefficients under a specified counterfactual. The residual may therefore reflect unequal returns to observed characteristics, omitted occupation and tenure, employer characteristics, measurement error, functional-form assumptions, selection into regular employment and other unobserved heterogeneity (Oaxaca, 1973; Blinder, 1973; Fortin et al., 2011; Jann, 2008). Its large size is nevertheless substantively important because only a minority of the observed gap is associated with the characteristics included in the model.

Taken together, the results show that gender inequality in Assam operates through four connected margins: labour-force participation, employment structure, sectoral allocation and earnings. Women participate at substantially lower rates, are more concentrated in self-employment and agriculture, have less favourable access to regular salaried employment in rural areas, and earn less than men even within regular salaried CWS employment.

The findings are broadly consistent with the literature's shift from single-cause explanations toward a framework combining labour supply, labour demand and occupational structure. The especially low urban female participation is consistent with Klasen and Pieters

(2015), while the strong agricultural concentration and employment-status differences support the argument that sectoral composition matters for women's work (Lahoti & Swaminathan, 2016). The earnings results are consistent with evidence of persistent gender wage gaps among salaried workers in India (Deshpande et al., 2018; Soni & Pattanaik, 2025). The contribution of the present study is to show that these margins coexist within the same 2025 Assam microdata and remain visible after multivariate adjustment.

6. Conclusion

This study examined gender disparities in Assam using PLFS 2025 microdata, moving beyond participation to employment structure, industrial concentration and earnings. The evidence shows a multidimensional disadvantage. Women's LFPR is substantially below men's, with the largest participation gap in urban Assam. This pattern is consistent with national evidence that economic development and urbanisation do not automatically create sufficient suitable employment for women (Klasen & Pieters, 2015; Desai & Joshi, 2019).

Employment structure provides a second margin of inequality. Women are disproportionately concentrated in self-employment and agriculture, while men have greater representation in construction, trade and transport. Participation therefore does not provide a complete picture of employment opportunity or quality. The earnings evidence adds a third margin: among regular salaried/wage workers under CWS, women's mean and median monthly earnings are substantially below men's, and the adjusted female association remains negative, although smaller in urban areas.

The Oaxaca–Blinder decomposition shows that observed characteristics explain only 14.39% of the mean log-earnings gap under the male-reference counterfactual. This is an accounting result rather than an estimate of discrimination. The residual can incorporate unequal returns as well as omitted occupation, tenure, employer characteristics and selection into regular salaried employment (Fortin et al., 2011; Jann, 2008).

The policy implication is that reducing gender inequality requires attention to both entry into employment and the structure of employment once women enter. Expanding access to suitable non-farm jobs, strengthening pathways into regular salaried work, improving transport and workplace accessibility, and reducing constraints associated with unpaid care are evidence-informed priorities rather than estimated intervention effects.

The study has three principal limitations. First, the cross-sectional design does not identify causal relationships or transitions between non-participation, self-employment and regular salaried work. Second, the microdata do not provide sufficiently detailed measures of unpaid care, job tenure, employer characteristics, bargaining conditions and some dimensions of occupational quality. Third, the regression analysis uses the available survey multiplier and FSU-clustered model-based standard errors rather than replicate-weight variance estimation. These limitations constrain causal interpretation and the precision with which mechanisms can be identified.

Future research should combine comparable PLFS rounds with richer time-use, occupational and job-quality information. Repeated cross-sectional or longitudinal approaches could distinguish changes in participation from changes in employment composition, while selection-aware and distributional wage methods could clarify the mechanisms underlying the earnings gap. Within Assam, particular attention should be given to movement from agricultural and self-employment into non-farm regular work.

Overall, Assam's gender labour-market challenge is not adequately described by a participation gap alone. The disadvantage is distributed across labour-force attachment, employment type, sectoral allocation and remuneration. Addressing these margins together provides a more complete basis for understanding gender inequality in the state.

Data availability: The analysis uses the publicly released PLFS 2025 unit-level data and documentation from the Ministry of Statistics and Programme Implementation, Government of India.

Competing interests: The authors declare that there is no competing interest.

Consent to participate: Not applicable to the analysis of secondary public-use survey microdata.

Ethics approval: The manuscript uses secondary PLFS public-use microdata, hence, no ethical approval is required.

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Data and Reproducibility Note

All Assam-level empirical results are generated from the PLFS 2025 public-use microdata filtered for State Code 18 (Assam). The all-India comparison is limited to figures reported in the PLFS 2025 Annual Report. The manuscript does not impute missing numerical results or import state-level empirical estimates from secondary literature. The analytical file contains 42,465 person records and 10,154 household records. Weighted estimates use the supplied multiplier; regression results use FSU-clustered standard errors and district fixed effects. Survey documentation is used for variable definitions and survey design. Regression coefficients are interpreted as adjusted associations, and decomposition components as accounting terms rather than measures of discrimination.