Valuing Unpaid Work in Bangladesh: Evidence from Time Use and Labour Force Surveys

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Abstract

This study quantifies the monetary value of unpaid work in Bangladesh by integrating data from the Bangladesh Time Use Survey (TUS) 2021 and the Labour Force Survey (LFS) 2022. Despite its significant contribution to household welfare and the economy, unpaid work remains excluded from official national accounts. Grounded in Becker's (1965) theory of time allocation, the analysis applies the opportunity cost approach to impute potential market wages for individuals' unpaid hours using standard Mincer wage equations estimated from the LFS. The results show that unpaid work accounts for approximately 21.2 percent of Bangladesh's GDP, with women contributing about 81 percent of this value. The results also reveal pronounced gender, educational, and rural–urban disparities in time allocation and unpaid work value, highlighting the disproportionate burden borne by women and suggesting an unequal allocation of time between market and non-market activities. Overall, the findings underscore that Bangladesh's productive capacity extends beyond market transactions and indicate that existing patterns of unpaid work reflect potential labour misallocation with important policy implications for promoting gender equality, expanding care infrastructure, and advancing Sustainable Development Goal.

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1 Introduction

In 2025, the Government of Bangladesh announced plans to formally include the monetary value of unpaid domestic and care work in the country's national income accounts.[1] This landmark initiative represents a major step towards recognizing the vast but historically invisible economic contribution of household labour, most of which is performed by women. By expanding the concept of economic production to include activities outside the market, this policy acknowledges that unpaid domestic and care work constitutes a significant yet undervalued component of the economy. According to estimates by the International Labour Organization (ILO), unpaid domestic and care work can amount to more than 40 percent of GDP in some countries, when valued in monetary terms.[2] For Bangladesh, where women spend disproportionately more time on household and caregiving activities than men, the integration of unpaid work into official statistics has substantial implications for both gender equality and the measurement of economic activity.

Over the past two decades, Bangladesh has made remarkable progress in poverty reduction, female literacy, and labour-force participation. However, persistent gender disparities remain in the division of labour. According to the Bangladesh Time Use Survey (TUS) 2021, women spend about six hours per day on unpaid domestic and care activities, while men spend less than one hour. These patterns are reinforced by traditional gender norms, inadequate childcare facilities, and limited access to paid employment for women. As a result, a substantial portion of women's productive time is absorbed by non-market work, restricting their economic participation and leading to the underestimation of national output.

Unpaid work forms the backbone of social and economic life.[3] Sousa-Poza, Widmer, and Schmid (1999) argue that unpaid work generates wealth and contributes substantially to household welfare, yet remains outside the production boundary of national accounts. Similarly, Varjonen, Hamunen, and Soinne (2014) emphasize that household production—unpaid services produced for own consumption—constitutes a major share of total production excluded from official GDP measures. Moreover, Folbre and Nelson (2000) highlight that unpaid care work contributes to the formation of human and social capital, thereby sustaining long-term economic growth.

1. The Daily Star (2025), *Women's unpaid work to finally get recognised.*

2. International Labour Organization, *Why Measuring Unpaid Domestic and Care Work Matters, and How We Can Help*, ILOSTAT, n.d.

3. Unpaid work refers to productive activities that generate goods or services but receive no direct monetary compensation. Budlender and Moussié (2013) define unpaid work as domestic and care work performed for household and family members—such as cooking, cleaning, caring for children, the elderly, or the sick—as well as voluntary community work. Although unpaid, these activities are indispensable for maintaining households and supporting the paid economy.

The analytical framework of this study is grounded in Becker's (1965) theory of time allocation, which views households as producers and consumers who allocate a fixed amount of time among market work, household production, and leisure to maximize utility. In this framework, time spent on unpaid domestic and care activities carries an opportunity cost—the income forgone from paid employment. Building on this idea, the opportunity cost approach used in this study estimates a monetary value for unpaid work based on predicted market wages. In the Bangladeshi context, this study addresses the question: What is the monetary value of unpaid work in Bangladesh, and what does it reveal about the allocation of time between market and non-market activities across gender, education, location, and key household characteristics? Addressing this question is important for recognizing the economic contribution of unpaid labour and for understanding how gendered time allocation may reflect underlying inefficiencies in the use of labour and time within the economy. By combining time use and labour force survey data, the analysis connects household production to the formal labour market and demonstrates that both paid and unpaid work contribute to the overall growth of the economy.

The recognition of unpaid work is integral to the 2030 Agenda for Sustainable Development, particularly Sustainable Development Goal (SDG) 5.4, which calls on countries to "recognize and value unpaid care and domestic work through the provision of public services, infrastructure and social protection policies, and the promotion of shared responsibility within the household."[4] Indicator 5.4.1 requires the proportion of time spent on unpaid domestic and care work, disaggregated by sex, age, and location. In response to this global mandate, the Bangladesh Bureau of Statistics (BBS) conducted the country's first Time Use Survey (TUS) in 2021. According to Esquivel et al. (2008), time-use surveys have a distinct advantage over conventional household surveys in capturing unpaid care work and the interdependence between work and non-work activities. Valuing unpaid work through such data is therefore a critical step towards achieving gender equality and inclusive growth. This research is particularly timely, given Bangladesh's 2025 plan to integrate unpaid work into GDP.

This study provides an up-to-date and methodologically consistent estimate of unpaid work in Bangladesh. It not only quantifies the total value of unpaid domestic and care work but also examines its demographic and socioeconomic determinants, gender distribution within households, and overall contribution to GDP. Specifically, the analysis estimates wage equations using LFS 2022, imputes predicted wages for TUS 2021 individuals, values unpaid work using the opportunity cost method, analyzes demographic and socioeconomic determinants and quantifies the share of unpaid work in GDP.

4. United Nations (2015). *Transforming our world: The 2030 Agenda for Sustainable Development.*

Despite growing recognition of unpaid work in academic and policy discussions, its empirical valuation in Bangladesh remains limited. Recent work by the United Nations Economic Commission for Europe (2024) combined the Time Use Survey (TUS) 2021 and the Labour Force Survey (LFS) 2022 to estimate the value of unpaid work using the replacement cost method.[5] This approach assigns market wages of equivalent paid occupations—such as domestic helpers, cleaners, or childcare providers—to unpaid activities, thereby estimating what it would cost to replace unpaid labour with hired services. However, it does not account for the opportunity cost of time—the income individuals forgo by not engaging in paid employment. The present study addresses this gap by adopting the opportunity-cost approach and integrating nationally representative microdata from the TUS 2021 and LFS 2022, enabling a more robust and policy-relevant valuation of unpaid domestic and care work in Bangladesh.

Although the importance of unpaid work has long been recognized in research and policy discourse, previous national estimates were based on small-scale or outdated surveys, providing only partial insight into women's unpaid contributions. The introduction of the TUS 2021 and LFS 2022 offers a major advancement. While recent attempts relied on the replacement-cost approach, this paper applies the opportunity-cost method, valuing unpaid work according to individuals' potential earnings predicted from labour-market wage structures. This method captures the forgone income associated with time spent on unpaid activities and offers a more comprehensive assessment of Bangladesh's total economic output.

This study presents the first opportunity cost-based valuation of unpaid work in Bangladesh. It advances existing empirical approaches through a two-step wage imputation that accounts for gender and area heterogeneity and extends the analysis to explore differences within households. The results show that unpaid work constitutes a major component of Bangladesh's economy, equivalent to about one-fifth of GDP, with women contributing the vast majority of this value. Education, rural residence, and the presence of young children are found to significantly influence the distribution of unpaid work across households. The findings offer policy insights for incorporating unpaid work into national accounts and advancing gender-responsive economic planning.

By quantifying the contribution of unpaid work to GDP, this paper highlights that Bangladesh's productive capacity extends beyond market transactions. Recognizing this contribution is crucial for promoting a more equitable division of labour, strengthening social protection for unpaid caregivers, and enhancing women's participation in paid employment.

5. United Nations Economic Commission for Europe (2024). *Measuring the Value of Unpaid Household Work in Bangladesh.* Prepared by the Asian Development Bank.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature, Section 3 describes the data, Section 4 outlines the methodology, Section 5 presents the results, Section 6 discusses policy recommendations, and Section 7 concludes.

2 Literature Review

This review summarizes findings from key studies examining the measurement and determinants of unpaid domestic and care work, with particular emphasis on gender differences, socioeconomic factors, and regional variations in South Asia and Bangladesh.

Since the 1970s, many countries have developed various methodological frameworks to quantify the magnitude and value of unpaid work. However, Aguirre and Ferrari (2014, as cited in Ospina-Cartagena and García-Suaza (2020)) note that measuring such work poses a significant challenge, as they are not traded in the market and therefore lack observable prices. From a theoretical perspective, Becker (1965), in his Theory of the Allocation of Time, provides a foundation for understanding how individuals allocate time among paid work, household production and leisure. These time-use decisions ultimately determine individuals' labor market status and respond to relative prices of goods and labor. Becker (1965) argues that time itself is an economic resource with an implicit value determined by the forgone earnings from alternative uses. He further notes that the opportunity cost of time varies across activities and contexts—for example, the cost of time may be lower on weekends or evenings when market work is unavailable. By treating households as both producers and consumers who combine time and goods to produce household commodities, Becker introduces the concept of full income, which includes money income and the value of forgone earnings. Building on Becker's (1965) framework, Folbre (1986), Ilahi (2000), and Daunfeldt and Hellström (2007) emphasize that time allocation decisions are influenced not only by relative wages and productivity but also by broader social and institutional factors, including family composition.

As outlined by Besporstov and Sinclair (2022), the economic valuation of unpaid household work typically relies on either output-based or input-based approaches. The output-based method assigns a market value to the goods and services produced within households, based on their equivalent purchase prices in the market. However, most empirical studies adopt input-based methods, which value the labour time devoted to unpaid work using appropriate wage rates. Within the input-based framework, two main valuation methods are used. The opportunity cost approach measures the value of unpaid work using the wage rates of the actual individuals performing the unpaid activities, thereby reflecting the income they forgo by not engaging in paid employment. In contrast, the replacement cost approach esti-

mates what it would cost to hire someone to perform the same tasks, using either generalist wages (e.g., for domestic helpers) or specialist wages (e.g., for cooks, childcare providers, or cleaners) corresponding to each activity. Unlike the opportunity cost method, the replacement cost method does not depend on the individual's own wage rate but rather on the market wage of a substitute. While the replacement cost method assumes equal productivity between household members and market workers, the opportunity cost method incorporates labour market inequalities, such as gender wage gaps.

The International Labour Organization (2018) estimates that unpaid domestic and care work constitutes a substantial but largely invisible component of global economic activity. When valued at hourly minimum wages, such work amounts to approximately USD 11 trillion, equivalent to about 9 percent of global GDP.[6] Ferrant and Thim (2019) report that, at the country level, the share is even higher, ranging from 14 percent in South Africa and Canada to 23 percent in Argentina, France, and New Zealand, and reaching up to 33 percent in China. The authors further find that women undertake more than 75 percent of unpaid household work worldwide, indicating that much of the unpaid work in the global economy is carried out by women.

Despite overall economic growth, gender disparities in unpaid work remain pervasive. Ferrant and Thim (2019) observe that, globally, women spend about three times more hours on unpaid care work than men, with the imbalance ranging from 1.5 times in North America to as high as 6.7 times in South Asia. Ferrant, Pesando, and Nowacka (2014) argue that increases in GDP do not automatically lead to a more equitable redistribution of unpaid labor. Although rising incomes and improvements in infrastructure can reduce women's time spent on physically demanding household tasks, such as fetching water, men's participation in unpaid care work tends to rise only marginally. These findings suggest that economic progress alone is insufficient to overcome entrenched gendered divisions of labour without targeted policies addressing care responsibilities and social norms.

Esplen (2009) emphasizes that women's unpaid work significantly restricts their access to education, income, and political participation, thereby perpetuating cycles of gender inequality. The author argues that unpaid care work is both time-intensive and undervalued, placing a disproportionate burden on women, particularly those in low-income households who cannot afford paid care services. Although women's unpaid labour sustains the functioning of the market economy, it continues to be excluded from formal measures of productivity and national output.

The imbalance in unpaid care work is particularly pronounced in South Asia, which includes Afghanistan, Bangladesh, Bhutan, India, Pakistan, the Maldives, Sri Lanka, and

6. International Labour Organization (2018), *Care Work and Care Jobs for the Future of Decent Work*.

Nepal.[7] Women in the region devote an average of 7.7 hours per day to unpaid care and domestic activities, approximately seven times more than men.[8] Bhopal (1997) attributes this disparity to deep-rooted patriarchal norms and the "cultural typing" of care roles that confine women's activities largely to domestic spaces. Across the region, women remain primarily responsible for cooking, cleaning, and caregiving, while men continue to dominate paid employment and public life.

Bhopal (1997) further finds that structural and institutional factors continue to reinforce gendered divisions of labor across South Asia. For instance, in Pakistan, Ali et al. (2022) find that early marriage and limited access to formal employment opportunities often confine women to unpaid caregiving roles. Matta (2019) adds that the absence of laws mandating paternity leave throughout the region perpetuates the assumption that men are the primary economic providers. Similarly, Mukherjee (2017) observes that social protection systems and labour policies are typically designed around men's employment risks, leaving women's unpaid contributions outside the scope of economic policy. Such institutional biases perpetuate the invisibility of unpaid work, despite its central role in sustaining households and the wider economy.

Ferrant and Thim (2019) argue that rural women face compounded burdens of unpaid work due to limited infrastructure and access to services. Their evidence from Ethiopia, Peru, and South Africa indicates that rural women spend substantially more time on routine domestic tasks than their urban counterparts—by 39, 42, and 24 minutes per day, respectively. Dutta (2018) similarly observes that in South Asia, inadequate access to water, fuel, and childcare services compels women to devote longer hours to subsistence-related activities.

Raihan and Bidisha (2018) argue that women's participation in the labour market is widely recognized as critical for improving women's economic status and enhancing overall economic efficiency and inclusive growth. However, persistent gender norms and mobility restrictions continue to limit women's access to paid employment, keeping their labour force participation below its potential despite their substantial contributions through unpaid domestic and care work. According to the Labour Force Survey (LFS) 2022, the total female labour force participation rate (FLFP) increased from 36.0% in 2010 to 42.8% in 2022, but this overall increase masks a growing rural–urban divergence: rural FLFP rose sharply from 36.4% to 51.0%, while urban FLFP declined from 34.5% to 23.7% over the same period.

In Bangladesh, the burden of unpaid work is deeply rooted in patriarchal social structures that define and constrain women's roles within the household. Paul (1992) notes that

7. United Nations Statistical Division (2017), *Strengthening Statistical Capacity in Support of Progress towards the Internationally Agreed Development Goals in Countries of South Asia.*

8. United Nations Economic and Social Commission for Asia and the Pacific (2019), *Unpaid Work in Asia and the Pacific.*

gendered time allocation is strongly influenced by women's limited activity space in rural areas, where their daily activities are largely confined to the domestic sphere. Women perform a wide range of household tasks, including cooking, cleaning, fetching water, childcare, elder care, poultry and cattle rearing, kitchen gardening, and maintenance of the homestead, while men engage primarily in income-generating work conducted in public spaces. Building on this, Paul (1992) and Kabeer (2018) argue that these gendered divisions of labour are sustained by deep-rooted social norms and expectations that associate caregiving and domestic responsibilities with women.

Historically, Bangladesh has been central to the discussion of women's unpaid labour. Hamid (1996) conducted one of the earliest empirical attempts to estimate the value of unpaid work within the national accounts. The analysis suggested that if unpaid work were included, Bangladesh's GDP in 1989/90 would have increased by approximately 29 percent. Hamid (1996) also estimated that women's contribution to national production would rise from 25 to 41 percent, while men's share would decline from 75 to 59 percent. Moreover, the study revealed that conventional GDP measures captured nearly all of men's production but less than half of women's, and that women accounted for 89 percent of total time spent on non-market work, compared to only 11 percent by men.

Overall, the literature demonstrates that unpaid work represents a substantial yet undervalued component of economic activity, particularly in emerging economies such as Bangladesh. While earlier studies, including Hamid (1996), provided important initial estimates, they were limited by small-scale data and methodological constraints and did not incorporate recent methodological advances or nationally representative surveys. More recent advances, including the introduction of nationally representative time use and labour force surveys, now make it possible to produce more accurate and policy-relevant valuations. However, empirical work in Bangladesh has so far relied primarily on the replacement cost approach, leaving a gap in understanding the opportunity cost of unpaid work and its distribution across gender, education, and location, an issue this study seeks to address.

3 Data

This study uses two nationally representative datasets: the Bangladesh Time Use Survey 2021 (TUS 2021) and the Bangladesh Labour Force Survey 2022 (LFS 2022). Both surveys are conducted by the Bangladesh Bureau of Statistics (BBS), the national statistical office responsible for producing official statistics. The raw microdata were obtained directly from BBS and processed for analysis.

The two datasets are complementary. The TUS 2021 provides detailed information on

how individuals allocate their time across various activities, including unpaid domestic and care work, but does not contain wage or earnings data. In contrast, the LFS 2022 contains detailed labour market and earnings data but does not record time use. Combining the two datasets allows for imputing wages for TUS respondents based on characteristics observed in both datasets and determining a monetary value for their unpaid work, thereby enabling an evaluation of its contribution to the economy.

3.1 Time Use Survey 2021

The Bangladesh Time Use Survey 2021 was the country's first nationally representative time-use survey. Its primary goal was to capture how men and women allocate their time across productive, unproductive, and unpaid activities, with particular attention to making women's unpaid domestic and care work visible in official statistics. To ensure international comparability, the survey adopted the International Classification of Activities for Time Use Statistics (ICATUS 2016), developed by the United Nations Statistics Division.

Data collection involved two instruments:

(a) Household questionnaire: capturing demographic and socioeconomic characteristics such as age, sex, education, and employment status.

(b) Individual time diary: recording all activities performed over a 24-hour reference period for each household member aged 15 years and older, including secondary activities.

All reported activities were coded according to ICATUS categories, allowing for standardized measurement of time use. For this study, the sample is restricted to individuals aged 15–65 to maintain comparability with the LFS and to exclude elderly respondents with very low labour market participation. The final estimating sample for this study comprises 13,038 individuals, of whom 69% are female, 31% are male, 70% reside in rural areas and 30% reside in urban areas. Key variables constructed from this dataset include paid hours per day, unpaid hours per day, predicted hourly wage, and daily unpaid work value (Table 3). All time-use measures are recorded on a daily basis from 24-hour diaries, and are later aggregated to weekly and annual values in the valuation stage.

3.2 Labour Force Survey 2022

The Bangladesh Labour Force Survey (LFS) is a household-based survey historically conducted every four to five years since 1980. Beginning in 2015, it was redesigned to a quarterly format to provide more frequent labour market indicators. The LFS 2022 annual dataset combines data from all four quarters—January–March, April–June, July–September, and

October–December—producing nationally representative estimates of labour force participation, employment, unemployment, and earnings.

The LFS 2022 collects detailed information on individuals aged 15 years and older, including labour force status, occupation, industry, hours worked, and monthly earnings from both main and secondary jobs. For this analysis, the sample was restricted to individuals aged 15–65 with non-missing information on key variables (wages, hours worked, education, sex, and location), resulting in a final estimating sample of 60,711 observations. Reported monthly earnings were later converted to hourly wages. Within this sample, 15% are female and 85% are male, with 49% living in urban areas and 51% in rural areas.

This section presents a comparison of key demographic characteristics between the LFS and the TUS, along with descriptive statistics on time use, paid and unpaid hours, and wages.

The demographic profiles of the two datasets are broadly comparable, though important differences emerge. The mean age of respondents is slightly higher in the TUS (36.8 years) than in the LFS (34.5 years), reflecting its inclusion of a greater share of older individuals within the 15–65 age range. A more striking difference is observed in the gender composition: women represent 69.4% of the TUS sample but only 15.5% of the LFS sample. This demonstrates the fact that the LFS estimation sample is restricted to individuals with positive earnings, whereas the TUS captures all individuals regardless of labour force participation. The rural share is also higher in the TUS (69.8%) compared to the LFS (50.8%), consistent with the TUS's household-based design that oversamples rural areas to capture unpaid work. These comparisons are summarized in Table 1.

The education profiles of the two datasets follow similar patterns, with the majority of respondents in both samples having completed primary or lower secondary schooling. However, the share of respondents with no formal education is substantially higher in the TUS (23.3% compared to just 1.1% in the LFS), again reflecting the inclusion of individuals outside the labour force. The LFS, by contrast, contains a higher proportion of respondents with post-secondary education, particularly at the graduate level. Table 2 reports the key variables for the LFS estimation sample, including log hourly wage, age, sex, rural/urban location, and education. The mean log hourly wage is 4.00, corresponding to an average observed wage of 71.6 BDT in levels (not shown in the table).

Tables 3 and 4 summarize key variables from the TUS 2021 estimation sample and present time-use patterns by sex and area. Individuals in the TUS spend an average of 2.4 hours per day in paid activities and 5.9 hours in unpaid domestic and care work. The predicted hourly wage is 52.4 BDT, which translates into an average daily value of unpaid work of 291.5 BDT (Table 3). Disaggregating paid and unpaid hours by sex and rural-urban location, it

is observed that women spend substantially more time on unpaid work than men (7.3 vs. 2.6 hours per day), while men spend more time in paid activities (5.3 vs. 1.1 hours per day). Rural respondents report slightly fewer paid hours, but more unpaid hours compared to their urban counterparts (Table 4).

Further breakdowns by education highlight the persistence of gender gaps across all groups. Women spend more than three times as many hours on unpaid work as men. Rural women report the highest unpaid work burden, averaging 7.5 hours per day, compared to 2.8 hours for rural men. A similar but slightly smaller gap is observed in urban areas.

Unpaid work hours also vary systematically with education. Among women, unpaid hours are highest for those with Class 1–5 and Class 6–9 education (7.7 and 7.6 hours, respectively), and somewhat lower for those with higher secondary or diploma-level education. Men's unpaid work shows little variation across education categories, remaining close to 2.5–2.7 hours per day. This pattern is evident in Table 5 and reinforces the conclusion that, regardless of education or location, women bear the overwhelming burden of unpaid work.

The wage comparisons (Table 6) confirm that, in both datasets, men earn substantially higher wages than women, and urban workers earn more than their rural counterparts. For instance, in the LFS sample, urban men earn an average of 82.1 BDT per hour, compared to 73.3 BDT for urban women; the rural wage gap is narrower but still present (63.48 vs. 60.22 BDT). Predicted wages for TUS are lower on average, but display a similar pattern of gender and rural–urban disparities.

4 Methodology

The analysis proceeds in several stages. The first stage involves estimating predicted hourly wages using data from the Bangladesh Labour Force Survey (LFS) 2022. Predicted hourly wages are estimated using standard Mincer regressions that include education and age as a proxy for experience, estimated separately for four sex–location subgroups. The estimated wage equations are then applied to the Bangladesh Time Use Survey (TUS) 2021 to impute wages for all individuals, including those not engaged in paid employment. Although both surveys are nationally representative, their target populations differ: the LFS covers labour-force participants while the TUS includes all individuals aged 15 and above, regardless of employment status. These imputed wages serve as the basis for valuing unpaid domestic and care work under the opportunity cost approach.

4.1 Data Preparation

The four quarterly datasets of the 2022 LFS were combined to create a single, nationally representative annual dataset. This aggregation provides a comprehensive overview of employment and wage structures over the year. To maintain comparability with the TUS, key variables such as age, sex, education, and rural–urban residence were aligned across the two datasets. The estimating sample was restricted to individuals aged 15–65, thereby focusing on the working-age population while excluding children and elderly individuals with negligible labour force participation. Binary variables were defined for sex (female = 1) and rural-urban residence (rural = 1), allowing the estimation to capture structural differences by sex and location. Education levels were standardized into seven categories: Class 1–5, Class 6–9, Secondary School Certificate (SSC), Higher Secondary Certificate (HSC), Diploma, Bachelor's degree, and Graduate degree to reflect Bangladesh's formal education system.

In the TUS 2021, activities were coded according to the International Classification of Activities for Time-Use Statistics (ICATUS 2016), which provides a globally comparable framework for measuring how individuals allocate time within a 24-hour period. Within this framework, time devoted to paid activities corresponds to ICATUS codes 100–199, whereas unpaid work encompasses codes 200–599. The latter includes:

(a) production of goods for own final use,

(b) unpaid domestic services for household and family members,

(c) unpaid caregiving services, and

(d) unpaid volunteer, trainee, and other unpaid work.

Total minutes in each category were calculated and converted to paid and unpaid hours per day.

4.2 Calculation of Hourly Wages

For the LFS 2022, hourly wages were derived from reported earnings. Total monthly earnings from both primary and secondary jobs were divided by total weekly hours worked, converted to a monthly equivalent using 4.345, the average number of weeks per month. This formulation ensures comparability across individuals with multiple income sources and irregular work schedules. Missing earnings in the main and secondary jobs were replaced with zeros, and weekly hours were set to zero for individuals reporting no earnings in either job to avoid losing observations due to non-response and to maintain sample representativeness. The corresponding wage equation is expressed as:

$$w = \frac{E_{\text{main}} + E_{\text{secondary}}}{4.345 \times (H_{\text{main}} + H_{\text{secondary}})} \tag{1}$$

where the numerator represents combined monthly earnings from the main and secondary jobs, and the denominator converts total weekly working hours to a monthly equivalent.

To improve estimation accuracy, age was demeaned within each of the four sex–location subgroups (urban females, rural females, urban males, and rural males). This transformation reduces multicollinearity between age and its squared term. All regressions were estimated using survey probability weights to ensure nationally representative results. Although the LFS and TUS differ in sample composition, particularly in gender and rural–urban representation, the use of these weights corrects for such differences and ensures that estimates reflect the national population.

4.3 Wage Regression Model

The estimation of hourly wages proceeds in two steps. In the first step, separate wage equations are estimated for each of the four sex-location subgroups, restricted to individuals with positive earnings. This disaggregation is necessary because substantial differences exist between men and women, and between rural and urban areas in Bangladesh, in terms of labour market participation, educational attainment, and access to formal employment opportunities. The dependent variable is the natural logarithm of hourly wages, while the explanatory variables include demeaned age, its squared term, and education categories. Estimating separate models for urban females, rural females, urban males, and rural males allows the effects of education and age, as a proxy for experience, on wages to vary across sex and rural–urban location.

To correct for retransformation bias, a smearing estimator is applied when converting predicted log wages back into levels. The smearing factor for each subgroup g is computed as:

$$\bar{s}_g = \frac{1}{N_g} \sum_{i=1}^{N_g} \exp(\hat{\varepsilon}_{ig})$$

where $\hat{\varepsilon}_{ig}$ are the residuals from the log-wage regression and N_g is the number of observations in subgroup g. This adjustment ensures that the imputed wages used for the TUS respondents provide unbiased estimates of the expected market wage for each subgroup.

The estimation model is expressed as:

$$\ln(w_i) = \beta_0 + \beta_1 \text{Age}_i + \beta_2 \text{Age}_i^2 + \sum_{j=2} \gamma_j \text{Education}_{ij} + \varepsilon_i \tag{2}$$

where w_i is the hourly wage of individual i, Age_i is the demeaned age within each sex–location subgroup, and Age_i^2 captures the documented nonlinear effects of experience on wages. Education_{ij} is a vector of dummy variables for education categories, with no formal education serving as the reference group. The coefficients γ_j measure the difference in log wages for each education category relative to the reference group. The error term ε_i captures unobserved determinants of wages.

For consistency between the datasets, age in the TUS sample was demeaned within each of the four sex–location subgroups following the same procedure used in the LFS. Subgroup-specific squared age terms were generated to capture potential nonlinear effects of age on wage. Finally, the estimated coefficients from the LFS wage regressions were applied to the TUS sample to generate predicted log hourly wages. For each subgroup, demeaned age, its squared term, and education categories were multiplied by their corresponding regression coefficients and summed with the constant term.

4.4 Valuation of Unpaid Work

The monetary value of unpaid work is estimated using the opportunity cost method, which assigns a value to unpaid hours based on the predicted market wage of the individual performing the activity. This approach reflects the income foregone by allocating time to unpaid domestic and care work instead of paid employment. It assumes that time devoted to unpaid work represents an alternative use of time that could otherwise generate market income, thereby capturing the economic cost of household production.

Daily unpaid work value is calculated as the product of predicted hourly wages and the number of unpaid hours reported per day in the time diary. Formally, for each individual i, the value of unpaid work can be expressed as:

$$\text{UnpaidValue}_i = \widehat{w}_i \times \text{UnpaidHours}_i \tag{3}$$

where $\widehat{w}_i$ is the predicted hourly wage for individual i, obtained from the first step wage regressions, and UnpaidHours_i is the total number of unpaid work hours per day reported in the time diary.

To analyze the determinants of unpaid work value, a regression model was estimated using the natural logarithm of daily unpaid work value as the dependent variable. The explanatory variables include sex, age, education, rural–urban status, household size, and the presence of a child aged nine or younger. A day-of-week variable, labeled from Saturday through Friday, was incorporated to account for systematic differences in time use across the week. These day-of-week indicators serve as fixed effects, capturing unobserved daily

patterns that may influence unpaid work value.

The estimating equation takes the following general form:

$$\begin{aligned}\ln(\text{UnpaidValue}_i) &= \beta_0 + \beta_1 \,\text{Female}_i + \beta_2 \,\text{Age}_i + \sum \gamma \,\text{Education}_i \\ &\quad + \beta_3 \,\text{Rural}_i + \beta_4 \,\text{HouseholdSize}_i + \beta_5 \,\text{Child}_i + \sum \delta \,\text{Day}_i + \varepsilon_i.\end{aligned} \tag{4}$$

In equation (4), Education_i and Day_i denote vectors of dummy variables for education levels and days of the week, respectively, with "None" and "Saturday" serving as the omitted reference categories. The error term ε_i captures unobserved factors influencing unpaid work value.

Predicted unpaid work values were then obtained from this model. For each individual, the predicted log values were exponentiated and adjusted using subgroup-specific smearing factors to correct for retransformation bias. Daily predictions were then aggregated over the week to obtain the weekly predicted value of unpaid work, providing a comprehensive measure of household production across time.

4.5 Allocation of Unpaid Work

To analyze the distribution of unpaid work within households, the TUS data were aggregated to the household level. Household size was defined as the total number of members in each household, and total unpaid hours were calculated separately for women and men. The female and male components of unpaid work were denoted by H^f and H^m, respectively. Households reporting no unpaid work were excluded to ensure meaningful comparisons across households engaged in unpaid labour.

The household-level dataset retained key variables, including household size, presence of a child aged nine or below, and rural/urban residence.

When women and men within a household allocate their time between paid and unpaid activities, the key factor influencing this division is who faces the higher opportunity cost of staying at home. The opportunity cost of unpaid time corresponds to the wage a person forgoes in the labour market. Thus, what matters is the relative wage between women and men. If women earn more than men ($w^f > w^m$), their unpaid time becomes more costly, leading them to devote relatively more time to paid work and less to unpaid work. Consequently, the ratio of unpaid work hours (H^f/H^m) is expected to decline as the wage ratio (w^f/w^m) increases. However, social norms or traditional household roles may influence this relationship.

To empirically examine this relationship, a regression using sample weights was then

estimated with the logarithm of the ratio of female to male unpaid hours as the dependent variable and the logarithm of the ratio of female to male hourly wages as the main explanatory variable, controlling for household size, presence of children, and rural/urban location. The estimating equation is expressed as:

$$\ln\left(\frac{H_h^f}{H_h^m}\right) = \beta_0 + \beta_1 \ln\left(\frac{w_h^f}{w_h^m}\right) + \beta_2 \,\text{HouseholdSize}_h + \beta_3 \,\text{Child}_h + \beta_4 \,\text{Rural}_h + \varepsilon_h \quad (5)$$

where HouseholdSize_h is the number of members in household h, Child_h is a binary indicator equal to one if at least one child aged ≤ 9 is present, and Rural_h is a binary indicator equal to one for rural households. The error term ε_h captures unobserved household characteristics that may influence the log ratio of unpaid hours.

4.6 Calculation of GDP Share of Unpaid Work

Individual-level weekly predicted unpaid values were aggregated to the household level, and one record per household was retained. Weighted means of weekly unpaid value per household were computed separately for rural and urban areas. These means were scaled using official household counts (27,819,445 rural; 13,188,772 urban) to estimate total rural and urban unpaid work values. Summing these totals provided a national weekly value, which was annualized by multiplying by 52.

Nominal GDP in Bangladeshi Taka (BDT) was derived by converting reported GDP in USD (USD 460.13 billion) using the 2022 exchange rate of 93 BDT per USD. The share of GDP attributable to unpaid work was then computed as:

$$\text{GDP Share} = \frac{\text{Annual National Value of Unpaid Work}}{\text{GDP}_{\text{BDT}}} \times 100 \quad (6)$$

5 Results

This section presents the regression results for the estimation sample. The results are organized as follows: log hourly wage regressions, log unpaid work value regression, the regression of the log ratio of female-to-male unpaid hours at the household level, and the monetary value of unpaid work.

The results of log hourly wage regressions estimated separately for urban females, rural females, urban males, and rural males are presented in Table 7. The coefficients on age are positive and statistically significant across all groups, though significance is weaker for

rural females, indicating that wages generally increase with age. However, the negative and significant coefficients on age squared for both male subgroups suggest diminishing returns to age, implying that wage growth eventually slows down or even declines at older ages. This concave age–wage profile is consistent with the standard Mincer regression framework and is less distinct among females, where the age-squared terms are small and statistically insignificant, indicating a flatter wage trajectory over the life cycle.

Education shows a strong and consistent positive association with log hourly wages. The magnitude of the coefficients increases steadily with higher educational attainment, reflecting substantial wage premiums for more educated individuals. Graduate degrees show the largest effects, especially for women, with coefficients ranging from about 1.0 for rural males to 1.8 for rural females (all statistically significant at the 1% level), emphasizing the substantial wage differences by education. Returns to education appear larger for women than for men, particularly at higher levels (HSC, Bachelor's, Graduate), suggesting that education plays a more important role in enhancing women's earnings potential.

Table 8 presents the results of the log unpaid work value regression, which examines how individual and household characteristics influence the monetary value of unpaid work. The coefficient on the female dummy is large and statistically significant at the 1% level, indicating that women's unpaid work value is more than twice that of men, even after controlling for age, education, location, household composition, and day-of-week effects.

Age is positively associated with unpaid work value: each additional year of age is linked to a 1.2% increase in unpaid work value, suggesting greater household responsibility as individuals grow older. Compared to those with no education, holding a graduate degree is associated with over four times higher unpaid work value, reflecting the opportunity cost of their higher potential earnings. Rural residence is associated with a significantly higher value of unpaid work, likely because rural households spend more time on domestic and care activities due to limited access to market substitutes.

Household characteristics also play a role. Larger households show a small but statistically significant decline in average unpaid work value per person, suggesting that unpaid responsibilities are distributed among members. In contrast, households with at least one child aged nine or younger exhibit substantially higher unpaid work value, consistent with increased childcare needs in such households.

The day-of-week coefficients show that unpaid work is unevenly distributed across the week. Saturday records the highest unpaid work value, averaging 304.5 BDT per person per day in the estimation sample. This pattern likely portrays the cultural and religious significance of Friday as a prayer and social day in Bangladesh, with households often deferring heavier domestic chores to Saturday.

At the household level, the regression of the log ratio of female-to-male unpaid hours examines how relative wages and household characteristics influence the division of unpaid work. As shown in Table 9, the coefficient on the log wage ratio is positive (0.062) but statistically insignificant, suggesting that wage differences between women and men do not determine how unpaid work is divided within households. This likely reflects the influence of social norms and traditional gender roles that outweigh economic reasoning in determining household time allocation in Bangladesh.

The presence of a child aged nine or younger has a large, statistically significant positive effect (0.267), indicating that women devote relatively more time to unpaid work when young children are present. In contrast, household size has no significant effect (0.017), while rural households exhibit a significantly lower female-to-male ratio of unpaid hours (–0.201), suggesting that the gender gap in unpaid work is narrower in rural areas, possibly because men participate relatively more in household tasks or agricultural and subsistence activities than in urban settings.

After examining household-level differences, the analysis proceeds to estimate the overall monetary value of unpaid work and its share in GDP. The average daily value of unpaid work is estimated at 345.8 BDT for women and 168.6 BDT for men (not reported in tables), implying that women generate more than twice the monetary value of unpaid work compared to men. Aggregating to the national level, the opportunity cost approach indicates that unpaid work accounts for 21.2% of GDP. Of this, women contribute 17.1 percentage points, while men contribute 4.1 percentage points, meaning that women are responsible for approximately 81% of the total value of unpaid work. The estimate is broadly consistent with international evidence, where unpaid work contributions are found to range between 10% and 39% of GDP.[9] These results demonstrate that despite lower market wages, women's economic contribution through unpaid work is significantly higher due to their greater time allocation to unpaid domestic and care work.

The UNECE (2024) study using the replacement cost method and the same survey data (TUS 2021 and LFS 2022) reports a similar estimate, valuing unpaid work at around 21% of GDP. The consistency of these findings across different valuation methods strengthens the reliability of national estimates of unpaid work in Bangladesh.

9. The Guardian (2025), *The Guardian View on Women's Unpaid Labour: Attitudes Have Shifted, But the Burden Hasn't.*

6 Policy Recommendations

The results have significant policy implications. First, recognizing the economic value of unpaid work is essential for improving its visibility in national statistics and informing more inclusive macroeconomic planning. However, improved GDP measurement alone does not automatically reduce gender inequality. A key channel for reducing inequality lies in addressing the misallocation of labour, where women's time is disproportionately concentrated in unpaid domestic and care work, limiting their participation in paid employment, income generation, and bargaining power within households. Second, policies should aim to reduce the unequal distribution of unpaid work between men and women. Expanding access to affordable childcare and eldercare services, investing in rural infrastructure such as water supply and transport, and promoting flexible work arrangements can significantly ease women's unpaid work burden. Third, public awareness campaigns and workplace initiatives should encourage shared household responsibilities between men and women. Shifting social norms through education and media can gradually reshape attitudes towards domestic and caregiving roles. Finally, the regular implementation of time-use surveys is crucial for monitoring progress towards Sustainable Development Goal (SDG) 5.4 and ensuring that policy interventions remain gender-responsive.

7 Conclusion

This study provides an opportunity cost–based valuation of unpaid work in Bangladesh using nationally representative microdata from the 2021 Time Use Survey and the 2022 Labour Force Survey. Grounded in Becker's (1965) theory of time allocation, the analysis bridges household production and the formal labour market by assigning a monetary value to time spent on unpaid work. The findings confirm that unpaid work constitutes a major yet unrecognized component of Bangladesh's GDP, accounting for approximately 21.2 percent of national output. Women contribute more than four-fifths of this value, underscoring the extent to which gendered divisions of labour shape both household welfare and overall economic output.

The results reveal persistent disparities across gender, education, and location. Women spend significantly more time on unpaid activities than men, while men earn higher predicted wages in both urban and rural areas. Educational attainment is positively associated with hourly wages and the value of unpaid work, suggesting that education enhances productivity in both market and non-market settings. Rural households exhibit greater unpaid work value, reflecting limited access to market substitutes such as childcare and domestic services.

These patterns highlight the dual nature of inequality in Bangladesh: women's time remains concentrated in unpaid work, and their economic contributions continue to be largely invisible in conventional measures of GDP. They also suggest that the current distribution of paid and unpaid labour reflects a broader misallocation of labour resources, where individuals' productive capacity is not fully utilized in the formal economy.

By quantifying the magnitude of unpaid work, this study reinforces the importance of Bangladesh's ongoing efforts to integrate household production into official statistics and policy frameworks. Recognition of unpaid work not only provides a better understanding of economic activity but also strengthens the case for gender-responsive development planning. Nonetheless, this study has a limitation: the opportunity cost approach assumes perfect substitutability between paid and unpaid work time and does not account for differences in the intensity or effort of household tasks. In addition, although the Labour Force Survey includes information on informal employment, measurement challenges remain in fully capturing the shadow economy. As informal earnings are not fully reflected in the wage imputation, the estimates may be understated.

Ultimately, including unpaid work into Bangladesh's national accounts represents more than a statistical adjustment—it is a crucial step towards valuing care, promoting shared responsibility within households, and advancing the broader goals of inclusive and sustainable economic growth envisioned under SDG 5.4.

8 Use of Generative AI and AI-assisted tools

During the preparation of my thesis, I used ChatGPT to improve the clarity and language of my writing, and assist with LaTeX formatting of equations and tables. After using this tool, I reviewed and edited the content as needed and take full responsibility for the content of my thesis.

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Appendix

Table 1: Comparison of Key Characteristics: LFS vs. TUS

	LFS	TUS
Mean age (15–65)	34.51	36.76
Female share	15.50	69.40
Male share	84.50	30.60
Rural share	50.77	69.84
Urban share	49.23	30.16
Education (%)		
None	1.14	23.32
Class 1–5	35.56	24.88
Class 6–9	27.35	27.40
SSC	10.15	10.62
HSC	8.52	7.09
Diploma	1.60	0.19
Bachelor's	6.44	3.59
Graduate	9.23	2.90

Notes: LFS = Labour Force Survey 2022 (N = 60,711); TUS = Time Use Survey 2021 (N = 13,038).

Table 2: Summary of Key Variables: LFS 2022

	Mean	Std. Dev.
Log hourly wage	4.00	0.70
Age	34.51	11.12
Female (=1)	0.15	0.36
Rural (=1)	0.51	0.50
Education	2.66	1.97

Notes: N = 60,711.

Table 3: Summary of Key Variables: TUS 2021 (Estimation Sample)

	Mean	Std. Dev.
Paid hours	2.38	3.78
Unpaid hours	5.90	3.89
Hourly wage (BDT)	52.40	24.75
Unpaid value (BDT)	291.53	241.34

Notes: Hours and unpaid value are measured per day. N = 13,038.

Table 4: Paid and Unpaid Hours per Day by Sex and Area (TUS)

	Overall	Female	Male	Rural	Urban
Paid hours	2.38	1.11	5.25	2.35	2.44
Unpaid hours	5.90	7.33	2.61	6.06	5.50

Notes: Values represent average hours per day spent in paid and unpaid work, calculated from the TUS 2021 sample (age 15–65).

Table 5: Unpaid Hours per Day by Sex, Area, and Education (TUS)

	Urban	Rural
Male	2.11	2.82
	(2.32)	(2.92)
Female	6.89	7.54
	(3.44)	(3.36)
Education	**Male**	**Female**
None	2.71	6.81
	(2.84)	(3.22)
Class 1–5	2.49	7.67
	(2.82)	(3.21)
Class 6–9	2.60	7.64
	(2.82)	(3.43)
SSC	2.69	7.24
	(2.68)	(3.59)
HSC	2.73	6.81
	(2.85)	(3.72)
Diploma	2.23	5.85
	(2.54)	(4.16)
Bachelor's	2.60	7.46
	(2.47)	(3.77)
Graduate	2.67	7.22
	(2.41)	(3.62)

Notes: Means reported with standard deviations in parentheses. Values are hours per day (age 15–65).

Table 6: Mean Hourly Wage by Sex and Area

	TUS (Predicted)		LFS (Observed)	
	Urban	Rural	Urban	Rural
Male	78.53	58.28	82.10	63.48
Female	57.66	42.61	73.34	60.22

Table 7: Log Hourly Wage Regressions (LFS)

	Urban Female	Rural Female	Urban Male	Rural Male
Age	0.008***	0.003*	0.014***	0.007***
	(0.001)	(0.001)	(0.000)	(0.000)
Age Squared	0.000	0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Education				
Class 1–5	0.193***	0.405***	-0.020	0.126***
	(0.073)	(0.099)	(0.053)	(0.030)
Class 6–9	0.334***	0.616***	0.068	0.225***
	(0.074)	(0.099)	(0.053)	(0.031)
SSC	0.476***	0.824***	0.230***	0.353***
	(0.081)	(0.107)	(0.053)	(0.032)
HSC	0.738***	1.112***	0.408***	0.499***
	(0.086)	(0.113)	(0.054)	(0.034)
Diploma	1.221***	1.346***	0.752***	0.839***
	(0.091)	(0.170)	(0.062)	(0.056)
Bachelor's	1.039***	1.505***	0.726***	0.776***
	(0.087)	(0.107)	(0.055)	(0.038)
Graduate	1.410***	1.767***	1.108***	1.010***
	(0.079)	(0.104)	(0.054)	(0.036)
Constant	3.408***	2.996***	3.913***	3.734***
	(0.072)	(0.096)	(0.052)	(0.030)
Observations	5875	3535	24013	27288
R^2	0.405	0.335	0.385	0.177

Table 8: Log Unpaid Work Value Regression (TUS)

Female (=1)	1.215***
	(0.025)
Age	0.012***
	(0.001)
Education	
Class 1–5	0.405***
	(0.027)
Class 6–9	0.619***
	(0.029)
SSC	0.751***
	(0.039)
HSC	0.987***
	(0.044)
Diploma	0.967***
	(0.245)
Bachelor's	1.394***
	(0.055)
Graduate	1.726***
	(0.061)
Rural (=1)	0.125***
	(0.023)
Household size	-0.033***
	(0.009)
Has child ≤9 (=1)	0.327***
	(0.021)
Sunday	-0.111***
	(0.036)
Monday	-0.105***
	(0.037)
Tuesday	-0.149***
	(0.036)
Wednesday	-0.049
	(0.035)
Thursday	-0.090***
	(0.034)
Friday	-0.130***
	(0.037)
Constant	3.421***
	(0.065)
Observations	13038
R^2	0.344

Table 9: Determinants of the Log Ratio of Female-to-Male Unpaid Work Hours

Log wage ratio ($\ln(w^f/w^m)$)	0.062
	(0.090)
Household size	0.017
	(0.030)
Has child $\leq$9 (=1)	0.267***
	(0.051)
Rural (=1)	-0.201***
	(0.060)
Constant	1.767***
	(0.103)
Observations	3306
R^2	0.017

Notes: Dependent variable: $\ln(H_h^f/H_h^m)$. Robust standard errors in parentheses.