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Income Distribution and Gendered Time-Use Patterns in Northeast India

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Introduction

The measurement and valuation of time within household and community contexts have long occupied feminist and development economists concerned with the intersection of production, reproduction, and social inequality (Charmes, 2021). The gendered allocation of unpaid work—particularly care and domestic tasks—remains a persistent site of structural asymmetry that both reflects and reproduces broader hierarchies of class, income, and social identity (Naidu & Rao, 2022). While these themes have been examined extensively in metropolitan India, considerably less empirical attention has been directed towards the country's Northeast, a region characterised by ethnic heterogeneity, diverse kinship systems, and varying levels of development (Samantroy, 2017).

Drawing on data from the Time Use Survey (TUS) 2024 published by the National Statistics Office, Ministry of Statistics and Programme Implementation, Government of India (National Statistics Office, 2024) this article examines how patterns of social reproduction and gendered time use manifest across the eight Northeast Indian states. The study also aims to empirically investigate how income distribution interacts with the allocation of time to paid and unpaid work, as well as how gender affects these relationships. Building upon the works of Naidu and Rai (2022) the paper conceptualises "Total Reproductive Labour" (TRL)—defined as the total time devoted to *unpaid domestic services (UDS)* and *unpaid caregiving services (UCS)*—as a key indicator of social reproduction.

The empirical analysis employs national TUS microdata, restricted to respondents in the Northeast region, to generate gender-disaggregated estimates of average (mean) and median time allocations on various activities, participation rates in those activities, and corresponding gender gaps. Given the distributional skewness of time-use variables, Bayesian Quantile Regression (BQR) is applied to examine the determinants of reproductive labour across different points of the conditional distribution, rather than at the mean. The quantile framework is particularly well-suited for modelling heterogeneous effects, as it reveals how predictors such as income, age, and sector affects individuals differently across the distribution of unpaid work burdens, from those with lighter ones to heavier ones.

Gender, Social Reproduction, and Time

The concept of *social reproduction* refers to the processes through which everyday life and human capacities are maintained, including biological reproduction, care work, domestic labour, and community activities (Samantroy, 2015, 2017; & Rai, 2022). Feminist theorists have argued that these forms of labour are vital to economic and social functioning but it is systematically undervalued and largely invisible in conventional national accounts (Charmes, 2021). The gendered asymmetry of time use thus underpins both the material and symbolic subordination of women, linking the "care economy" to macro-level outcomes such as productivity, labour supply, and intergenerational well-being (Nikore, 2022; World Economic Forum, 2024).

Within India, unpaid work constitutes a substantial proportion of women's total time, with significant variations across states and social groups (Ratheesh & Anitha, 2022). The Northeast region, while often portrayed as more gender-egalitarian due to the presence of matrilineal or bilateral kinship systems in some states, nonetheless exhibits marked inequalities in labour division and labour market participation (Shimray, 2004; Samantroy, 2017). The interplay of income, education, and household composition further influences the allocation of time across paid work, unpaid domestic services, and caregiving.

Data and Methodology

From a methodological standpoint, the choice to focus on quantiles rather than means is theoretically consistent with the feminist economics argument that "average" measures conceal meaningful heterogeneity (Wang et al., 2025). We pay heed to the strictures warned against by Stewart (2018) who argues that time use activity captures person-days and not long-term tendencies, thereby making the mean the preferred measure of central tendency over quantiles. However our exploratory data analysis revealed strikingly similar patterns in quantile measures of gendered time-use that spanned the diverse states of the NER, thus making it a potential candidate a measure of central tendency and variation. Furthermore in time-use distributions characterised by a mass of zero observations (non-participants) and a long right tail (intensive caregivers), mean estimates can misrepresent typical experience. Quantile regression allows us to model the conditional median or other quantiles, thus providing a more robust picture of gendered inequalities across the spectrum of unpaid labour intensity.

Data Source

The study uses unit-level data from the Time Use Survey 2024 conducted by the National Sample Survey Office (NSSO). The sample covers individuals aged six years and above residing in the eight Northeastern states: Sikkim, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, Meghalaya, and Assam. Following standard practice, person-day records were cleaned, merged with household data, and aggregated to obtain total minutes per activity category per person per day. Activities were coded following the ICATUS (International Classification of Activities for Time-Use Statistics) one-digit scheme.

For each individual, the durations of *unpaid domestic services (UDS)* and *unpaid caregiving services (UCS)* were summed to derive Total Reproductive Labour (TRL). Sampling weights and survey design variables (FSU, strata, sub-strata, and multipliers) were applied using the *srvyr* and *bayesQRsurvey* packages in R. Analyses and which are restricted to individuals aged 15–59 (working-age population).

Income Variable

Household living standards are proxied by *Monthly Per Capita Expenditure (UMPCE)*, which was divided into quintiles using survey-weighted cut-offs. Each respondent is assigned to one of five income quintiles—Q1 (lowest) to Q5 (highest)—allowing us to examine how reproductive labour varies across the income distribution.

Model Specification

Given the highly skewed nature of time-use data and the large proportion of zeroes, Bayesian Quantile Regression (BQR) was adopted. Let (Y_i) denote the minutes per day spent in total reproductive labour by individual (i), and (X_i) a vector of covariates including income quintile, gender, age, and sector. For a given quantile *tau* in (0,1) the model can be written as:

$$Q_{Y|X}(\tau) = \beta_0(\tau) + \beta_1(\tau)X_1 + \beta_2(\tau)X_2 + \dots$$

where the outcome variable is the conditional quantile function of Y_i given X_i, and predictor coefficients are the quantile-specific coefficients.

Under the asymmetric Laplace distribution (ALD) likelihood, the Bayesian estimation seeks to estimate the coefficients by minimizing an asymmetrically weighted sum of absolute errors. . The posterior distributions of predictor coefficients are estimated using Markov Chain Monte Carlo (MCMC) sampling with 50,000 iterations and a 10,000-draw burn-in. Posterior means and 95% credible intervals are reported.

Separate models were estimated for (i) a pooled specification with gender–income interaction terms and (ii) gender-specific median ($\tau = 0.50$) regressions. The pooled model covers $\tau = 0.25$, 0.50, and 0.75 to capture the lower, median, and upper quantiles of the TRL distribution.

Results

Descriptive Overview

The descriptive statistics highlight substantial gender gaps in unpaid work across all Northeast states.

Weighted Mean Time Allocation (Minutes/Day) (Age 6+)						
	Gender_Label	Paid Work	UDS	UCS	TRL (UDS+UCS)	R:P Ratio
Arunachal Pradesh	Female	39.9	320.5	67.3	387.8	9.72
Arunachal Pradesh	Male	273.9	52.9	24.9	77.8	0.28
Assam	Female	41.1	261.1	49.2	310.3	7.55
Assam	Male	287.1	31.4	16	47.4	0.17
Manipur	Female	102.9	202.6	61.3	263.9	2.56
Manipur	Male	245.6	20.9	31.5	52.5	0.21

Meghalaya	Female	71.7	218	61.1	279.1	3.89
Meghalaya	Male	243.3	35	15.2	50.2	0.21
Mizoram	Female	101	193.8	110.6	304.4	3.01
Mizoram	Male	275.8	23.5	27.1	50.6	0.18
Nagaland	Female	26.7	180.4	78.9	259.3	9.71
Nagaland	Male	96.1	45.5	34.2	79.8	0.83
Sikkim	Female	90.9	248.8	55.1	303.9	3.34
Sikkim	Male	290.6	54.1	19.9	74	0.25
Tripura	Female	52.2	215.2	44.9	260	4.98
Tripura	Male	272.6	32.2	14.6	46.8	0.17

Table 1. Weighted Mean Time Allocation (Minutes/Day) (Age 6+).

Table 1 presents mean minutes per day devoted to paid work, UDS, UCS, and TRL, disaggregated by gender and state. Women spend between 260–390 minutes per day on reproductive labour (UDS + UCS), compared to 45–80 minutes among men. The highest female TRL is observed in Arunachal Pradesh (387.8 min) and Mizoram (304.4 min), while the lowest is in Manipur (263.9 min). Men's contributions remain minimal across states. The ratio of reproductive to paid labour (R:P) ranges from 2.5 to nearly 10 among women, but rarely exceeds 1 among men. These stark contrasts underscore the persistent gendered division of labour in domestic and care work.

Gender Gap in Reproductive Labour

Gender Gap in Total Reproductive Labor (TRL) (Excess Minutes Spent by Women, Age 6+)			
State_Name	**Female TRL (Min)**	**Male TRL (Min)**	**Gap (F - M)**
Arunachal Pradesh	387.8	77.8	310
Assam	310.3	47.4	262.9
Manipur	263.9	52.5	211.5
Meghalaya	279.1	50.2	228.9
Mizoram	304.4	50.6	253.8
Nagaland	259.3	79.8	179.5
Sikkim	303.9	74	229.9
Tripura	260	46.8	213.2

Table 2. Gender Gap in Total Reproductive Labour (Excess Minutes Spent by Women, Age 6+).

Comment: Table 2 shows the difference in TRL between women and men, by state.

Across states, the average gender gap exceeds 220 minutes per day, reaching over 300 minutes in Arunachal Pradesh and 260 minutes in Assam. The smallest gap (approximately 180 minutes) is seen in Nagaland. These magnitudes suggest that women in the Northeast devote between three and five additional hours per day to unpaid reproductive work relative to men.

Median TRL by Income Quintile

To explore income differentials, median TRL is computed by income quintile and gender.

Median Total Reproductive Labor (TRL) by Income Quintile (Minutes/Day) - Aggregate Northeast Region			
Gender	**Quintile**	**Median TRL (Min)**	**Median S.E.**
Female	Q1 (Lowest)	330	10.2

Female	Q2	360	7.6
Female	Q3	345	7.6
Female	Q4	315	7.6
Female	Q5 (Highest)	285	6.4
Male	Q1 (Lowest)	15	7.6
Male	Q2	15	7.6
Male	Q3	0	7.6
Male	Q4	0	7.6
Male	Q5 (Highest)	0	5.1

Table 3. Median TRL by Income Quintile (Minutes/Day), Aggregate Northeast Region.

Table 3 shows that women display a clear inverse income gradient in unpaid work: median TRL declines from 330 minutes in the lowest quintile to 285 minutes in the highest quintile. Men's median TRL remains near zero across all quintiles. This pattern suggests that as household resources increase, women's time in unpaid work decreases marginally, while men's participation remains negligible.

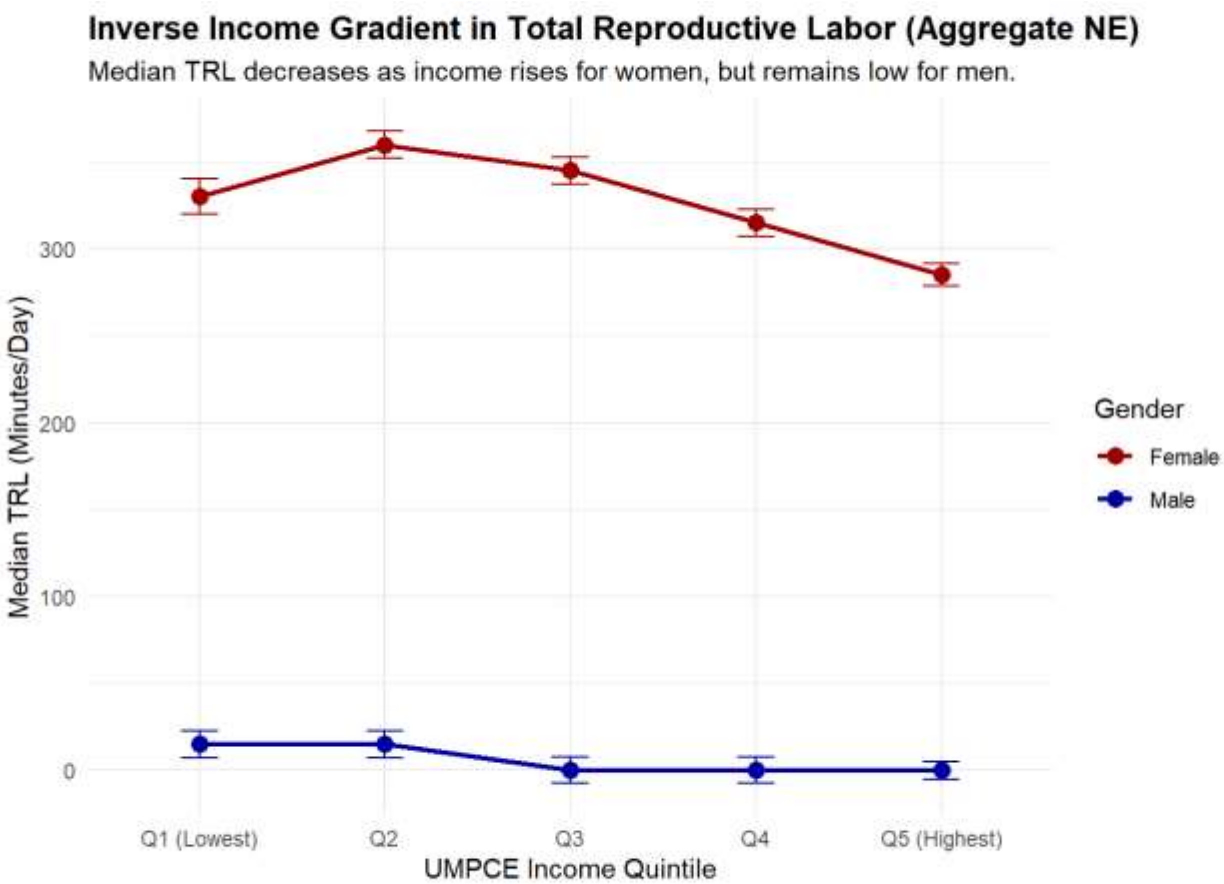

Figure 1. Inverse Income Gradient in Total Reproductive Labour (Aggregate Northeast).

Comment: The plotted lines in figure 1 show a downward slope for women across income quintiles and a nearly flat line near zero for men.

Participation Rates in Unpaid Work

State_Name	Gender_Label	UDS Rate (%)	UDS S.E.	UCS Rate (%)	UCS S.E.
Arunachal Pradesh	Female	89.5	0.9	63.9	2.4
Arunachal Pradesh	Male	53.0	2.7	32.3	2.9
Assam	Female	80.7	0.6	38.6	0.9
Assam	Male	34.3	1.0	22.6	0.9
Manipur	Female	78.6	1.1	40.9	2.0
Manipur	Male	30.8	1.7	32.6	1.7
Meghalaya	Female	81.9	0.9	43.5	1.6
Meghalaya	Male	40.6	1.9	17.1	1.2
Mizoram	Female	90.4	0.6	53.8	2.2
Mizoram	Male	35.7	2.5	29.7	2.2
Nagaland	Female	85.6	0.9	41.9	1.6
Nagaland	Male	52.0	1.9	30.9	1.4
Sikkim	Female	89.5	1.0	37.3	2.2
Sikkim	Male	58.0	1.9	24.9	1.9
Tripura	Female	83.0	0.7	35.0	1.1
Tripura	Male	35.0	1.4	21.3	1.3

Table 4. Weighted Participation Rates in Unpaid Social Reproduction (Percentage, Age 6+).

In this table 4 it shows that women's participation in unpaid domestic services (UDS) is nearly universal, exceeding 80–90% in every state. In contrast, men's participation rarely exceeds 50%, and falls as low as 30–35% in several states. Participation in unpaid caregiving (UCS) is lower overall but follows similar gendered patterns. These findings confirm that the gender gap in unpaid work stems not only from intensity (time spent) but also from participation incidence.

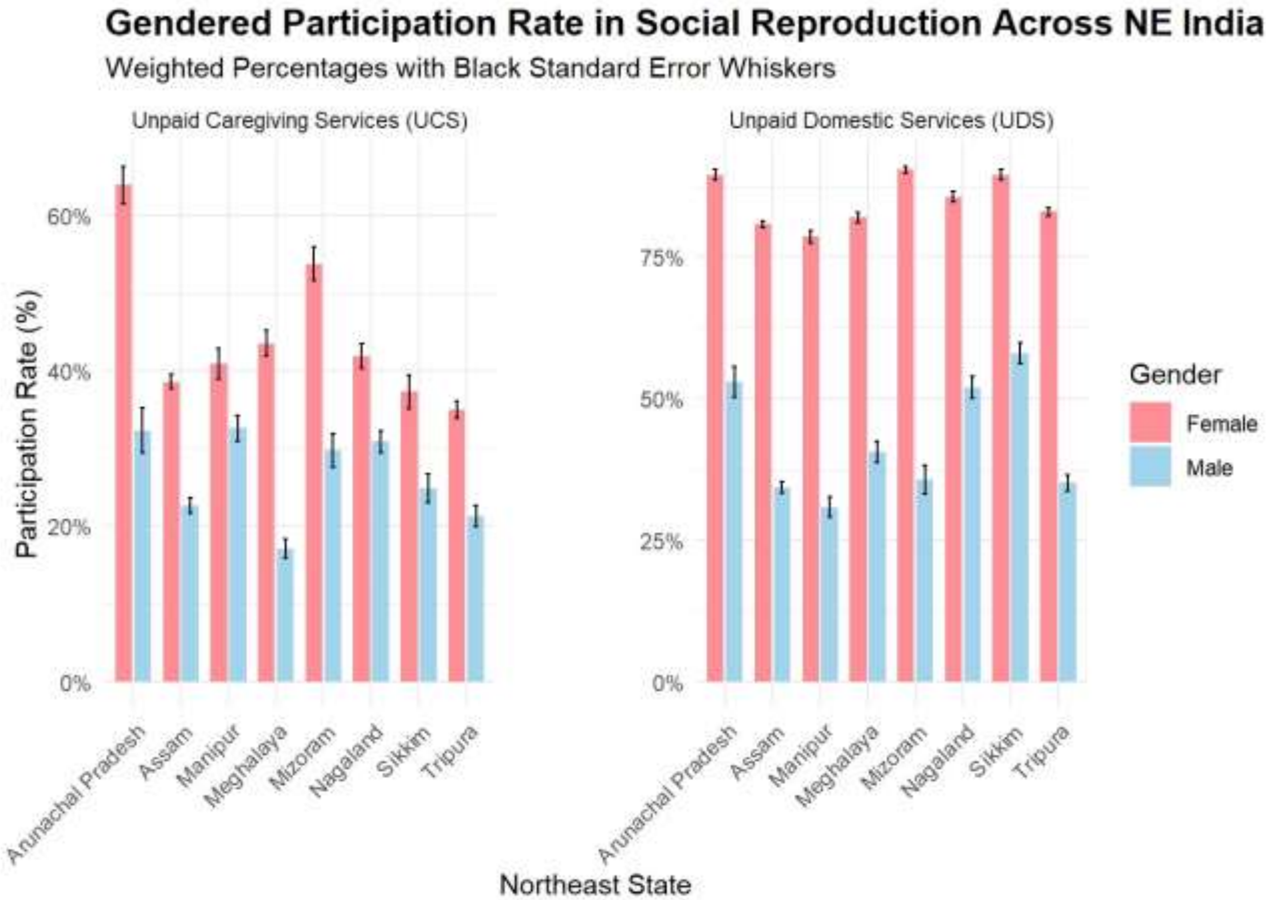

Figure 2. Gendered Participation Rate in Social Reproduction Across Northeast India.

Bar chart in figure 2 shows that female rates is consistently higher than that of male rates for both UDS and UCS, with standard error whiskers.

Bayesian Quantile Regression Results

Pooled Interaction Model (τ = 0.25, 0.50, 0.75)

Bayesian Quantile Regression: Pooled Interaction Model (τ=0.25, 0.50, 0.75)						
Coefficient	Mean (τ=0.25)	95% CI (τ=0.25)	Mean (τ=0.50)	95% CI (τ=0.50)	Mean (τ=0.75)	95% CI (τ=0.75)
(Intercept)	**11.75**	(7.20, 15.90)	**137.03**	(135.80, 139.50)	**160.85**	(157.90, 163.75)
UMPCE_Quintile_ClassQ2	**7.58**	(1.20, 13.91)	**4.77**	(3.40, 6.20)	**4.9**	(3.70, 6.37)
UMPCE_Quintile_ClassQ3	**-4.3**	(-11.00, 2.20)	**-5.9**	(-8.40, -4.30)	**-1.81**	(-3.27, 0.01)

UMPCE_Quintile_ClassQ4	**-23.37**	(-30.60, -16.20)	**-13.78**	(-15.20, -12.40)	**-17.55**	(-18.60, -16.30)
UMPCE_Quintile_ClassQ5 (Highest)	**-45.05**	(-53.30, -37.00)	**-35.77**	(-37.40, -34.30)	**-27.55**	(-28.60, -26.30)
Gender_LabelMale	**-271.07**	(-272.70, -269.00)	**-342.41**	(-344.00, -341.00)	**-386.76**	(-388.00, -385.00)
Age_Numeric	**16.1**	(15.90, 16.40)	**15.29**	(15.10, 15.50)	**18.89**	(18.50, 19.20)
I(Age_Numeric^2)	**-0.21**	(-0.21, -0.20)	**-0.21**	(-0.21, -0.20)	**-0.26**	(-0.26, -0.25)
Sector_Factor2	**8.38**	(7.78, 9.01)	**7.78**	(7.01, 8.53)	**-9.06**	(-9.68, -8.37)
UMPCE_Quintile_ClassQ2:Gender_LabelMale	**-12.44**	(-14.70, -10.10)	**-11.77**	(-14.30, -9.16)	**-11.76**	(-13.70, -9.68)
UMPCE_Quintile_ClassQ3:Gender_LabelMale	**-4.03**	(-6.21, -2.30)	**-9.34**	(-11.30, -7.28)	**-14.63**	(-17.00, -12.00)
UMPCE_Quintile_ClassQ4:Gender_LabelMale	**17.15**	(14.90, 19.20)	**11.24**	(9.77, 12.70)	**6.64**	(5.25, 7.88)
UMPCE_Quintile_ClassQ5 (Highest):Gender_LabelMale	**35.21**	(32.90, 37.30)	**25.18**	(23.10, 27.20)	**16.63**	(14.50, 18.70)

Table 5. Bayesian Quantile Regression: Pooled Interaction Model (τ = 0.25, 0.50, 0.75).

The pooled Bayesian quantile regression results, as shown in table 5, reveal a consistent negative association between

income quintile and TRL across quantiles, stronger at the upper tail (τ = 0.75). Compared to the lowest quintile (Q1), the highest quintile (Q5) exhibits reductions of approximately −45 min (τ = 0.25) to −28 min (τ = 0.75).
Gender effects are large and robust: the coefficient for *Male* is −271 min at τ = 0.25 and rises in magnitude to −387 min at τ = 0.75, implying that men perform substantially less unpaid labour than women even among high-burden households. Age has a concave relationship with TRL—positive at lower ages and flattening or reversing at older ages, as captured by the negative quadratic term.

Gender-Specific Median Models (τ = 0.50)

Bayesian Quantile Regression: Gender-Specific Median (*τ*=0.50) Models				
Coefficient	Mean (Female, *τ*=0.50)	95% CI (Female, *τ*=0.50)	Mean (Male, *τ*=0.50)	95% CI (Male, *τ*=0.50)
(Intercept)	**-633.39**	(-637.783, -8.715)	**-100.78**	(-102.385, -1.410)
UMPCE_Quintile_ClassQ2	**-6.86**	(-8.715, -637.783)	**-0.54**	(-102.385, -1.410)
UMPCE_Quintile_ClassQ3	**-13.07**	(-8.715, -637.783)	**-6.47**	(-102.385, -1.410)
UMPCE_Quintile_ClassQ4	**-18.99**	(-8.715, -637.783)	**-6.5**	(-102.385, -1.410)
UMPCE_Quintile_ClassQ5 (Highest)	**-29.68**	(-8.715, -637.783)	**-10.86**	(-102.385, -1.410)
Age_Numeric	**60.21**	(-8.715, -637.783)	**8.07**	(-102.385, -1.410)
I(Age_Numeric^2)	**-0.8**	(-8.715, -637.783)	**-0.1**	(-102.385, -1.410)
Sector_Factor2	**-28.8**	(-8.715, -637.783)	**4.36**	(-102.385, -1.410)

Table 6. Bayesian Quantile Regression: Gender-Specific Median (τ = 0.50) Models.

Among women, higher income quintiles are associated with progressively lower TRL, confirming the inverse gradient. The coefficient for the top quintile is approximately **−29.7 minutes**, significant within the 95% credible interval. Age exerts a strong positive effect up to mid-life, followed by a flattening slope. For men, coefficients are smaller in magnitude, with weak associations between income and TRL. The urban-rural sector effect indicates that rural women spend roughly **29 minutes more** in reproductive labour relative to urban counterparts, consistent with reduced access to market substitutes for household work.

Quantile Comparison (τ = 0.25 vs 0.75)

Bayesian Quantile Regression: Comparison of Coefficients (τ=0.25 vs τ=0.75)

Coefficient	τ=0.25 (Lower Burden)		τ=0.75 (Upper Burden)	
	Mean	95% CI	Mean	95% CI
(Intercept)	**11.75**	(7.20, 15.90)	**161**	(158.00, 165.00)
UMPCE_Quintile_ClassQ2	**7.55**	(1.20, 13.70)	**4.92**	(3.70, 6.37)
UMPCE_Quintile_ClassQ3	**-5.94**	(-11.00, -2.10)	**-1.86**	(-3.27, 0.25)
UMPCE_Quintile_ClassQ4	**-23.4**	(-27.20, -19.20)	**-17.6**	(-18.60, -16.20)
UMPCE_Quintile_ClassQ5 (Highest)	**-45.1**	(-47.00, -37.30)	**-27.5**	(-28.60, -26.30)
Gender_LabelMale	**-271**	(-272.00, -269.00)	**-387**	(-388.00, -385.00)
Age_Numeric	**16.1**	(15.90, 16.40)	**18.9**	(18.70, 19.00)
I(Age_Numeric^2)	**-0.21**	(-0.21, -0.20)	**-0.26**	(-0.26, -0.25)
Sector_Factor2	**8.38**	(7.78, 9.01)	**-9.06**	(-9.68, -8.38)
UMPCE_Quintile_ClassQ2:Gender_LabelMale	**-12.4**	(-14.70, -10.10)	**-11.8**	(-13.70, -9.68)

UMPCE_Quintile_ClassQ3:Gender_LabelMale	**-4.03**	(-6.22, -1.90)	**-14.6**	(-17.00, -12.10)
UMPCE_Quintile_ClassQ4:Gender_LabelMale	**17.1**	(14.90, 19.20)	**6.66**	(5.25, 7.88)
UMPCE_Quintile_ClassQ5 (Highest):Gender_LabelMale	**35.2**	(32.90, 37.30)	**16.6**	(14.50, 18.70)

Table 7. Bayesian Quantile Regression: Comparison of Coefficients (τ = 0.25 vs τ = 0.75).

At the lower quantile (τ = 0.25), representing individuals with lighter unpaid work burdens, income gradients are modest. However, at τ = 0.75, corresponding to high-burden households, the negative income effect is larger, and the gender gap widens. This suggests that income moderates unpaid labour primarily among those already heavily engaged in domestic and care work.

Bayesian Quantile Regression: Comparison of Coefficients (τ=0.25 vs τ=0.75)

Coefficient	Tau_0.25_Mean	Tau_0.75_Mean	Tau_0.25_CI_Formatted	Tau_0.75_CI_Formatted
character	character	character	character	character
	τ = 0.25 (Lower Burden)	τ = 0.25 (Lower Burden)	τ = 0.75 (Upper Burden)	τ = 0.75 (Upper Burden)
Coefficient	Mean	95% CI	Mean	95% CI
(Intercept)	11.7501835253079	160.84826563092	(15.955, 5.327)	(164.654, 3.196)

Bayesian Quantile Regression: Comparison of Coefficients (τ=0.25 vs τ=0.75)

Coefficient	Tau_0.25_Mean	Tau_0.75_Mean	Tau_0.25_CI_Formatted	Tau_0.75_CI_Formatted
character	character	character	character	character
UMPCE_Quintile_ClassQ2	7.58206617784591	4.89522858098837	(15.955, 5.327)	(164.654, 3.196)
UMPCE_Quintile_ClassQ3	-4.29862098955566	-1.81210041638019	(15.955, 5.327)	(164.654, 3.196)
UMPCE_Quintile_ClassQ4	-23.3690830851455	-17.5546010283981	(15.955, 5.327)	(164.654, 3.196)
UMPCE_Quintile_ClassQ5 (Highest)	-45.0516390627547	-27.5486782795687	(15.955, 5.327)	(164.654, 3.196)
Gender_LabelMale	-271.073388798741	-386.757178148186	(15.955, 5.327)	(164.654, 3.196)
Age_Numeric	16.1027779468367	18.8875017071739	(15.955, 5.327)	(164.654, 3.196)
I(Age_Numeric^2)	-0.20988083161507	-0.255140527899305	(15.955, 5.327)	(164.654, 3.196)
n: 16				

Figure 3. Comparison of Quantile Coefficients (τ = 0.25 vs τ = 0.75).

In figure 3 the plotted coefficients show steeper declines for income quintiles and greater negative gender effects at higher quantiles.

Discussion

Gender and the Persistence of Reproductive Asymmetry

Despite the Northeast's distinctive cultural context—where matrilineal inheritance or greater female social visibility is sometimes assumed—the data demonstrate that gendered inequalities in unpaid labour are both pervasive and pronounced. The female-to-male ratios of reproductive labour range from 4:1 to over 10:1, paralleling or exceeding national averages. These findings complicate the popular perception of the Northeast as a more gender-equal region, revealing that symbolic or cultural matriliny does not necessarily translate into equal distribution of domestic labour (Nikore, 2022).

Income and Social Stratification

The inverse income gradient observed among women aligns with broader evidence that economic resources enable partial substitution of unpaid work through market goods and services (Samantroy, 2017). However, the magnitude of decline—less than one hour across quintiles—indicates that even affluent women in the region remain significantly burdened. For men, the flat profile across quintiles underscores that income growth alone does not incentivise greater male participation in care or domestic work.

Quantile Heterogeneity and Policy Implications

By modelling quantiles rather than means, this study highlights distributional heterogeneity often concealed in average effects. The steep gender differential at $\tau = 0.75$ implies that interventions targeted at high-burden households—those where women perform over five hours of unpaid work daily—would yield the greatest equity gains.

Policy measures should focus on expanding *infrastructural supports for care* (e.g., community childcare centres, elderly-care programmes) and promoting *time-saving technologies* in rural areas. Moreover, awareness campaigns and workplace policies must address entrenched gender norms that render unpaid work a "natural" female responsibility.

Methodological Considerations

The Bayesian quantile regression approach offers several advantages over classical least squares. It permits full posterior inference for each quantile, accommodates survey weights, and produces robust estimates under non-normality and heteroscedasticity. Nevertheless, it also entails limitations. The analysis here uses person-day data, which capture short-term activity patterns rather than persistent behaviour (Stewart, 2018). Future work could integrate multi-day diaries or longitudinal surveys to examine intra-household temporal dynamics.

Conclusion

This article provides one of the first comprehensive, survey-weighted, Bayesian quantile analyses of gendered time use in Northeast India. The findings reveal stark gender gaps in both participation and intensity of unpaid work, modest but consistent inverse income gradients among women, and minimal male involvement across the distribution. The heterogeneity uncovered through quantile analysis underscores the importance of moving beyond mean-based indicators when assessing social reproduction.

From a theoretical standpoint, the results reaffirm that gendered divisions of labour are deeply embedded within the social fabric, transcending economic strata and regional cultural differences. As the empirical evidence from the TUS 2024 demonstrates, the daily time women spend sustaining households and communities remains a crucial yet invisible foundation of economic and social life. Recognising, redistributing, and reducing this unpaid burden are essential for any meaningful pursuit of gender equality and inclusive development.

Notes

1. The TUS 2024 collects data for one reference day per respondent. While this captures broad patterns, day-to-day variability may attenuate observed relationships.
2. *Unpaid domestic services (UDS)* include cooking, cleaning, washing, and related household chores; *unpaid caregiving services (UCS)* include child, elder, and sick care.
3. Bayesian quantile regression was implemented via the bayesQRsurvey package with MCMC sampling; convergence diagnostics (trace plots and posterior densities) confirmed stability.
4. All tables and figures referred to in text are derived from the author's empirical outputs (R scripts and TUS 2024 data).

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