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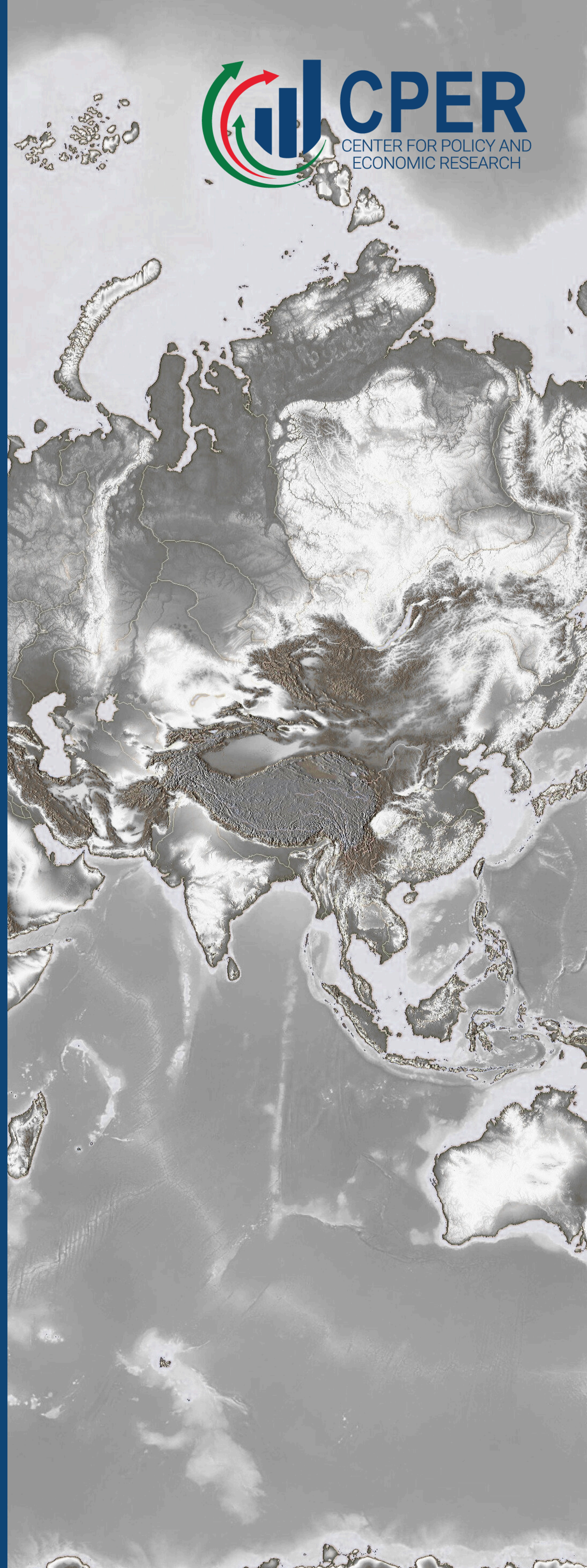

Economic Divides

Disparities in Wages and Household Earnings in Bangladesh

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Center for Policy and Economic Research (CPER)

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Abstract

This study examines the effects of human capital—specifically, education and work experience—and social factors, such as age, gender, location, and economic activity, on household income in Bangladesh, using data from the Household Income and Expenditure Surveys (HIES) for 2010 and 2016. Employing Ordinary Least Squares (OLS) and Instrumental Variable (IV) regression techniques, including Two-Stage Least Squares (2SLS) and the Generalized Method of Moments (GMM), the analysis reveals that both human capital and social factors have a moderate influence on income over time, with substantial income variability explained by these variables. Findings from the OLS and IV models indicate that returns to education and additional years of work experience have a consistently positive impact on income across both rural and urban areas in the two survey years. However, wage disparities widened significantly in 2016: the gender wage gap increased to 44.1%, the rural-urban gap to 19.4%, and the industrial-service sector gap to 5%, all of which were notably higher than in 2010. Urban males and females earned significantly more than their rural counterparts in both years. The study also highlights a persistent wage advantage in the service sector compared to the agricultural and industrial sectors in 2016. At the same time, the wage differential between agricultural and non-agricultural sectors narrowed, indicating improved wage growth within the agricultural sector. Furthermore, the marginal return to an additional year of education was found to be higher for females than males, underscoring the critical economic value of investing in women's education. Given that both human capital and social variables play a significant role in shaping income dynamics, strategic policy interventions and targeted investments are essential for addressing wage inequality, reducing socio-economic disparities, and fostering inclusive development in Bangladesh.

Keywords: Bangladesh, economic development, gender wage gap, HIES 2016, human capital, income inequality

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1. Introduction

In recent decades, Bangladesh has demonstrated remarkable economic growth and notable progress in various socio-economic sectors, including reductions in maternal mortality and poverty rates, improvements in literacy, women's empowerment, infrastructure development, ICT advancement, and strengthened rural-urban linkages and communication systems. The country's attainment of middle-income status can be primarily attributed to the strategic implementation of the Seventh Five-Year Plan, Vision 2021, and the Perspective Plan (2011–2021).

Building on the achievements of Vision 2021, the government introduced the Perspective Plan 2021–2041 (commonly referred to as Vision 2041), which aspires to elevate Bangladesh to an upper-middle-income country by 2030 and a developed nation by 2041. Notably, the country recorded an impressive GDP growth rate of 8.15% in the fiscal year (FY) 2018–19, the highest in the Asia-Pacific region. However, the COVID-19 pandemic curtailed growth, with the GDP declining to 3.51% in FY 2019–20 and rebounding slightly to 5.47% in FY 2020–21. Economic recovery is now gaining momentum, driven by government stimulus packages, robust remittance inflows, a strong export performance, increased agricultural output, infrastructure expansion, and the growth of the manufacturing and service sectors, alongside substantial public expenditure.

Despite being on the cusp of a significant economic transition, Bangladesh continues to face several structural and socio-economic challenges. These include high unemployment rates, income inequality, gender wage disparities, limited access to decent employment, insufficient labor rights protections, high costs of living, corruption, limited access to basic services for low-income populations, and lagging innovation and technological progress.

To effectively address these multidimensional challenges, it is essential to examine the impact of human capital—particularly education and job experience—as well as relevant socio-demographic factors, such as age, gender, and type of economic activity, on household income.

Therefore, the primary objective of this study is to analyze the dynamics of household income and wage inequality in Bangladesh. By applying appropriate econometric methodologies to nationally representative Household Income and Expenditure Survey (HIES) data from 2010 and 2016, this study aims to fill critical gaps in the literature and provide new insights for policymaking.

Specifically, the study seeks to answer the following research questions:

a. Do the determinants of income differ between the HIES 2010 and HIES 2016 datasets?
b. How do social factors—such as gender, age, marital status, and rural-urban residence—and non-social (human capital) factors—such as education and work experience—affect income over time?
c. Have improvements in human capital and social inclusivity contributed to higher income levels and more equitable growth in Bangladesh?

While per capita income has increased in recent decades, issues such as income inequality, persistent poverty, and gender-based wage disparities remain unresolved. This study aims to generate robust empirical evidence on the key factors influencing income and inequality, thereby informing policy decisions that promote equitable income distribution and inclusive economic growth.

2. Literature Review

A substantial body of research has established a strong relationship between education and income, consistently showing that investments in education yield positive economic returns (Mamun et al., 2021; Conlon & Patrignani, 2013; Shafiq, 2007). Bhutoria (2016) found that the economic returns to formal education are significantly positive at the individual level, though they vary by qualification, field of study, age, work experience, and gender. Similarly, studies by Chowdhury et al. (2018), Alam (2009), and Sharif (2013) underscored the crucial role of human capital development in fostering economic growth in Bangladesh.

Evidence further indicates a direct association between human capital investments—primarily in education—and economic growth (World Bank, 2019; Cram, 2017; Scully, 2002). Additionally, investments in human and physical capital are believed to reduce income inequality and contribute to fairer income distribution (UN, 2016; Shahparia & Davoudi, 2014). In the context of China, Su and Heshmati (2013) found that education and occupation are significant determinants of household income in urban areas. In the United Kingdom, men and women with comparable levels of education continue to experience wage disparities, despite education remaining a significant predictor of labor market earnings (Blundell et al., 1997). Acemoglu and Pischke (1999) added that beyond formal education, on-the-job training enhances worker productivity, which in turn raises wage levels.

While the majority of research supports a positive relationship between education and income, a few studies reported an insignificant association (Leeuwen & Foldvari, 2011; Ning, 2010). However, such findings are relatively rare and considered context-specific exceptions.

Beyond human capital, social and spatial factors—such as gender, rural-urban disparities, and regional economic contexts—are widely acknowledged as critical determinants of wage inequality across countries (Herrera et al., 2019; Liu et al., 2019; Waugh et al., 2016; Equitable Growth, 2018; Young, 2013).

Human capital development is not only linked to sustained GDP growth and reduced inequality but also to broader well-being and dignity (UN, 2019; Saygili et al., 2018; UN, 2018; Dorset et al., 2010). In recognition of this, Bangladesh's development frameworks, including the Seventh and Eighth Five-Year Plans, highlight the importance of investing in both human and physical capital to drive innovation, technological advancement, and institutional efficiency.

The Seventh Five-Year Plan (2016–2020) emphasized empowering citizens as a core development strategy, encapsulated in the plan's theme: Accelerating Growth, Empowering Citizens. The Eighth Five-Year Plan (2021–2026) further accentuated the roles of innovation, governance, poverty reduction, and capital development to facilitate the nation's transformation as envisioned in Vision 2041. Moreover, the National Education Policy (2010) advocated for widespread access to quality education, including technical, vocational, and ICT training, with a particular focus on rural populations.

Bangladesh has made considerable strides in raising literacy rates and increasing the proportion of the workforce with secondary and tertiary education. However, while numerous studies have explored the impact of education on income and inequality both globally and in Bangladesh, few have specifically analyzed the effects of human capital (education and experience) and social variables (age, gender, locality, and type of economic activity) using nationally representative HIES data. This gap constrains evidence-based policymaking in areas such as labor markets, social welfare, and human development.

3. Methodology and Data

3.1 Model Specification

The study employed ordinary least squares (OLS) and two-stage least squares (2SLS) regression methods to analyze the impact of human capital and social factors on household income, using the generalized method of moments (GMM) to verify the robustness of the results. OLS is a standard statistical technique used in econometrics for linear models, based on the mean of the conditional distribution of the dependent variable. However, this study considered the extended Mincer's (1974) earnings equation within the framework of Becker (2009).

$$lnY_i = X'_i\beta_i + u_i, \qquad i = 1, 2, 3, \dots, n \tag{1}$$

where Y is the monthly wage, X is the vector of predictors (set of individual characteristics),[1] and β is the slope and intercept parameters of the wage equation. The model has considered both data sets from HIES 2010 and HIES 216 separately.

The estimated OLS method has adjusted the standard error for heteroskedasticity in both data sets. However, the regression model always faces a risk of endogeneity. In cases of endogeneity, at least one predictor correlates with the error term due to the presence of omitted variables or measurement errors. When a regression model exhibits this problem, OLS estimates become inconsistent and biased, rendering the estimator inappropriate (Verbeek, 2008). Addressing the omitted variables issue requires obtaining proxy variables correlated with the omitted ones. Nonetheless, we performed Ramsey's (1969) regression specification-error test for omitted variables, where the null hypothesis was rejected (indicating the model has no omitted variables) at a 5% significance level, leading us to conclude that more variables are needed for both HIES 2010 and 2016.

Additionally, this study tested Davidson and MacKinnon's (1993) Durbin–Wu–Hausman endogeneity test (orthogonality conditions) to detect potential endogeneity or reverse causality in the wage equation. In 2010, the chi-square statistic was 17.95 (p-value = 0.000), and in 2016, it was 19.532 (p-value = 0.000), indicating that the null hypothesis of exogeneity is rejected at the 5% level for both estimates. More specifically, there is contemporaneous endogeneity between the year of education and wage, so the OLS estimates would not be consistent with instrumental variable (IV) estimates. Therefore, Equation (1), the structural equation model, can be rewritten as follows:

[1] The predictors include year of education, experience, experience squared, and dummy variables for gender, marital status, area, field of economic activity, and occupation.

$$lnwage_i = \beta_0 + \beta_1 Education_i + \beta_2 Experience_i + \beta_3 Experience_i^2 + \beta_4 Gender_i + \beta_5 MaritalStatus_i + \beta_6 Area_i + \beta_7 FieldofEconomicActivity_i + \beta_8 Occupation_i + u_i \quad (2)$$

where education is endogenous and other variables are exogenous. Equation (2) is estimated using the two-stage least squares (2SLS) regression, a specific case of the IV method, followed by the generalized method of moments (GMM) regression to test robustness. However, in the 2SLS regression, education is estimated in the first stage with the parents' education variable, which reflects the actual impact of education on wages. The 2SLS estimator is robust to multicollinearity and misspecification (Kennedy, 2008). The 2SLS first-stage reduced form equation is as follows:

$$Education_i = \delta_0 + \delta_1 ParentsEducation_i + \delta_2 Experience_i + \delta_3 Experience_i^2 + \delta_4 Gender_i + \delta_5 MaritalStatus_i + \delta_6 Area_i + \delta_7 FieldofEconomicActivity_i + \delta_8 Occupation_i + v_i \quad (3)$$

Consequently, obtaining the predicted values of $\widehat{Education}_i$, which contain only exogenous information, is used as an instrument in the second stage to establish the relationship. In the 2SLS second stage, the structural equation replaces the endogenous variable $Education_i$ with its predicted values as follows:

$$lnwage_i = \beta_0 + \beta_1 \widehat{Education}_i + \beta_2 Experience_i + \beta_3 Experience_i^2 + \beta_4 Gender_i + \beta_5 MaritalStatus_i + \beta_6 Area_i + \beta_7 FieldofEconomicActivity_i + \beta_8 Occupation_i + u_i \quad (4)$$

Furthermore, this study also employs the generalized method of moments (GMM) estimator, a consistent approach for empirically estimating IV regression (Hansen, 1982), to verify the robustness of the results using Equations (3) and (4). The GMM demonstrates how to use two sets of sample moment conditions, which can be written as $\bar{y} = \hat{\mu}$ and $\frac{[(y_1-\hat{\mu})^2+.....+(y_n-\hat{\mu})^2]}{n} = 3\hat{\mu}$, in a way that weights the two sample moment conditions to produce an asymptotically optimal estimator (Wooldridge, 2001). The 2SLS estimates address endogeneity in the regression model, while GMM handles this issue with minimal standard error. Generally, GMM is used to improve efficiency by accounting for neglected serial correlation and heteroskedasticity, and it can be applied to multiple equations.

3.2 Data and Variables

This study utilizes two nationally representative datasets from the Household Income and Expenditure Survey (HIES), conducted by the Bangladesh Bureau of Statistics (BBS) in 2010 and 2016. The HIES 2010 dataset includes information on 55,580 individuals (35,894 from rural areas and 19,686 from urban areas) across 12,240 households. In contrast, HIES 2016 encompasses data from 186,076 individuals (130,435 from rural areas and 55,641 from urban areas) in 46,080 households.

After filtering for household wage earners aged 15 to 60,[2] and removing missing values and duplicate entries, the final analytic sample was reduced to 6,603 observations for 2010 and 16,801 observations for 2016. The cleaned dataset for 2010 comprises 5,912 male and 691 female earners, with 3,658 from rural and 2,947 from urban areas. For 2016, the final sample comprises 16,337 male and 464 female earners, with 9,671 observations from rural areas and 7,130 from urban areas.

The dependent variable in this study is monthly wage income. The key independent variables include:

- Years of education
- Job experience
- Gender dummy
- Marital status dummy
- Area dummy (rural/urban)
- Economic activity sector dummy
- Occupation dummy

To address potential endogeneity between education and wages, parental education is employed as an instrumental variable (IV). The parental wage variable is excluded from both datasets. This approach follows the methodology recommended by Wooldridge (2015) for handling endogenous regressors in wage models.

Table 1 presents descriptive statistics for all variables used. The average monthly wage was BDT 5,341.97 (approximately US$62.55) in 2010, increasing to BDT 11,552.40 (approximately US$135.28) in 2016—a more than doubling over the six years. Notably, wage disparities between males and females, as well as between rural and urban populations, also more than doubled during this period.

The average years of education rose from 4.81 years in 2010 to 7.13 years in 2016, with gains observed across all gender and location subgroups. While male and female education levels remained relatively close in both years, significant disparities were observed between rural and urban populations, especially in 2016. Parental education followed a similar pattern, reinforcing its suitability as an instrument. The average work experience among earners increased from 24.58 years in 2010 to 26.77 years in 2016—an increase of approximately two years—across both male-female and rural-urban groups.

Labor market participation rates also shifted significantly. In 2010, 90% of earners were male and 10% were female. By 2016, male participation had risen to 97%, while female participation had fallen to just 3%, indicating a troubling decline in female labor force involvement. In terms of marital status, 80% of respondents were married and 20% unmarried in 2010; by 2016, these proportions had shifted to 98% married and 2% unmarried.

The rural-urban distribution also shifted slightly: 55% rural and 45% urban in 2010, compared to 58% rural and 42% urban in 2016. Across both years, labor force participation in the non-agricultural sector consistently exceeded that of the agricultural sector, regardless of gender and rural-urban divides.

[2] Individuals below 15 years of age have not been included in this study, as the age group of 5-14 years is considered child labor in Bangladesh (Salmon, 2005). Additionally, households with members over 60 years are not reflected in this study because the retirement age in Bangladesh is 59 years, according to the Public Service Retirement Act of 1974b.

Moreover, the service sector emerged as the dominant employment sector, employing more than half of all earners in both 2010 and 2016. This dominance was consistent across gender and rural-urban categories, highlighting a structural transition toward service-based employment in the Bangladeshi economy.

This study employs kernel density estimates of logarithmic monthly wages, as illustrated in Figures 1 and 2, to analyze the distribution of wages by gender and area of residence (rural vs. urban). These figures clearly illustrate contrasting wage patterns across both gender and geographical dimensions. To statistically validate these differences, a two-sample Kolmogorov-Smirnov (K-S) test is conducted. The test rejects the null hypothesis at a p-value of 0.000, indicating that the distributions of logarithmic wages across gender and area are significantly different and do not originate from the same population distribution. Additionally, the results suggest that the wage distributions deviate from normality, reinforcing the need for robust estimation methods in subsequent analysis.

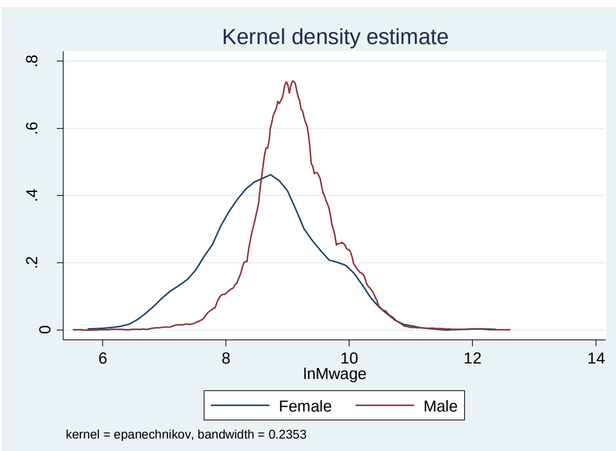

Figure 1. Kernel Density Estimates of Log Monthly Wage Distribution by Gender

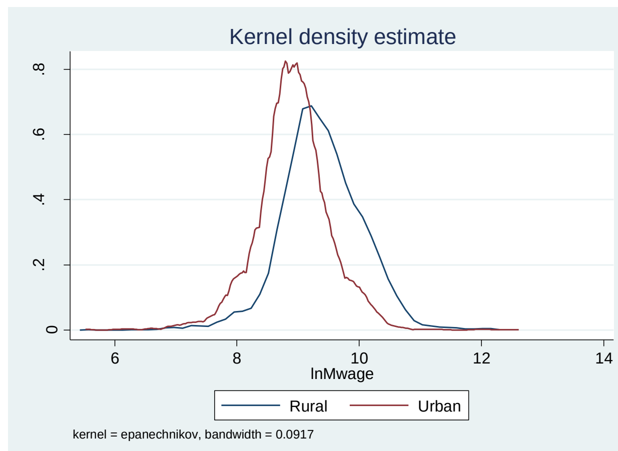

Figure 2. Kernel Density Estimates of Log Monthly Wage Distribution by Area

Table 1. Summary Statistics for 2010 and 2016

	2010					2016				
	Full	**Male**	**Female**	**Rural**	**Urban**	**Full**	**Male**	**Female**	**Rural**	**Urban**
Monthly Income	5341.970 (5199.736)	5431.031 (5127.561)	4579.978 (5728.212)	4127.206 (3521.038)	6848.984 (6411.401)	11552.4 (11367.68)	11629.250 (11347.760)	8846.431 (11744.06)	9051.181 (9154.588)	14945 (13070.970)
Year of Education	4.814 (5.420)	4.800 (5.340)	4.933 (6.063)	3.455 (4.705)	6.499 (5.764)	7.127 (4.112)	7.120 (4.104)	7.371 (4.396)	6.276 (3.705)	8.280 (4.349)
F/M Year of Education	3.538 (5.136)	3.505 (5.067)	3.816 (5.690)	2.38 (4.249)	4.974 (5.744)	6.125 (3.885)	6.107 (3.873)	6.763 (4.235)	5.535 (3.517)	6.925 (4.203)
experience	24.581 (12.245)	24.715 (12.206)	23.427 (12.520)	25.824 (12.261)	23.038 (12.049)	26.771 (9.201)	26.822 (9.178)	24.976 (9.837)	27.110 (9.161)	26.312 (9.236)
Gender:										
Male	0.895 (0.306)	…	…	0.901 (0.299)	0.888 (0.315)	0.972 (0.164)	…	…	0.977 (0.151)	0.967 (0.180)
Female	0.105 (0.306)	…	…	0.099 (0.299)	0.112 (0.315)	0.028 (0.164)	…	…	0.023 (0.151)	0.033 (0.180)
Marital Status:										
Married	0.803 (0.398)	0.825 (0.380)	0.609 (0.488)	0.809 (0.393)	0.795 (0.403)	0.981 (0.137)	0.996 (0.065)	0.459 (0.499)	0.982 (0.133)	0.980 (0.141)
Unmarried and Others	0.197 (0.398)	0.175 (0.380)	0.391 (0.488)	0.191 (0.393)	0.205 (0.403)	0.019 (0.137)	0.004 (0.065)	0.541 (0.499)	0.018 (0.133)	0.020 (0.141)
Area:										
Rural	0.554 (0.497)	0.557 (0.497)	0.524 (0.500)	…	…	0.576 (0.494)	0.578 (0.494)	0.487 (0.500)	…	…
Urban	0.446 (0.497)	0.443 (0.497)	0.476 (0.500)	…	…	0.424 (0.494)	0.422 (0.4940	0.513 (0.500)	…	…
Field of Economic Activity:										
Agriculture	0.275 (0.446)	0.285 (0.452)	0.184 (0.388)	0.452 (0.498)	0.055 (0.227)	0.277 (0.448)	0.282 (0.450)	0.110 (0.313)	0.466 (0.499)	0.021 (0.144)
Non-Agriculture	0.725 (0.446)	0.715 (0.452)	0.816 (0.388)	0.548 (0.498)	0.945 (0.227)	0.723 (0.448)	0.718 (0.450)	0.890 (0.313)	0.534 (0.499)	0.979 (0.144)
Occupation:										
Service Sector	0.502 (0.500)	0.492 (0.500)	0.585 (0.493)	0.367 (0.482)	0.669 (0.471)	0.531 (0.499)	0.528 (0.499)	0.653 (0.477)	0.379 (0.485)	0.738 (0.440)
Agricultural Sector	0.285 (0.451)	0.298 (0.458)	0.168 (0.374)	0.464 (0.499)	0.062 (0.242)	0.285 (0.451)	0.290 (0.454)	0.099 (0.299)	0.476 (0.499)	0.026 (0.158)
Industrial Sector	0.214 (0.410)	0.210 (0.407)	0.247 (0.432)	0.169 (0.375)	0.268 (0.443)	0.184 (0.387)	0.182 (0.386)	0.248 (0.432)	0.145 (0.352)	0.237 (0.425)
Observations	**6603**	**5912**	**691**	**3656**	**2947**	**16801**	**16337**	**464**	**9671**	**7130**

4. Results and Discussion

4.1 Estimates of OLS and IV (2SLS and GMM) Regression

Table 2 presents the main empirical results based on the HIES 2010 and 2016 datasets, where the logarithm of monthly wages was estimated using Ordinary Least Squares (OLS) and Instrumental Variable (IV) regression techniques, specifically Two-Stage Least Squares (2SLS) and the Generalized Method of Moments (GMM).[3] The results show that years of education, a key predictor, had a positive and statistically significant effect on wages in both years. The coefficient of determination (R^2) for both OLS and IV regressions was approximately 0.30, indicating a moderate level of explanatory power. However, diagnostic tests revealed endogeneity and the possibility of reverse causality between education and wages. To address this, the study employed IV regressions using parental education as an instrument, in line with the methodology of Wooldridge (2015).

The OLS estimates show that the average return to an additional year of education was 6.1% in 2010 and 5.9% in 2016, which is consistent with prior studies (Feigenbaum & Tan, 2020; Mamun & Arfanuzzaman, 2020). In contrast, IV estimates from both the 2SLS and GMM approaches yield a higher and consistent return of 6.8% in both years. All estimates are statistically significant at the 0.1% level, and the results from IV-2SLS and IV-GMM are virtually identical across specifications, indicating the robustness of the instrumental variable approach.

The study also finds that job experience has a significant and positive impact on monthly wages. In 2010, OLS estimates suggest that each additional year of experience results in a 2.6% wage increase, while the IV estimate indicates a 3.0% increase. In 2016, this effect slightly declined, with OLS and IV estimates of 2.1% and 2.4%, respectively. To account for potential nonlinearities, a quadratic term for experience was included in the model. The coefficient for the squared term is negative and statistically significant at the 1% level in both years, suggesting diminishing marginal returns to experience. These findings are consistent with the established Mincerian earnings function (Mincer, 1958) and reaffirmed by Mamun and Arfanuzzaman (2020), who similarly identified education and experience as key determinants of wage outcomes in Bangladesh.

In addition to continuous variables, the analysis incorporated several dummy variables to examine group-based wage differentials. The gender dummy reveals that females earned significantly less than males in both periods. In 2010, the OLS and IV estimates show gender wage gaps of 38.2% and 38.4%, respectively. The gap widened further in 2016, reaching 44.1% (OLS) and 43.9% (IV), indicating a worsening gender wage disparity. Marital status also influenced wage levels. In 2010, unmarried individuals, including those who were widowed, divorced, or separated, earned 7.9% less than married individuals, based on OLS estimates. However, the IV estimates in this case were small and statistically insignificant. By 2016, this wage gap increased, with unmarried individuals and others earning 18.8% less (OLS) and 18.4% less (IV) than their married counterparts.

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[3] The assumption of homogeneity is tested using the Breusch-Pagan heteroscedasticity test. This study employs heteroscedasticity-robust standard errors to address any detected heteroscedasticity. Additionally, the study tests for multicollinearity and omitted-variable bias using the variance inflation factor (VIF) and the Ramsey regression specification error test (Ramsey RESET test) variables.

This study also confirms that urban workers earned more than rural workers, consistent with findings by Asadullah (2006). In 2010, urban wage premiums were 16.3% (OLS) and 15.3% (IV); these increased to 19.4% (OLS) and 18.6% (IV) in 2016, reflecting persistent spatial wage inequality. Wages in the non-agricultural sector were significantly higher than in the agricultural sector in both years. However, the wage gap narrowed by approximately six percentage points in 2016, indicating modest gains in agricultural wages. Occupational sector differences also remained pronounced. In 2010, workers in the agricultural sector earned more than those in industry, while the service sector offered the highest wages overall. By 2016, wages in the agricultural and industrial sectors had declined relative to those in the services sector, with OLS estimates showing wage penalties of 20.7% and 5.6%, respectively. IV estimates for 2016 also indicate a 3.9% decline in industrial wages relative to the service sector, underscoring the long-term dominance of the service sector over industrial wages.

Table 2. OLS and IV (2SLS and GMM) Regression of Log Monthly Wage for 2010 and 2016

	2010			2016		
	OLS	**2SLS**	**GMM**	**OLS**	**2SLS**	**GMM**
Year of Education	0.061***	0.068***	0.068***	0.059***	0.068***	0.068***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
Experience	0.026***	0.030***	0.030***	0.021***	0.024***	0.024***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Experience Square	-0.039***	-0.043***	-0.043***	-0.026***	-0.029***	-0.029***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Gender:						
Female	-0.382***	-0.384***	-0.384***	-0.441***	-0.439***	-0.439***
	(0.032)	(0.032)	(0.032)	(0.041)	(0.041)	(0.041)
Marital Status:						
Unmarried and Others	-0.079**	-0.051	-0.051	-0.188***	-0.184***	-0.184***
	(0.027)	(0.029)	(0.029)	(0.051)	(0.050)	(0.050)
Area:						
Urban	0.163***	0.153***	0.153***	0.194***	0.186***	0.186***
	(0.018)	(0.018)	(0.018)	(0.010)	(0.011)	(0.011)
Field of Economic Activity:						
Non-Agriculture	0.245***	0.236***	0.236***	0.180***	0.174***	0.174***
	(0.042)	(0.042)	(0.042)	(0.022)	(0.023)	(0.023)
Occupation:						
Agricultural Sector	0.058	0.075	0.075	-0.207***	-0.191***	-0.191***
	(0.043)	(0.043)	(0.043)	(0.022)	(0.023)	(0.023)
Industrial Sector	-0.020	-0.001	-0.001	-0.056***	-0.039***	-0.039***
	(0.021)	(0.021)	(0.021)	(0.011)	(0.012)	(0.012)
Constant	7.457***	7.355***	7.355***	8.216***	8.101***	8.101***
	(0.065)	(0.070)	(0.070)	(0.041)	(0.049)	(0.049)
N	6603	6603	6603	16801	16801	16801
R-squared	0.284	0.282	0.282	0.325	0.322	0.322
Adjusted R-squared	0.283	0.281	0.281	0.324	0.322	0.322
Root MSE	0.635	0.635	0.635	0.550	0.551	0.551

Note: Robust standard errors in parentheses.
* p<0.05, ** p<0.01, *** p<0.001

4.2 Estimates of Gender-Specific OLS and IV (2SLS and GMM) Regression

Table 3 presents the gender-disaggregated regression results, which estimate returns to education and experience using OLS, 2SLS, and GMM, based on HIES 2010 and 2016 data. For males, the average return to an additional year of education was 5.5% in 2010, rising slightly to 5.7% in 2016, according to OLS estimates. As with the full sample, gender-specific regressions also face endogeneity concerns, necessitating the use of IV (2SLS and GMM) methods. IV estimates reveal that the return for males increased from 6.1% in 2010 to 6.6% in 2016, slightly higher than the corresponding OLS values.

For females, the returns to education were significantly higher than for males. OLS estimates show average returns of 11.1% in 2010 and 11.5% in 2016, while IV estimates suggest even higher returns of 13.8% in 2010 and 13.2% in 2016, all statistically significant at the 1% level. Across both years and estimation methods, the education premium for females exceeded that of males by more than five percentage points, reinforcing the argument for targeted investment in women's education. This aligns with Dougherty (2005), who found that women's returns to education in the United States were 1.96 percentage points higher than those of men.

The effect of job experience also varied by gender and year. In 2010, returns to an additional year of experience were slightly higher for females than for males, as confirmed by both OLS and IV estimates. However, in 2016, the opposite was observed: the effect of experience was more pronounced for males, while it declined considerably for females. This decline may be attributed to an increase in the supply of female labor, often at lower wages, amid shifting labor market dynamics. The quadratic term of experience yielded negative and statistically significant coefficients, confirming the existence of diminishing marginal returns to experience. While the squared term remained significant for both genders, the effect of experience for females in 2016 was minimal and statistically insignificant, suggesting a flattening of the experience-income profile for women. In some cases, the positive coefficient on the squared experience term may indicate that returns re-accelerate at older ages; however, this trend appears weak and is sensitive to gender. These results are consistent with Asadullah (2006), who, using OLS and Heckman estimates, also found that education and experience have a positive impact on income. Additionally, Asadullah reported that women's wages can exceed those of men in specific contexts.

The role of marital status is also significant. In 2010, both OLS and IV estimates show that unmarried males earned less than married males. For females, the IV estimate suggests that unmarried women earned slightly more than married women, though the result is statistically insignificant. By 2016, both unmarried male and female workers earned less than their married counterparts, with OLS estimates indicating that unmarried females earned 25% less than married females.

Geographic differences further influenced wage outcomes. In 2010, both urban males and females earned significantly more than their rural counterparts, with urban females earning approximately 5% more than rural females, as indicated by both OLS and IV estimates. In 2016, this pattern persisted, but the urban wage premium for females decreased relative to that for males. Moreover, female wages declined noticeably in 2016 compared to 2010, with OLS estimating an 8% drop and GMM estimating a 5% drop, underscoring a potential deterioration in women's wage conditions despite improvements in education.

Sectoral wage disparities remained significant across both years. According to OLS and IV estimates, both male and female workers in the non-agricultural sector earned more than their agricultural counterparts in both 2010 and 2016. However, wages declined for both genders in 2016, possibly reflecting increased labor competition in the agricultural sector. Among males, the non-agricultural wage premium dropped from 26% in 2010 to 18% in 2016. In contrast, females in the non-agricultural sector experienced a wage increase—from 5.6% in 2010 to 16.5% in 2016—potentially due to rising education and skill levels among female workers in this sector.

In terms of occupation, male agricultural workers earned more than their counterparts in the service sector in 2010, but this trend reversed by 2016, when service sector wages surpassed those in agriculture. For females, agricultural workers consistently earned more than service sector workers in both years; however, their relative wage advantage declined sharply, from 11.4% in 2010 to 5.7% in 2016. For males in the industrial sector, wages remained lower than those in the service sector in both years. Conversely, females in the industrial sector earned more than those in services in both 2010 and 2016. However, this wage premium dropped dramatically from 17% in 2010 to just 3% in 2016, indicating growing sectoral inequality among women.

4.3 Estimates of Area-Specific OLS and IV (2SLS and GMM) Regression

Using OLS and IV regression techniques (2SLS and GMM), this study estimated the determinants of monthly income separately for rural and urban areas. As presented in Table 4, the returns to education were positive and statistically significant at the 1% level in both regions and across both years (2010 and 2016). Owing to more advanced industrialization and economic activity, the returns to schooling were consistently higher in urban areas. Specifically, the IV estimates for 2010 indicate that the return to an additional year of education was 4.2% in rural areas and 8.4% in urban areas, with urban returns being twice as high. In 2016, the return increased slightly in both areas, reaching 4.7% in rural areas and 8.6% in urban areas, thereby reinforcing the urban advantage in educational returns.

The returns to experience were also found to be positive, with both OLS and IV models yielding similar results in both years. However, the quadratic term for experience had a negative and statistically significant coefficient, indicating diminishing marginal returns to experience in both rural and urban contexts. Notably, the marginal impact of experience increased in rural areas in 2016 compared to 2010, while it declined in urban areas, indicating a shift in the relationship between experience and income.

Gender-based disparities remained pronounced across both years and regions. In both 2010 and 2016, women earned significantly less than men, as indicated by the gender dummy variable. However, the nature of the gender wage gap shifted: in 2010, the gap was larger in rural areas, with women earning 47% less than men, compared to 30% in urban areas. By 2016, this trend reversed—urban women earned approximately 50% less than urban men, while the rural gap narrowed to 35%. This suggests an increasing gender wage disparity in urban labor markets despite general economic growth.

Table 3. OLS and IV (2SLS and GMM) Regression of Log Monthly Wage by Gender in 2010 and 2016

	2010						**2016**					
	Male			**Female**			**Male**			**Female**		
	OLS	**2SLS**	**GMM**	**OLS**	**2SLS**	**GMM**	**OLS**	**2SLS**	**GMM**	**OLS**	**2SLS**	**GMM**
Year of Education	0.055***	0.061***	0.061***	0.111***	0.138***	0.138***	0.057***	0.066***	0.066***	0.115***	0.132***	0.132***
	(0.002)	(0.003)	(0.003)	(0.007)	(0.012)	(0.012)	(0.001)	(0.002)	(0.002)	(0.011)	(0.016)	(0.016)
Experience	0.030***	0.033***	0.033***	0.042***	0.057***	0.057***	0.023***	0.026***	0.026***	0.001	0.009	0.009
	(0.004)	(0.004)	(0.004)	(0.010)	(0.012)	(0.012)	(0.002)	(0.002)	(0.002)	(0.019)	(0.020)	(0.020)
Experience Square	-0.045***	-0.048***	-0.048***	-0.056**	-0.073***	-0.073***	-0.030***	-0.033***	-0.033***	0.032	0.024	0.024
	(0.006)	(0.006)	(0.006)	(0.020)	(0.020)	(0.020)	(0.004)	(0.004)	(0.004)	(0.035)	(0.036)	(0.036)
Marital Status:												
Unmarried and Others	-0.026	-0.004	-0.004	-0.057	0.008	0.008	-0.049	-0.042	-0.042	-0.248***	-0.247***	-0.247***
	(0.030)	(0.032)	(0.032)	(0.063)	(0.068)	(0.068)	(0.062)	(0.062)	(0.062)	(0.073)	(0.073)	(0.073)
Area:												
Urban	0.151***	0.143***	0.143***	0.226***	0.190**	0.190**	0.198***	0.190***	0.190***	0.141	0.141	0.141
	(0.019)	(0.019)	(0.019)	(0.067)	(0.067)	(0.067)	(0.010)	(0.011)	(0.011)	(0.078)	(0.077)	(0.077)
Field of Economic Activity:												
Non-Agriculture	0.262***	0.256***	0.256***	0.056	0.018	0.018	0.181***	0.174***	0.174***	0.165	0.165	0.165
	(0.042)	(0.042)	(0.042)	(0.176)	(0.181)	(0.18)	(0.022)	(0.023)	(0.023)	(0.230)	(0.224)	(0.224)
Occupation:												
Agricultural Sector	0.043	0.055	0.055	0.114	0.160	0.160	-0.211***	-0.197***	-0.197***	0.057	0.113	0.113
	(0.043)	(0.043)	(0.043)	(0.175)	(0.177)	(0.177)	(0.022)	(0.023)	(0.023)	(0.224)	(0.222)	(0.222)
Industrial Sector	-0.034	-0.021	-0.021	0.169*	0.275**	0.275**	-0.058***	-0.041***	-0.041***	0.030	0.064	0.064
	(0.022)	(0.022)	(0.022)	(0.080)	(0.087)	(0.087)	(0.011)	(0.012)	(0.012)	(0.087)	(0.092)	(0.092)
Constant	7.416***	7.338***	7.338***	6.633***	6.239***	6.239***	8.205***	8.099***	8.099***	7.472***	7.194***	7.194***
	(0.068)	(0.072)	(0.072)	(0.224)	(0.260)	(0.260)	(0.041)	(0.048)	(0.048)	(0.379)	(0.425)	(0.425)
N	5912	5912	5912	691	691	691	16337	16337	16337	464	464	464
R-squared	0.257	0.256	0.256	0.377	0.364	0.364	0.320	0.318	0.318	0.309	0.304	0.304
Adjusted R-squared	0.256	0.255	0.255	0.370	0.357	0.357	0.320	0.318	0.318	0.297	0.292	0.292
Root MSE	0.612	0.612	0.612	0.771	0.774	0.774	0.542	0.543	0.543	0.753	0.748	0.748

Note: Robust standard errors in parentheses.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 4. OLS and IV (2SLS and GMM) Regression of Log Monthly Wage in Rural and Urban Areas for 2010 and 2016

	2010						2016					
	Rural			Urban			Rural			Urban		
	OLS	**2SLS**	**GMM**	**OLS**	**2SLS**	**GMM**	**OLS**	**2SLS**	**GMM**	**OLS**	**2SLS**	**GMM**
Year of Education	0.038***	0.042***	0.042***	0.076***	0.084***	0.084***	0.042***	0.047***	0.047***	0.076***	0.086***	0.086***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)
Experience	0.017***	0.019***	0.019***	0.031***	0.035***	0.035***	0.020***	0.021***	0.021***	0.021***	0.024***	0.024***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Experience Square	-0.027***	-0.029***	-0.029***	-0.045***	-0.048***	-0.048***	-0.028***	-0.030***	-0.030***	-0.020**	-0.023***	-0.023***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Gender:												
Female	-0.471***	-0.471***	-0.471***	-0.296***	-0.297***	-0.297***	-0.348***	-0.349***	-0.349***	-0.495***	-0.489***	-0.489***
	(0.042)	(0.042)	(0.042)	(0.048)	(0.048)	(0.048)	(0.061)	(0.061)	(0.061)	(0.056)	(0.056)	(0.056)
Marital Status:												
Unmarried and Others	-0.064	-0.053	-0.053	-0.102*	-0.069	-0.069	-0.256***	-0.255***	-0.255***	-0.131	-0.122	-0.122
	(0.035)	(0.036)	(0.036)	(0.043)	(0.045)	(0.045)	(0.069)	(0.069)	(0.069)	(0.077)	(0.076)	(0.076)
Field of Economic Activity:												
Non-Agriculture	0.296***	0.292***	0.292***	0.139	0.127	0.127	0.204***	0.200***	0.200***	0.091	0.073	0.073
	(0.044)	(0.044)	(0.044)	(0.115)	(0.115)	(0.115)	(0.023)	(0.023)	(0.023)	(0.085)	(0.086)	(0.086)
Occupation:												
Agricultural Sector	0.069	0.075	0.075	-0.078	-0.055	-0.055	-0.201***	-0.192***	-0.192***	-0.360***	-0.345***	-0.345***
	(0.046)	(0.046)	(0.046)	(0.114)	(0.114)	(0.114)	(0.023)	(0.023)	(0.023)	(0.070)	(0.071)	(0.071)
Industrial Sector	-0.012	-0.005	-0.005	-0.018	0.005	0.005	-0.030	-0.020	-0.020	-0.070***	-0.049**	-0.049**
	(0.031)	(0.032)	(0.032)	(0.028)	(0.029)	(0.029)	(0.015)	(0.017)	(0.017)	(0.015)	(0.016)	(0.016)
Constant	7.638***	7.595***	7.595***	7.545***	7.425***	7.425***	8.356***	8.292***	8.292***	8.329***	8.192***	8.192***
	(0.081)	(0.089)	(0.089)	(0.134)	(0.137)	(0.137)	(0.054)	(0.067)	(0.067)	(0.095)	(0.102)	(0.102)
N	3656	3656	3656	2947	2947	2947	9671	9671	9671	7130	7130	7130
R-squared	0.177	0.177	0.177	0.303	0.301	0.301	0.214	0.213	0.213	0.278	0.274	0.274
Adjusted R-squared	0.175	0.175	0.175	0.301	0.299	0.299	0.213	0.212	0.212	0.277	0.273	0.273
Root MSE	0.585	0.585	0.585	0.678	0.678	0.678	0.534	0.534	0.534	0.562	0.563	0.563

Note: Robust standard errors in parentheses.
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Marital status also had a significant effect on income across regions. Between 2010 and 2016, unmarried workers in both rural and urban areas consistently earned less than their married counterparts. In 2010, the OLS estimates show a statistically significant adverse effect in urban areas, while in 2016, both OLS and IV regressions indicate that the adverse wage effect was more pronounced in rural areas.

Sectoral comparisons reveal consistent wage premiums in non-agricultural sectors across both rural and urban settings. In rural areas, wages in the non-agricultural sector were 30% higher than those in the agricultural sector in 2010. However, this premium declined to about 20% by 2016, reflecting narrowing wage differentials. This trend aligns with Mamun and Arfanuzzaman (2020), who also reported higher non-agricultural wages, especially at higher wage quantiles in urban settings.

Occupational patterns further support sectoral wage shifts. In 2010, the occupation dummy indicates that in rural areas, wages in the agricultural sector were higher than in the service sector, whereas the opposite was true in urban areas. By 2016, this pattern had reversed: agricultural wages were significantly lower than those in the service sector in both rural and urban areas. In 2010, wages in the industrial sector were 1.2% lower in rural areas and 1.8% lower in urban areas relative to the service sector. These gaps widened in 2016, with industrial wages falling to approximately 3% and 7% lower, respectively, than service sector wages, indicating a growing wage disadvantage in industrial employment across both spatial contexts.

5. Conclusion and Recommendation

The analysis of Household Income and Expenditure Survey (HIES) data from 2010 and 2016 reveals that the key determinants of income—such as gender, age, marital status, rural-urban residence, and human capital factors like education and work experience—have remained broadly consistent over time. These variables exert a minor to moderate influence on income levels. A comparison of income trends using Ordinary Least Squares (OLS), Instrumental Variable (IV) estimations (2SLS), and Generalized Method of Moments (GMM) indicates that while Bangladesh has experienced significant changes in its income distribution, returns to education and experience have slightly declined in 2016 compared to 2010.

Notably, the gender wage gap widened in 2016 relative to 2010, reflecting persistent gender inequality in the labor market. However, the results also show that women received a higher marginal return on education than men, with an increase of over 5% in both periods, according to both OLS and IV estimates. This underscores the importance of investing in women's education as a strategy for promoting gender equity and economic empowerment.

In addition, wage disparities between married and unmarried individuals, as well as between rural and urban residents, also increased in 2016. Conversely, the wage gap between the agricultural and non-agricultural sectors narrowed significantly, indicating substantial wage improvements in the agricultural sector. Despite this convergence, the service sector maintained wage dominance over both agriculture and industry in 2016, suggesting that it remains the most productive employment sector.

Higher wage levels in services may incentivize labor shifts away from agriculture and industry, potentially reducing labor surpluses and improving productivity across all sectors. Analysis further reveals that both male and female urban workers earned substantially more than their rural counterparts in both years. However, urban women experienced a slight decline in earnings between 2010 and 2016.

OLS and IV regressions confirm that workers in the non-agricultural sector consistently earned higher wages than those in agriculture. Although real wages for both male and female workers decreased in 2016, the returns to education and experience continued to have a positive influence on income across both rural and urban areas. Interestingly, the marginal effect of education on income increased slightly in 2016 in both settings, while the influence of work experience also grew, particularly in rural areas.

Despite some sectoral gains, the gender wage gap remained significant in both rural and urban areas across both years, with a shift in disparity from rural dominance in 2010 to urban dominance in 2016. Furthermore, rural non-agricultural wages were approximately 30% higher than agricultural wages in 2010; however, this premium decreased to around 20% by 2016. In both urban and rural contexts, wages in the industrial sector lagged behind those in the service sector, with the disparity widening in 2016.

These findings highlight the significant role of the labor market, human capital, and social factors in determining wage outcomes in Bangladesh. It is evident that investments in human capital, alongside structural reforms, have the potential to elevate earnings and foster inclusive economic growth.

Policy Recommendations:

a. Promote Sustainable Urbanization: As urban wages continue to rise, strategic urban development is crucial to stimulate national growth and alleviate pressure on urban infrastructure resulting from rural-urban migration.
b. Strengthen Rural Development: Investing in rural infrastructure, education, and employment opportunities can reduce regional income disparities and promote balanced growth.
c. Enhance Human Capital: Increased investments in education, vocational training, and lifelong learning—especially for women—can raise workforce productivity and earnings.
d. Boost Productivity in Agriculture and Industry: Technological upgrades and improved practices in these sectors can close the wage gap with services and ensure equitable sectoral development.
e. Reduce Gender Wage Disparities: Gender-sensitive labor policies and affirmative action can help close the wage gap and increase female labor force participation.
f. Foster Economic Diversification: Bangladesh should transition from a low-cost, labor-intensive economy to a knowledge-driven, innovation-led economy, drawing lessons from the developmental experiences of Singapore, South Korea, China, Hong Kong, Taiwan, and Bangalore, India.
g. Adopt Research-Based Industrial Policies: These should focus on productivity enhancement, digitization, import substitution, capital investment, and strengthening both physical and soft infrastructure.

Implementing these strategies can enable Bangladesh to reduce poverty, wage inequality, and regional disparities, while improving household incomes, labor market efficiency, and overall economic competitiveness.

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