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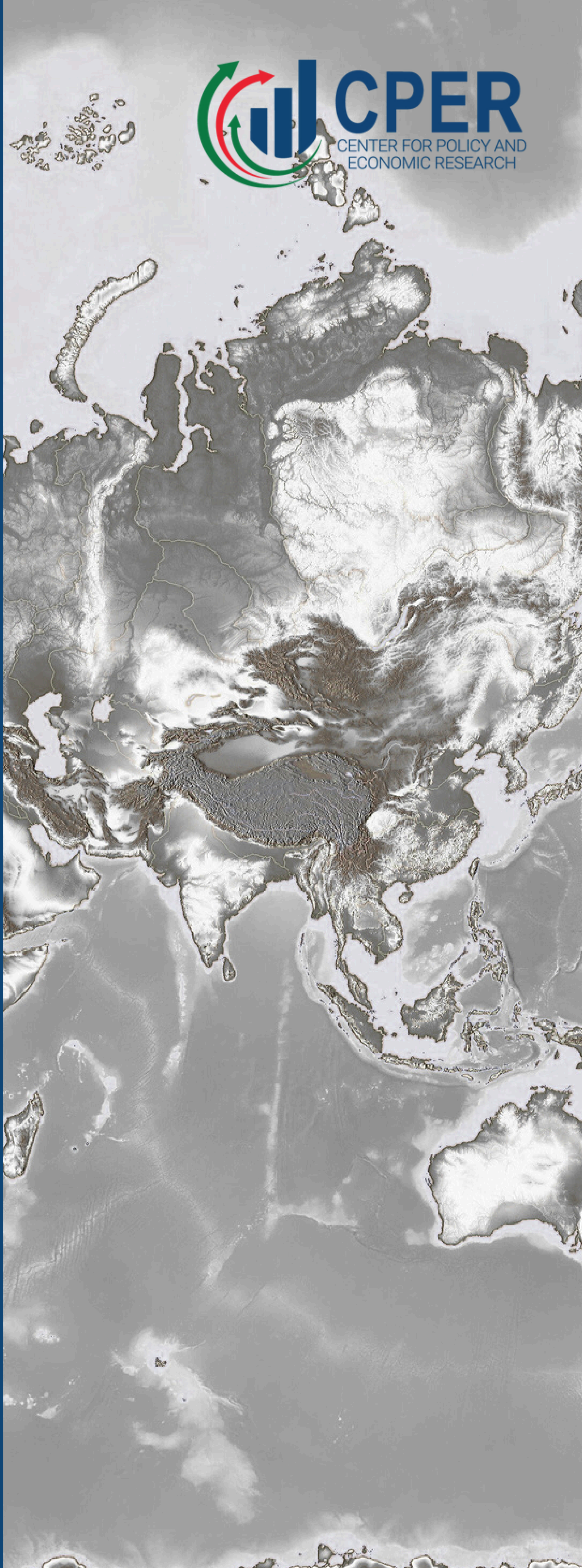

Return to Education and Work Experience in Bangladesh

An Instrumental Variable Quantile Regression Approach

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Abstract

This study examines the private returns to education and work experience in Bangladesh, focusing on heterogeneity across the wage distribution and moving beyond conventional average-effect estimates to provide robust causal evidence relevant to human capital and inequality policies. Using nationally representative data from the Household Income and Expenditure Survey (HIES) 2016–2017, the analysis applies Ordinary Least Squares (OLS), Instrumental Variable Generalized Method of Moments (IV-GMM), Quantile Regression (QR), and Instrumental Variable Quantile Regression (IVQR) techniques to address endogeneity in schooling and to capture distributional effects, with parental education serving as an instrument for individual educational attainment. The results show that both education and work experience significantly increase earnings. At the same time, endogeneity-corrected estimates indicate higher returns to education than OLS estimates, confirming that mean-based models underestimate the true causal effects. IVQR estimates reveal pronounced heterogeneity, unlike the QR, with returns to education rising monotonically across the wage spectrum, suggesting that higher-wage earners benefit disproportionately. At the same time, work experience yields positive but diminishing returns. Substantial gender and rural–urban wage gaps persist, although women experience relatively higher marginal returns to education, particularly at the lower end of the wage distribution. Although the cross-sectional nature of the data limits the analysis of dynamic wage trajectories and the instrument may not capture all intergenerational channels, the findings provide credible and policy-relevant insights. By being among the first studies to apply an IVQR framework, this research offers updated and nuanced evidence on how education and experience shape wage inequality in a developing-country context.

Keywords: Returns to education; Work experience; Income equity, Generalized method of moments; Instrumental variable quantile regression; Human capital; Bangladesh.

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Return to Education and Work Experience in Bangladesh: An Instrumental Variable Quantile Regression Approach

1. Introduction

Education and work experience are widely recognized as fundamental drivers of human capital accumulation and income generation, forming the theoretical backbone of the Mincerian earnings function and Becker's human capital theory (Becker, 1962; Mincer, 1958, 1974). These frameworks posit that individuals invest in education and skill development to enhance productivity, thereby increasing their lifetime earnings potential. Empirical research across both developed and developing economies consistently demonstrates that additional years of schooling and greater work experience yield significant wage premiums, though the magnitude and distribution of these returns can vary substantially by context and population subgroup (Mamun et al., 2021; Asadullah, 2006; Rahman & Al-Hasan, 2018; Rumberger, 1980; Duraisamy, 2002; Martins et al., 2004). In Bangladesh, a country undergoing rapid economic transformation and labor market restructuring, understanding the economic returns to education and experience is particularly salient for the formulation of equitable and effective education and labor policies (Mamun et al., 2021; Ullah, 2023).

Despite notable progress in educational access and attainment, Bangladesh continues to face challenges in translating educational investments into equitable labor market outcomes. Returns to education are not uniform; they differ markedly by gender, location, and skill level. Evidence indicates that individuals in urban areas and those with tertiary education typically earn higher incomes, while rural and less educated workers remain disadvantaged (Asadullah, 2006; Mamun et al., 2021; Rahman & Al-Hasan, 2018; Ullah, 2023). These disparities highlight the need to examine not only average effects but also the distributional heterogeneity of returns to education and experience—a dimension that traditional mean-based models often overlook (Rahman & Al-Hasan, 2018; Mamun et al., 2021).

Early empirical studies in Bangladesh predominantly employed Ordinary Least Squares (OLS) models to estimate mean returns to schooling, reporting average private returns ranging from 4% to 13% across education levels, with higher returns for women (Asadullah, 2006; Mamun et al., 2021). However, these studies often did not address endogeneity or sample selection bias, potentially underestimating accurate returns (Rahman & Al-Hasan, 2018; Mamun et al., 2021; Shafiq, 2007). More recent research has adopted advanced econometric techniques, such as instrumental variable (IV) methods and Heckman selection correction, to address omitted-variable bias and sample selection (Beyhum et al., 2022; Mamun et al., 2021; Mamun et al., 2022; Mamun et al., 2023). For example, Mamun et al. (2021) estimated average returns of 18% using IV techniques, while Mohammad and Inaba (2020) documented heterogeneous returns across the wage distribution using quantile regression with nationally representative HIES 2016 data.

The application of Instrumental Variable Quantile Regression (IVQR) has further advanced the literature by enabling the estimation of returns at different points of the wage distribution while correcting for endogeneity (Rahman & Al-Hasan, 2018). Rahman and Al-Hasan (2018) demonstrated that returns to schooling in Bangladesh increase along the wage distribution and are higher for females and urban residents (Rahman & Al-Hasan, 2018). International evidence corroborates these findings, showing that ignoring endogeneity leads to underestimation of returns and that education yields higher marginal benefits for upper-income earners (Girma & Kedir, 2005; Nosier et al., 2022). Studies in other developing contexts also emphasize the utility of IVQR for uncovering heterogeneity and addressing endogeneity bias arising from unobserved ability or family background (Chernozhukov & Hansen, 2006; Balestra & Backes-Gellner, 2017). Methodological advancements—such as smoothed estimating equations (Kaplan & Sun, 2016), averaging estimation (Liu, 2019), and k-class IVQR models (Kaplan & Liu, 2024)—have further enhanced the precision and robustness of IVQR estimation. These developments provide a strong econometric foundation for revisiting the Bangladeshi context using updated data and rigorous estimation strategies.

Despite the growing body of research, several gaps remain. Most studies in Bangladesh have focused on average effects using OLS or conventional IV methods, neglecting the distributional heterogeneity in returns to education and experience. While some have employed quantile regression, few have combined it with an IV framework that simultaneously addresses endogeneity and wage dispersion. Moreover, comprehensive analyses using nationally representative HIES 2016 data to jointly examine education and work experience across the entire wage distribution are scarce. As a result, policymakers lack up-to-date, credible evidence on how education and experience jointly influence income inequality and labor market efficiency.

This study intends to estimate the heterogeneous returns to education and work experience in Bangladesh using the Instrumental Variable Quantile Regression (IVQR) framework. The specific objectives are to:

1. Quantify the private returns to education across different quantiles of the wage distribution using nationally representative HIES 2016 data.
2. Estimate how work experience contributes to earnings heterogeneity across quantiles.
3. Correct for endogeneity in education and experience using valid instrumental variables.
4. Provide policy-relevant insights to inform education and labor market strategies aimed at improving income equity.

This research makes several important contributions. First, it is among the few studies to apply the IVQR approach to a nationally representative Bangladeshi dataset, HIES 2016, and to capture both the causal and distributional effects of education and experience on earnings. Second, by jointly analyzing education and work experience, including other variables, the study offers a comprehensive perspective on human capital returns in Bangladesh. Third, it provides updated estimates that reflect recent structural changes in the labor market. Finally, the study's methodological rigor and policy relevance offer valuable guidance for designing interventions to reduce wage inequality and maximize the economic returns from human capital investments.

The remainder of this paper is structured as follows. Section 2 outlines the econometric methodology, focusing on the IVQR framework. Section 3 describes the dataset and variable construction, including the identification of instrumental variables. Section 4 presents the empirical findings and discusses their implications for education and labor market policy. Section 5 concludes with policy recommendations and directions for future research.

2. Methodology

2.1 Conceptual Framework

This study follows the human capital framework of Becker (1993) and the Mincerian (1974) earnings function, which posits that education and work experience are key determinants of individual earnings. The standard Ordinary Least Squares (OLS) approach estimates the mean of the conditional wage distribution, assuming that the marginal effect of education and experience on wages is homogeneous across individuals. The baseline Mincerian wage equation can be expressed as:

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

where Y_i denotes the monthly wage, X_i is a vector of explanatory variables including education, experience, and demographic characteristics, β represents the parameters to be estimated, and u_i is the error term.

While the OLS estimator provides an unbiased estimate under the assumption of exogeneity, it becomes inconsistent when endogeneity is present, i.e., when one or more regressors are correlated with the error term due to omitted variables, measurement error, or reverse causality (Verbeek, 2008). Consequently, mean regression models may yield misleading results when the returns to education or experience differ across the wage distribution.

To examine potential endogeneity, several diagnostic tests were conducted. First, Ramsey's (1969) Regression Specification Error Test (RESET) was applied to detect omitted variable bias. The null hypothesis of correct model specification was rejected at the 5% level, suggesting that the model may be subject to omitted-variable bias. Second, the Durbin–Wu–Hausman test was employed to assess whether education is endogenous in the wage equation (Davidson & MacKinnon, 1993). The test statistic ($\chi^2 = 19.532$, $p < 0.01$) led to the rejection of the null hypothesis of exogeneity, confirming contemporaneous endogeneity between years of schooling and wages. Hence, OLS estimates are likely biased and inconsistent, warranting the use of an Instrumental Variable (IV) approach.

2.2 Model Specification

To address endogeneity, the study employs an Instrumental Variables (IV) framework within the Generalized Method of Moments (GMM) estimation. The extended Mincerian wage equation is specified as follows:

$$\begin{aligned} \mathrm{lnwage}_i = {} & \beta_0 + \beta_1 \mathrm{Education}_i + \beta_2 \mathrm{Experience}_i + \beta_3 \mathrm{Experience}_i^2 + \beta_4 \mathrm{Gender}_i + \beta_5 \mathrm{Religion}_i \\ & + \beta_6 \mathrm{MaritalStatus}_i + \beta_7 \mathrm{Area}_i + \beta_8 \mathrm{FieldofEconomicActivity}_i + \beta_9 \mathrm{Occupation}_i \\ & + u_i \end{aligned} \tag{2}$$

In this model, education ($\mathrm{Education}_i$) is treated as endogenous, while the other covariates are treated as exogenous. To instrument for education, parents' education is used as an exogenous instrument. This variable satisfies both the relevance condition (strongly correlated with the individual's education level) and the exogeneity condition (uncorrelated with the individual's current wage after controlling for education and other covariates).

2.3 The Generalized Method of Moments (GMM) Estimator

The Generalized Method of Moments (GMM), introduced by Hansen (1982), provides a flexible and efficient framework for estimating parameters in the presence of endogeneity and heteroskedasticity. The GMM estimator is derived from the orthogonality condition between the instruments and the error term:

$$E[\, Z_i' \,(Y_i - X_i\beta)] = 0 \tag{3}$$

where Z_i represents a vector of valid instruments. The method minimizes a quadratic form of the sample moments to produce an estimator that is both consistent and asymptotically efficient.

In this context, the GMM framework uses the instrument (parents' education) to obtain consistent estimates of the returns to education and experience. It also adjusts for potential heteroskedasticity in the wage equation, yielding more efficient standard errors than conventional IV methods (Wooldridge, 2010). Furthermore, GMM is advantageous in this setting because it allows for multiple moment conditions and can efficiently combine information across equations if necessary. This property enhances estimation efficiency and robustness when compared to traditional linear estimators.

2.4 Instrumental Variable Quantile Regression (IVQR)

While GMM effectively addresses endogeneity, it estimates the average return to education and experience across the wage distribution. However, the impact of education and experience may vary across different income levels. To explore this heterogeneity, the study employs the Instrumental Variable Quantile Regression (IVQR) approach developed by Chernozhukov and Hansen (2006).

The IVQR model can be expressed as:

$$Q_\tau(\ln wage_i \mid X_i, Z_i) = X_i'\beta_\tau + u_{i\tau}, \qquad \tau \in (0, 1) \tag{4}$$

where $Q_\tau(\cdot)$ denotes the conditional quantile of $\ln wage_i$ at quantile τ, and β_τ is the vector of parameters that may vary across quantiles.

This approach estimates the causal impact of education and experience at different points of the wage distribution, capturing heterogeneous effects among low-, middle-, and high-wage earners. Estimation is conducted using smoothed estimating equations (Kaplan & Sun, 2016), which improve convergence and inference. The IVQR framework thus extends the analysis beyond mean effects, providing a richer understanding of the distributional effects of education and experience on earnings.

3. Data and Variables

3.1 Data Source and Sample Selection

This study employs microdata from the Household Income and Expenditure Survey (HIES) 2016–2017, conducted by the Bangladesh Bureau of Statistics (BBS). The HIES is the most comprehensive nationally representative survey in Bangladesh, collecting detailed information on household income, expenditure, demographic composition, education, and employment characteristics. The 2016–2017 survey covered 1,86,076 individuals (Rural: 1,30,435; Urban: 55,641) from 46,080 households (Rural: 32,096; Urban: 13,980), representing all eight administrative divisions of Bangladesh.

For the purpose of this analysis, the sample was restricted to wage earners aged between 15 and 60 years.[2] Observations with missing or inconsistent information and duplicate entries were excluded to ensure data accuracy. After applying these filters, the final analytical sample consisted of 9,833 wage earners, including 9,501 males and 332 females, with 5,764 rural and 4,069 urban respondents. The selection process ensures the study focuses on active labor market participants, enabling more precise estimates of the returns to education and experience in Bangladesh's labor market.

3.2 Variable Definition

The dependent variable is the monthly wage income. Since the HIES provides both daily and monthly earnings (including in-kind payments), all wage data were converted into monthly equivalents. For daily workers, the average number of working days per month was used to standardize earnings. This variable captures the total labor income received by individuals, providing a consistent measure across all employment types.

The key explanatory variables include:

- Years of Education: the number of completed school years, serving as a measure of human capital investment.
- Experience: constructed as Experience = Age − 6 − Years of Education, following the convention of Mincer (1974) and Asadullah (2006).
- Gender, Marital Status, Area of Residence (Rural/Urban), Field of Economic Activity (Agriculture/Non-agriculture), and Occupation (Service, Industry, Agriculture): all included as binary or categorical variables to capture demographic and occupational heterogeneity.

Because the education variable is likely endogenous—due to unobserved ability, omitted variables, or reverse causality—parents' education is used as an instrumental variable (IV). This instrument satisfies the relevance and exogeneity conditions established in the empirical literature (Card, 1999; Wooldridge, 2016). Parental education is strongly correlated with individual educational attainment yet plausibly uncorrelated with individual wage shocks, making it a valid and widely accepted instrument for education in wage regressions.

3.3 Descriptive Statistics

Table 1 presents the descriptive statistics for the full sample and by gender and area of residence. The average monthly wage is BDT 11,107.84, with a standard deviation of BDT 11,915.34, indicating substantial variation in earnings. Male workers earn, on average, BDT 11,195.61, compared to BDT 8,595.92 for female workers—indicating a significant gender wage gap of roughly 23%. Urban workers

[2] Below 15 years of age has not been deliberated because age between 5-14 years is considered child labor in Bangladesh (Salmon, 2005). Besides, above 60 years is also not considered in this study due to the retirement age being 59 years in Bangladesh, according to the Public Service Retirement Act 1974b.

earn on average BDT 14,546.30, which is nearly 68% higher than the rural average of BDT 8,680.51, reflecting a pronounced urban–rural income divide in Bangladesh.

The mean years of education in the sample is 7.08 years, higher than the national average of 5.9 years in 2016 (UNDP, 2020). Educational attainment is slightly higher among females (7.21 years) than among males (7.08 years), though the smaller number of female wage earners in the sample may influence this. The urban workforce has notably higher educational attainment (8.27 years) than rural workers (6.25 years), highlighting spatial disparities in access to education and skill development opportunities. However, parents' years of education follow the same pattern as employees'.

The average work experience is 25.79 years, with male workers averaging slightly more experience than females (25.82 vs. 24.86 years). Rural workers tend to have marginally higher experience levels (26.14 years) than their urban counterparts (25.28 years), possibly reflecting the older age structure of rural labor markets.

The gender composition reveals a highly male-dominated labor force—96.6% male and only 3.4% female—underscoring the persistent gender imbalance in formal employment. Furthermore, 97.8% of workers are married, suggesting that labor market participation is closely tied to family responsibilities. In terms of sectoral distribution, approximately 30% of workers are employed in agriculture, 18% in industry, and 52% in services. The service sector dominates in both urban and rural areas, indicating structural shifts away from agriculture in Bangladesh's economy. Employment in non-agricultural sectors (70%) is considerably higher in urban areas, reflecting Bangladesh's ongoing structural transformation toward service-oriented employment (Mamun & Arfanuzzaman, 2020).

3.4 Wage Distribution Patterns

Figures 1 and 2 illustrate the kernel density estimates of the logarithmic monthly wage distributions by gender and area of residence. Both distributions exhibit a right-skewed pattern, indicating that most workers earn below the mean wage, while a small fraction earns substantially higher salaries. Figure 1 shows an apparent gender disparity in the wage distribution, with the entire male wage density to the right of the female distribution. This implies that male workers consistently earn higher wages across the whole distribution, not just at the mean. The wider spread for male workers suggests greater wage inequality within the male labor force, possibly due to heterogeneity in education, skills, and job type. Figure 2 compares the wage distributions between rural and urban workers. The urban wage distribution is significantly to the right of the rural distribution, indicating higher wages and greater dispersion in urban labor markets. This gap reflects structural and productivity differentials between rural and urban economies, as well as variations in access to education and high-paying occupations. The two-sample Kolmogorov–Smirnov (K–S) test confirms that the wage distributions differ significantly by both gender and area ($p < .001$), rejecting the null hypothesis that they originate from the same population. These findings emphasize persistent wage-structure inequalities across demographic and regional lines in Bangladesh.

4. Results and Discussion

4.1 Overview of the Estimation Results

The results provide comprehensive evidence on how education and work experience influence wage determination in Bangladesh. Using the 2016–2017 Household Income and Expenditure Survey (HIES), the study applies Ordinary Least Squares (OLS), Instrumental Variable Generalized Method of Moments (IV-GMM), Quantile Regression (QR), and Instrumental Variable Quantile Regression (IVQR) approaches. These estimations correct for endogeneity bias and reveal heterogeneity across the wage distribution, contributing to the growing literature on human capital and income inequality in developing economies (Becker, 1993; Asadullah, 2006; Balestra & Backes-Gellner, 2017).

Table 1. Summary Statistics

	Full	**Male**	**Female**	**Rural**	**Urban**
Monthly Income	11107.840	11195.610	8595.922	8680.510	14546.3
	(11915.34)	(11886.34)	(12476.65)	(8979.623)	(14447.73)
Year of Education	7.084	7.080	7.214	6.249	8.26641
	(3.954)	(3.947)	(4.163)	(3.578)	(4.156)
F/M Year of Education	6.270	6.254	6.716867	5.677	7.110
	(3.935)	(3.917)	(4.402)	(3.571)	(4.261)
Experience	25.786	25.819	24.861	26.142	25.282
	(9.504)	(9.468)	(10.468)	(9.453)	(9.554)
Gender:					
Male	0.966	…	…	0.971	0.959
	(0.181)			(0.168)	(0.197)
Female	0.034	…	…	0.029	0.041
	(0.181)			(0.168)	(0.197)
Religion:					
Muslim	0.864	0.865	0.837	0.845	0.891
	(0.343)	(0.342)	(0.370)	(0.362)	(0.312)
Non-Muslim	0.136	0.135	0.163	0.155	0.109
	(0.343)	(0.342)	(0.370)	(0.362)	(0.312)
Marital Status:					
Married	0.978	0.995	0.485	0.980	0.975
	(0.147)	(0.069)	(0.501)	(0.140)	(0.156)
Unmarried & Others	0.022	0.005	0.515	0.020	0.025
	(0.147)	(0.069)	(0.501)	(0.140)	(0.156)
Area:					
Rural	0.586	0.589	0.503	…	…
	(0.493)	(0.492)	(0.501)		
Urban	0.414	0.411	0.497	…	…
	(0.493)	(0.492)	(0.501)		
Field of Economic Activity:					
Agriculture	0.300	0.306	0.127	0.493	0.025
	(0.458)	(0.461)	(0.333)	(0.500)	(0.156)
Non-Agriculture	0.700	0.694	0.873	0.507	0.975
	(0.458)	(0.461)	(0.333)	(0.500)	(0.156)
Occupation:					
Service Sector	0.515	0.511	0.639	0.364	0.729
	(0.500)	(0.500)	(0.481)	(0.481)	(0.444)
Agricultural Sector	0.304	0.311	0.111	0.499	0.028
	(0.460)	(0.463)	(0.315)	(0.500)	(0.164)
Industrial Sector	0.181	0.179	0.250	0.137	0.243
	(0.385)	(0.383)	(0.434)	(0.344)	(0.429)
Observations	9,833	9,501	332	5,764	4,069

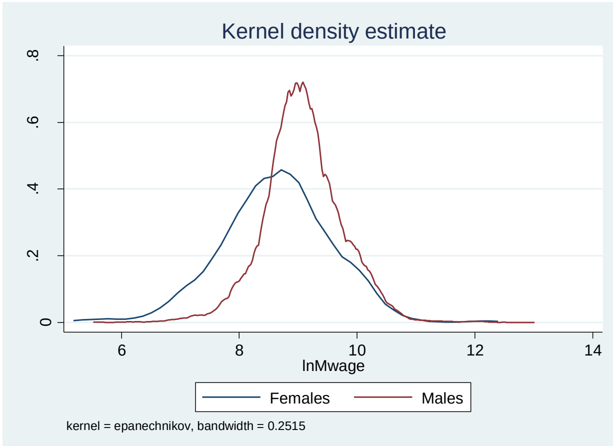

Figure 1. Kernel Density Estimates of Log Monthly Wage Distribution by Gender

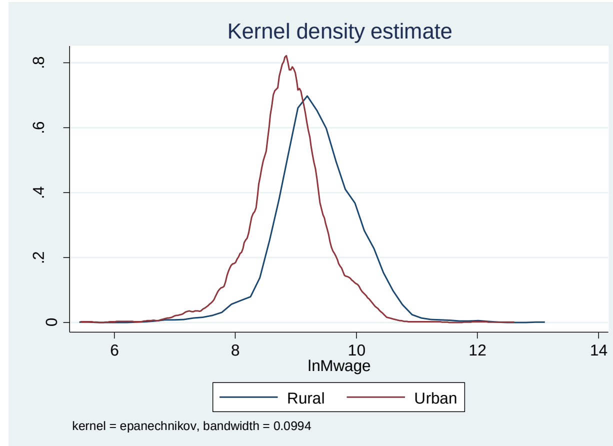

Figure 2. Kernel Density Estimates of Log Monthly Wage Distribution by Area

4.2 OLS and IV-GMM Estimates

Table 2 compares the OLS and IV-GMM regression results. The estimated coefficient of years of education is 0.0571 in the OLS model and increases to 0.0683 in the IV-GMM model, both statistically significant at the 1% level. This implies that, after correcting for endogeneity, an additional year of schooling raises monthly earnings by approximately 6.8%, compared to 5.7% in the OLS estimate. The upward adjustment suggests that OLS underestimates the true return to education due to measurement error or omitted ability bias, consistent with Card (1999) and Asadullah (2006).

The coefficient of work experience remains positive and significant in both models, indicating that each additional year of experience increases wages by about 1.9%, with diminishing returns as shown by the negative and significant squared term. This pattern reflects the classical Mincerian concavity of the earnings–experience profile (Mincer, 1974).

Gender differentials remain substantial. Female workers earn roughly 41% less than their male counterparts, even after controlling for observable factors. This persistent wage gap aligns with prior findings by Shafiq (2007) and Mamun & Arfanuzzaman (2020), indicating that structural labor market segregation and gender-based discrimination remain significant challenges in Bangladesh, including the informal labor market (Mamun, 2023; Mamun, 2024)

Urban employees earn around 19% higher wages than rural workers, confirming the urban wage premium documented in earlier studies (Kolstad et al., 2014; Rahman & Hasan, 2021). Similarly, employment in non-agricultural sectors yields approximately 21% higher wages than in agriculture, underscoring Bangladesh's ongoing structural transformation.

4.3 Quantile Regression (QR) Estimates

While OLS provides mean effects, quantile regression (QR) captures heterogeneity across the wage distribution (Table 3). The returns to education increase monotonically from 3.2% at the 10^{th} quantile to 6.7% at the 90th quantile, implying that education benefits higher-wage earners more strongly. This rising pattern suggests that the labor market rewards education disproportionately at the upper tail, possibly due to the demand for skilled labor in high-productivity sectors.

Table 2. OLS and IV (GMM) Regression of Log Monthly Wage

	OLS	**IVGMM**
Year of Education	0.0571***	0.0683***
	(0.00177)	(0.00319)
Experience	0.0159***	0.0189***
	(0.00304)	(0.00315)
Experience Square	-0.0202***	-0.0233***
	(0.00528)	(0.00536)
Gender:		
Female	-0.413***	-0.412***
	(0.0513)	(0.0509)
Religion:		
Muslim	0.0700***	0.0767***
	(0.0166)	(0.0167)
Marital Status:		
Unmarried and Others	-0.239***	-0.229***
	(0.0645)	(0.0643)
Area:		
Urban	0.202***	0.190***
	(0.0141)	(0.0142)
Field of Economic Activity:		
Non-Agriculture	0.220***	0.212***
	(0.0320)	(0.0321)
Occupation:		
Agricultural Sector	-0.182***	-0.163***
	(0.0318)	(0.0323)
Industrial Sector	-0.0597***	-0.0382*
	(0.0147)	(0.0157)
Constant	8.190***	8.052***
	(0.0564)	(0.0668)
N	9832	9832
R-squared	0.316	0.313
Adjusted R-squared	0.315	0.312
Root MSE	0.567	0.568

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

A similar trend is observed for work experience, with positive and significant coefficients across most quantiles, though the effect diminishes slightly at lower quantiles. These findings mirror those in Balestra and Backes-Gellner (2017) and Moniruzzaman and Emran (2021), who found that returns to education and experience are not uniform across income groups, indicating the presence of wage inequality driven by human capital heterogeneity.

Female workers face a pronounced disadvantage across all quantiles, earning between 19% and 87% less than male workers, with the gap narrowing toward the upper quantiles. This pattern suggests that highly educated women at higher wage levels face less discrimination, possibly due to better occupational matching or greater access to formal-sector jobs (Field & Ambrus, 2008; Mamun et al., 2021).

Table 3. Quantile Regression (QR) of Log Monthly Wage

	Q10	Q25	Q50	Q75	Q90
Year of Education	0.0317***	0.0480***	0.0603***	0.0655***	0.0672***
	(0.00313)	(0.00201)	(0.00177)	(0.00174)	(0.00225)
Experience	0.0127*	0.00881*	0.0158***	0.0224***	0.0248***
	(0.00589)	(0.00379)	(0.00333)	(0.00327)	(0.00423)
Experience Square	-0.0223*	-0.0103	-0.0186**	-0.0279***	-0.0292***
	(0.0104)	(0.00667)	(0.00586)	(0.00576)	(0.00744)
Gender:					
Female	-0.873***	-0.505***	-0.358***	-0.242***	-0.193***
	(0.0782)	(0.0504)	(0.0443)	(0.0435)	(0.0562)
Religion:					
Muslim	0.0769*	0.0887***	0.0801***	0.0550**	0.0690**
	(0.0323)	(0.0208)	(0.0183)	(0.0180)	(0.0232)
Marital Status:					
Unmarried and Others	-0.183	-0.347***	-0.268***	-0.175**	-0.0888
	(0.0960)	(0.0618)	(0.0543)	(0.0534)	(0.0690)
Area:					
Urban	0.185***	0.158***	0.181***	0.187***	0.217***
	(0.0263)	(0.0169)	(0.0149)	(0.0146)	(0.0189)
Field of Economic Activity:					
Non-Agriculture	0.316***	0.231***	0.207***	0.235***	0.220***
	(0.0562)	(0.0362)	(0.0318)	(0.0313)	(0.0404)
Occupation:					
Agricultural Sector	-0.111*	-0.174***	-0.178***	-0.165***	-0.204***
	(0.0566)	(0.0365)	(0.0321)	(0.0315)	(0.0407)
Industrial Sector	0.0803**	0.000417	-0.0577***	-0.113***	-0.159***
	(0.0306)	(0.0197)	(0.0173)	(0.0170)	(0.0220)
Constant	7.703***	8.043***	8.200***	8.376***	8.582***
	(0.106)	(0.0680)	(0.0598)	(0.0587)	(0.0759)
N	9832	9832	9832	9832	9832
R-squared					
Adjusted R-squared					
Root MSE					

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

4.4 Instrumental Variable Quantile Regression (IVQR) Estimates

To account for endogeneity in education and explore distributional heterogeneity, the study employed IVQR estimation (Table 4). Results show that returns to education increase across the wage distribution—from 5.0% at the 10th quantile to 7.7% at the 90th quantile—after controlling for endogeneity. These results are higher than the OLS and QR estimates, suggesting that OLS and QR underestimate the true causal effect of education due to omitted ability or family background biases.

Table 4. Instrumental Variable Quantile Regression (IVQR) Regression of Log Monthly Wage

	Q10	**Q25**	**Q50**	**Q75**	**Q90**
Year of Education	0.0504***	0.0580***	0.0702***	0.0722***	0.0767***
	(0.00735)	(0.00597)	(0.00290)	(0.00274)	(0.00396)
Experience	0.0181**	0.0122**	0.0190***	0.0229***	0.0276***
	(0.00645)	(0.00379)	(0.00331)	(0.00353)	(0.00368)
Experience Square	-0.0283*	-0.0147*	-0.0223***	-0.0273***	-0.0324***
	(0.0110)	(0.00620)	(0.00543)	(0.00657)	(0.00619)
Gender:					
Female	-0.868***	-0.515***	-0.366***	-0.249***	-0.190***
	(0.132)	(0.0717)	(0.0676)	(0.0630)	(0.0372)
Religion:					
Muslim	0.0816*	0.0989***	0.0850***	0.0640***	0.0766***
	(0.0342)	(0.0192)	(0.0179)	(0.0178)	(0.0220)
Marital Status:					
Unmarried and Others	-0.139	-0.346***	-0.256***	-0.172*	-0.0786
	(0.145)	(0.0797)	(0.0734)	(0.0787)	(0.0844)
Area:					
Urban	0.176***	0.153***	0.167***	0.178***	0.191***
	(0.0261)	(0.0167)	(0.0160)	(0.0147)	(0.0194)
Field of Economic Activity:					
Non-Agriculture	0.301***	0.211***	0.199***	0.227***	0.223***
	(0.0567)	(0.0443)	(0.0353)	(0.0269)	(0.0330)
Occupation:					
Agricultural Sector	-0.105	-0.178***	-0.169***	-0.149***	-0.171***
	(0.0637)	(0.0486)	(0.0381)	(0.0301)	(0.0388)
Industrial Sector	0.0886**	0.0155	-0.0422**	-0.0937***	-0.132***
	(0.0303)	(0.0190)	(0.0148)	(0.0168)	(0.0237)
Constant	7.480***	7.927***	8.076***	8.307***	8.459***
	(0.123)	(0.0831)	(0.0735)	(0.0697)	(0.0893)
N	9832	9832	9832	9832	9832
R-squared					
Adjusted R-squared					
Root MSE					

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

This pattern is consistent with findings by Chernozhukov and Hansen (2006) and Asadullah (2006), and more recently with Mamun & Arfanuzzaman (2020), who reported stronger returns when education endogeneity is corrected using instrumental variable methods. The rising gradient across quantiles implies that education not only raises average earnings but also amplifies income inequality, as the benefits of education accrue disproportionately to individuals at higher wage levels.

The coefficients of experience and experience squared follow the expected signs, indicating positive but diminishing returns. This concave relationship implies that work experience contributes significantly to wage growth early in one's career but plateaus after a certain threshold, aligning with Becker's (1993) human capital accumulation theory.

4.5 Gender-Specific Analysis

Tables 5–7 present the results of the gender-disaggregated estimations using OLS, IV-GMM, Quantile Regression (QR), and Instrumental Variable Quantile Regression (IVQR) methods. These analyses allow for a more nuanced understanding of how education and work experience affect male and female earnings differently across the income distribution, while addressing potential endogeneity in the education variable.

The results reveal clear gender-specific patterns in the returns to education. Among male workers, the IV-GMM estimates (Table 5) indicate that an additional year of education increases monthly earnings by approximately 6.8%, holding other factors constant. In contrast, the corresponding return for female workers rises to 9.9%, suggesting that education has a disproportionately higher marginal impact on women's earnings despite their lower overall wage levels. This finding corroborates earlier research in South Asia by Shafiq (2007) and Aslam et al. (2012), who documented that women tend to experience steeper returns to education because schooling enhances their likelihood of entering formal, higher-paying occupations and reduces constraints in accessing skilled employment.

However, it is crucial to interpret these higher female returns within context. Women in Bangladesh represent a smaller share of the formal labor force, and those who do participate are typically more educated, urban-based, and employed in professional or service-oriented occupations. Consequently, the higher estimated returns partly reflect positive selection bias, where only relatively advantaged women are included in wage employment (Klasen & Pieters, 2015; Rahman & Al-Hasan, 2019). Despite this, the strong association between education and earnings for women underscores the potential of education to act as a transformative mechanism for economic empowerment and social mobility.

The quantile regression estimates (Table 6) further reveal that the impact of education varies across the female wage distribution. At the 10th quantile (Q10), returns to education reach nearly 12% per additional year of schooling, gradually declining to around 9% at the 90th quantile (Q90). This declining trend across quantiles suggests that education disproportionately benefits low-income women, possibly because it enables them to transition from informal, subsistence-based work to formal or semi-formal occupations with higher, more stable earnings. This pattern aligns with evidence from Field and Ambrus (2008) and Mamun et al. (2020), who found that education has a powerful effect on lifting women out of low-wage, insecure employment in Bangladesh.

In contrast, the male quantile regression results (Table 7) demonstrate a more gradual increase in returns across the wage distribution, from approximately 5% at Q10 to 7.5% at Q90. This suggests that education enhances male earnings capacity consistently across the income spectrum, but with less heterogeneity than for women. The relatively flatter slope of male returns implies that men's labor market outcomes are less sensitive to differences in education level, likely because men are already concentrated in wage-earning roles across both formal and informal sectors, where the link between education and wage progression is more linear (Asadullah, 2006; Kolstad et al., 2014).

The experience variables for both genders maintain the expected signs, indicating positive but diminishing returns to work experience. For men, experience contributes significantly to wage growth up to mid-career, after which returns taper, consistent with the traditional Mincerian profile. For women, experience also yields positive returns, but the magnitude is smaller and statistically weaker—reflecting interrupted work histories due to childcare, household responsibilities, and limited access to long-term career opportunities (Klasen & Pieters, 2015).

Collectively, these results suggest that education serves as a more powerful equalizing force for women than for men, particularly among lower-income earners. However, despite higher marginal returns to education, the absolute wage gap remains substantial, driven by occupational segregation, limited job mobility, and persistent gender bias in hiring and promotion practices. The findings are consistent with Becker's (1993) human capital framework, but they also highlight the influence of social and institutional constraints that restrict women from fully capitalizing on their educational investments (Patrinos & Psacharopoulos, 2020).

4.6 Rural–Urban Analysis

Tables 8–10 present a comparative analysis of returns to education and work experience across rural and urban labor markets in Bangladesh, estimated using the OLS, IV-GMM, QR, and IVQR approaches. This comparison is central to understanding spatial heterogeneity in human-capital returns and how structural differences across regions shape wage formation.

The IV-GMM results (Table 8) reveal that the average return to an additional year of education is 5.1 percent in rural areas compared with 8.3 percent in urban areas, suggesting a clear and persistent urban advantage. This disparity underscores the uneven distribution of economic opportunities across Bangladesh. Urban labor markets tend to be more diversified and technologically intensive, with higher concentrations of formal employment, manufacturing, and service-sector activities that reward schooling more strongly. In contrast, rural economies remain dominated by agriculture and informal self-employment, where educational attainment has weaker influence on productivity and wage determination (Asadullah, 2006; Mamun & Arfanuzzaman, 2021).

The larger urban premium also reflects differences in the quality of education and access to complementary resources. Urban residents benefit from better schooling infrastructure, exposure to information technology, and access to professional networks, which collectively enhance the productivity of education. Rural workers, by contrast, face limited access to quality secondary and tertiary institutions and a narrower set of jobs requiring formal qualifications. These structural asymmetries translate into lower returns to education even when years of schooling are comparable.

Turning to the distributional results, Table 9 presents the Quantile Regression (QR) results for rural and urban areas, showing heterogeneity in the returns to education and work experience between rural and urban labor markets in Bangladesh. In rural areas, the estimated returns to education rise modestly from 3.1% at the 10th quantile (Q10) to 6.1% at the 90th quantile (Q90), indicating that education contributes positively to earnings but with smaller effects among low-income workers. This suggests that many rural jobs—especially in agriculture and informal sectors—provide limited opportunities for educated individuals to translate schooling into higher productivity or wages. The wage gains become more pronounced at higher quantiles, where rural workers are more likely to be employed in non-farm or semi-formal occupations, which better reward education.

In urban areas, however, education exerts a stronger and more consistent influence across the wage distribution. Returns increase from 6.6% at Q10 to 9.0% at Q90, reflecting a steeper educational gradient and the greater demand for skilled labor in service-oriented and industrial sectors. These results highlight that urban labor markets are more responsive to human capital, with higher education translating into substantially higher earnings, particularly at the upper end of the income spectrum. Experience also shows a positive but diminishing effect in both settings, though the magnitude is greater in urban areas, suggesting better opportunities for skill accumulation and wage progression.

The IVQR estimates (Table 10) show pronounced heterogeneity across the wage spectrum. In rural areas, returns to education rise modestly from 3.1 percent at the 10^{th} quantile (Q10) to 6.1 percent at the 90^{th} quantile (Q90). This pattern suggests that while education slightly increases earnings among low-income rural workers, the marginal benefit is greater for higher-income individuals—typically those employed in non-farm or semi-formal occupations. The findings resonate with evidence from Moniruzzaman and Emran (2021), who reported that rising educational attainment in rural Bangladesh has improved wages primarily for workers transitioning out of agriculture.

In urban areas, the IVQR results indicate more substantial, steeper returns—from 6.6 percent (Q10) to 9.0 percent (Q90)—demonstrating that urban labor markets reward human capital more robustly and non-uniformly across income levels. The steep gradient implies that higher education disproportionately benefits workers in the upper wage deciles, reflecting the premium attached to cognitive, managerial, and technical skills in competitive urban sectors. These results align with international evidence from Balestra and Backes-Gellner (2017) and regional studies by Rahman and Al-Hasan (2019), which show that education amplifies wage inequality when skill-biased technological change favors high-productivity urban jobs.

Work-experience coefficients further support the presence of spatial segmentation. In rural areas, experience yields smaller but significant returns, indicating limited scope for learning-by-doing due to seasonal employment and the prevalence of low-productivity tasks. In contrast, the urban experience premium is stronger and remains significant across all quantiles, suggesting that continuous exposure to dynamic industries enables faster skill accumulation and career progression (Kolstad et al., 2014). The concavity of the experience–wage relationship persists in both regions, confirming the classical Mincerian pattern of diminishing marginal returns as workers age.

These findings collectively highlight the dual-economy nature of Bangladesh's labor market. The coexistence of a high-return, education-intensive urban economy alongside a low-return, subsistence-based rural sector reinforces regional inequality. Moreover, the upward-sloping IVQR profiles imply that as education expands, the benefits may accrue disproportionately to skilled urban workers, potentially widening the rural–urban wage gap if access to quality education and formal jobs remains unequal (Patrinos & Psacharopoulos, 2020).

From a policy standpoint, the evidence calls for targeted interventions to increase the economic returns to education in rural areas. Strengthening vocational and technical training, improving rural school quality, and enhancing connectivity between rural labor and non-farm industries could increase the productivity of education outside cities. Parallel efforts to ensure equitable access to higher education and urban job markets are vital to prevent spatially entrenched inequality.

Table 5. OLS and IV (GMM) Regression of Log Monthly Wage for Gender

	Male		Female	
	OLS	IVGMM	OLS	IVGMM
Year of Education	0.0558***	0.0676***	0.0964***	0.0994***
	(0.00177)	(0.00319)	(0.0135)	(0.0221)
Experience	0.0178***	0.0207***	-0.00262	-0.00148
	(0.00302)	(0.00313)	(0.0225)	(0.0229)
Experience Square	-0.0234***	-0.0265***	0.0234	0.0224
	(0.00525)	(0.00534)	(0.0392)	(0.0393)
Religion:				
Muslim	0.0754***	0.0822***	-0.0202	-0.0169
	(0.0167)	(0.0168)	(0.100)	(0.103)
Marital Status:				
Unmarried and Others	-0.0956	-0.0795	-0.275**	-0.274**
	(0.0804)	(0.0808)	(0.0920)	(0.0915)
Area:				
Urban	0.199***	0.187***	0.298**	0.298**
	(0.0140)	(0.0141)	(0.0988)	(0.0972)
Field of Economic Activity:				
Non-Agriculture	0.220***	0.212***	0.155	0.152
	(0.0322)	(0.0323)	(0.214)	(0.211)
Occupation:				
Agricultural Sector	-0.188***	-0.168***	0.00774	0.0145
	(0.0320)	(0.0325)	(0.219)	(0.221)
Industrial Sector	-0.0580***	-0.0355*	-0.0549	-0.0482
	(0.0146)	(0.0157)	(0.109)	(0.109)
Constant	8.173***	8.030***	7.717***	7.672***
	(0.0564)	(0.0668)	(0.407)	(0.474)
N	9500	9500	332	332
R-squared	0.313	0.309	0.250	0.249
Adjusted R-squared	0.312	0.308	0.229	0.228
Root MSE	0.556	0.557	0.808	0.796

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

Table 6. Quantile Regression (QR) of Log Monthly Wage for Gender

	Q10		Q25		Q50		Q75		Q90	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Year of Education	0.0302***	0.118***	0.0468***	0.0886***	0.0602***	0.0977***	0.0640***	0.118***	0.0660***	0.0911***
	(0.00319)	(0.0250)	(0.00205)	(0.0189)	(0.00178)	(0.0157)	(0.00170)	(0.0126)	(0.00231)	(0.0192)
Experience	0.0130*	0.000575	0.0102**	0.0243	0.0169***	-0.0265	0.0234***	-0.00543	0.0256***	0.00940
	(0.00607)	(0.0395)	(0.00390)	(0.0300)	(0.00339)	(0.0249)	(0.00324)	(0.0200)	(0.00439)	(0.0304)
Experience Square	-0.0223*	0.0162	-0.0127	-0.0362	-0.0207***	0.0654	-0.0296***	0.0456	-0.0306***	0.0164
	(0.0106)	(0.0715)	(0.00684)	(0.0542)	(0.00594)	(0.0450)	(0.00568)	(0.0362)	(0.00770)	(0.0550)
Religion:										
Muslim	0.0859**	-0.172	0.0963***	-0.0567	0.0828***	0.0796	0.0623***	-0.0393	0.0674**	0.128
	(0.0331)	(0.236)	(0.0212)	(0.179)	(0.0184)	(0.148)	(0.0176)	(0.119)	(0.0239)	(0.181)
Marital Status:										
Unmarried and Others	-0.0907	-0.262	-0.125	-0.474***	-0.129	-0.410***	-0.0461	-0.215*	-0.0428	-0.0363
	(0.162)	(0.174)	(0.104)	(0.132)	(0.0902)	(0.110)	(0.0862)	(0.0884)	(0.117)	(0.134)
Area:										
Urban	0.177***	0.390*	0.157***	0.301*	0.177***	0.230*	0.184***	0.350***	0.215***	0.161
	(0.0269)	(0.183)	(0.0173)	(0.138)	(0.0150)	(0.115)	(0.0144)	(0.0925)	(0.0195)	(0.140)
Field of Economic Activity:										
Non-Agriculture	0.329***	0.171	0.221***	-0.0829	0.209***	-0.00694	0.241***	0.110	0.217***	0.303
	(0.0573)	(0.451)	(0.0368)	(0.342)	(0.0320)	(0.284)	(0.0306)	(0.228)	(0.0414)	(0.347)
Occupation:										
Agricultural Sector	-0.107	0.493	-0.191***	-0.0624	-0.181***	-0.0202	-0.167***	-0.0202	-0.206***	-0.259
	(0.0577)	(0.476)	(0.0371)	(0.361)	(0.0322)	(0.299)	(0.0308)	(0.241)	(0.0417)	(0.366)
Industrial Sector	0.0821**	-0.0237	0.00108	-0.0796	-0.0621***	0.122	-0.114***	0.0280	-0.150***	-0.306
	(0.0314)	(0.211)	(0.0202)	(0.160)	(0.0175)	(0.133)	(0.0168)	(0.107)	(0.0227)	(0.162)
Constant	7.690***	6.551***	8.038***	7.443***	8.187***	8.192***	8.363***	7.956***	8.583***	8.194***
	(0.108)	(0.785)	(0.0695)	(0.595)	(0.0604)	(0.494)	(0.0577)	(0.398)	(0.0782)	(0.604)
N	9500	332	9500	332	9500	332	9500	332	9500	332
R-squared										
Adjusted R-squared										
Root MSE										

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

Table 7. Instrumental Variable Quantile Regression (IVQR) of Log Monthly Wage for Gender

	Q10		Q25		Q50		Q75		Q90	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Year of Education	0.0501***	0.102**	0.0578***	0.0758*	0.0707***	0.0961**	0.0711***	0.124***	0.0754***	0.106***
	(0.00779)	(0.0385)	(0.00466)	(0.0322)	(0.00299)	(0.0293)	(0.00309)	(0.0263)	(0.00367)	(0.0251)
Experience	0.0195**	-0.00552	0.0140***	0.00531	0.0206***	-0.0121	0.0241***	0.00124	0.0286***	0.00599
	(0.00642)	(0.0413)	(0.00384)	(0.0362)	(0.00310)	(0.0281)	(0.00339)	(0.0199)	(0.00393)	(0.0182)
Experience Square	-0.0303*	0.0205	-0.0176*	-0.00898	-0.0247***	0.0438	-0.0298***	0.0355	-0.0346***	0.0259
	(0.0125)	(0.0641)	(0.00719)	(0.0550)	(0.00547)	(0.0510)	(0.00553)	(0.0419)	(0.00627)	(0.0411)
Religion:										
Muslim	0.0933**	-0.133	0.102***	-0.00624	0.0867***	0.0133	0.0693***	-0.00966	0.0762***	0.0790
	(0.0343)	(0.157)	(0.0243)	(0.124)	(0.0175)	(0.127)	(0.0170)	(0.102)	(0.0205)	(0.103)
Marital Status:										
Unmarried and Others	0.000744	-0.275	-0.0769	-0.433**	-0.0757	-0.430***	-0.0530	-0.235**	-0.0465	-0.0854
	(0.129)	(0.153)	(0.125)	(0.134)	(0.0961)	(0.0945)	(0.0580)	(0.0731)	(0.105)	(0.0909)
Area:										
Urban	0.171***	0.379	0.149***	0.294*	0.162***	0.260**	0.177***	0.270**	0.194***	0.241*
	(0.0282)	(0.197)	(0.0166)	(0.128)	(0.0162)	(0.0987)	(0.0158)	(0.0823)	(0.0206)	(0.0991)
Field of Economic Activity:										
Non-Agriculture	0.300***	0.170	0.210***	0.0297	0.206***	-0.0920	0.227***	0.102	0.219***	0.279
	(0.0560)	(0.282)	(0.0431)	(0.561)	(0.0405)	(0.178)	(0.0247)	(0.135)	(0.0361)	(0.163)
Occupation:										
Agricultural Sector	-0.109	0.391	-0.185***	0.0481	-0.167***	-0.162	-0.153***	-0.0392	-0.175***	-0.125
	(0.0610)	(0.327)	(0.0479)	(0.526)	(0.0425)	(0.188)	(0.0225)	(0.172)	(0.0388)	(0.201)
Industrial Sector	0.0931**	-0.00539	0.0157	-0.0335	-0.0437*	0.0947	-0.0930***	0.0782	-0.128***	-0.157
	(0.0291)	(0.195)	(0.0168)	(0.133)	(0.0183)	(0.116)	(0.0161)	(0.107)	(0.0225)	(0.179)
Constant	7.454***	6.749***	7.905***	7.598***	8.046***	8.151***	8.296***	7.859***	8.461***	8.091***
	(0.132)	(0.855)	(0.0848)	(0.820)	(0.0667)	(0.592)	(0.0703)	(0.437)	(0.0775)	(0.468)
N	9500	332	9500	332	9500	332	9500	332	9500	332
R-squared										
Adjusted R-squared										
Root MSE										

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

Table 8. OLS and IV (GMM) of Log Monthly Wage for Rural and Urban Areas

	Rural		Urban	
	OLS	IVGMM	OLS	IVGMM
Year of Education	0.0399***	0.0514***	0.0746***	0.0834***
	(0.00258)	(0.00475)	(0.00237)	(0.00426)
Experience	0.0123**	0.0153***	0.0183***	0.0205***
	(0.00420)	(0.00437)	(0.00445)	(0.00457)
Experience Square	-0.0178*	-0.0210**	-0.0188*	-0.0208*
	(0.00712)	(0.00726)	(0.00802)	(0.00809)
Gender:				
Female	-0.405***	-0.408***	-0.403***	-0.401***
	(0.0779)	(0.0771)	(0.0689)	(0.0686)
Religion:				
Muslim	0.0449*	0.0523*	0.108***	0.112***
	(0.0202)	(0.0205)	(0.0282)	(0.0281)
Marital Status:				
Unmarried and Others	-0.290**	-0.285**	-0.174	-0.163
	(0.0932)	(0.0929)	(0.0889)	(0.0887)
Field of Economic Activity:				
Non-Agriculture	0.248***	0.241***	0.134	0.121
	(0.0336)	(0.0337)	(0.101)	(0.101)
Occupation:				
Agricultural Sector	-0.169***	-0.148***	-0.372***	-0.360***
	(0.0338)	(0.0347)	(0.0889)	(0.0892)
Industrial Sector	-0.0307	-0.00900	-0.0734***	-0.0564**
	(0.0217)	(0.0233)	(0.0200)	(0.0212)
Constant	8.370***	8.231***	8.233***	8.122***
	(0.0739)	(0.0909)	(0.116)	(0.126)
N	5764	5764	4068	4068
R-squared	0.205	0.201	0.261	0.258
Adjusted R-squared	0.203	0.200	0.259	0.256
Root MSE	0.557	0.558	0.571	0.571

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

Table 9. Quantile Regression (QR) of Log Monthly Wage for Rural and Urban Areas

	Q10		Q25		Q50		Q75		Q90	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Year of Education	0.0108*	0.0594***	0.0302***	0.0706***	0.0426***	0.0786***	0.0518***	0.0826***	0.0543***	0.0814***
	(0.00471)	(0.00466)	(0.00302)	(0.00319)	(0.00257)	(0.00246)	(0.00229)	(0.00286)	(0.00290)	(0.00362)
Experience	0.00956	0.00497	0.0108*	0.0117	0.0114*	0.0222***	0.0150***	0.0274***	0.0188***	0.0303***
	(0.00852)	(0.00927)	(0.00546)	(0.00635)	(0.00464)	(0.00490)	(0.00414)	(0.00568)	(0.00525)	(0.00720)
Experience Square	-0.0185	-0.00467	-0.0163	-0.0106	-0.0142	-0.0258**	-0.0192**	-0.0301**	-0.0228*	-0.0316*
	(0.0147)	(0.0167)	(0.00944)	(0.0115)	(0.00801)	(0.00884)	(0.00715)	(0.0103)	(0.00906)	(0.0130)
Gender:										
Female	-0.821***	-0.858***	-0.444***	-0.529***	-0.365***	-0.329***	-0.376***	-0.188**	-0.183*	-0.183*
	(0.119)	(0.116)	(0.0763)	(0.0791)	(0.0648)	(0.0610)	(0.0578)	(0.0708)	(0.0733)	(0.0897)
Religion:										
Muslim	0.0636	0.128*	0.0832**	0.123**	0.0637**	0.0831**	0.0311	0.122***	0.0509	0.104*
	(0.0426)	(0.0580)	(0.0273)	(0.0397)	(0.0232)	(0.0307)	(0.0207)	(0.0356)	(0.0262)	(0.0451)
Marital Status:										
Unmarried and Others	-0.292*	-0.0723	-0.463***	-0.257*	-0.288***	-0.226**	-0.165*	-0.193*	-0.0838	-0.0543
	(0.141)	(0.147)	(0.0907)	(0.100)	(0.0769)	(0.0775)	(0.0687)	(0.0899)	(0.0871)	(0.114)
Field of Economic Activity:										
Non-Agriculture	0.344***	0.370*	0.254***	0.177	0.227***	0.0306	0.243***	0.196*	0.259***	0.198
	(0.0653)	(0.157)	(0.0419)	(0.108)	(0.0356)	(0.0830)	(0.0318)	(0.0963)	(0.0403)	(0.122)
Occupation:										
Agricultural Sector	-0.0983	-0.317*	-0.132**	-0.421***	-0.173***	-0.363***	-0.190***	-0.170	-0.197***	-0.204
	(0.0666)	(0.150)	(0.0427)	(0.103)	(0.0362)	(0.0791)	(0.0323)	(0.0918)	(0.0410)	(0.116)
Industrial Sector	0.0997*	0.0290	0.0346	-0.0153	-0.0288	-0.0465*	-0.111***	-0.103***	-0.132***	-0.181***
	(0.0494)	(0.0430)	(0.0317)	(0.0294)	(0.0269)	(0.0227)	(0.0240)	(0.0264)	(0.0304)	(0.0334)
Constant	7.868***	7.655***	8.108***	7.996***	8.385***	8.292***	8.614***	8.283***	8.752***	8.548***
	(0.147)	(0.208)	(0.0941)	(0.143)	(0.0798)	(0.110)	(0.0713)	(0.128)	(0.0904)	(0.162)
N	5764	4068	5764	4068	5764	4068	5764	4068	5764	4068
R-squared										
Adjusted R-squared										
Root MSE										

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

Table 10. Instrumental Variable Quantile Regression (IVQR) of Log Monthly Wage for Rural and Urban Areas

	Q10		Q25		Q50		Q75		Q90	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Year of Education	0.0311**	0.0655***	0.0384***	0.0758***	0.0520***	0.0836***	0.0597***	0.0868***	0.0615***	0.0903***
	(0.0113)	(0.00844)	(0.00652)	(0.00618)	(0.00483)	(0.00434)	(0.00295)	(0.00510)	(0.00580)	(0.00609)
Experience	0.0177	0.00880	0.0109*	0.0132*	0.0142**	0.0229***	0.0176***	0.0281***	0.0207***	0.0325***
	(0.00923)	(0.00901)	(0.00484)	(0.00558)	(0.00531)	(0.00524)	(0.00380)	(0.00503)	(0.00423)	(0.00569)
Experience Square	-0.0294	-0.00992	-0.0155	-0.0131	-0.0173*	-0.0254**	-0.0224***	-0.0307***	-0.0249**	-0.0339***
	(0.0155)	(0.0179)	(0.00835)	(0.0103)	(0.00829)	(0.00835)	(0.00516)	(0.00863)	(0.00761)	(0.0102)
Gender:										
Female	-0.824***	-0.844***	-0.503***	-0.554***	-0.374***	-0.329***	-0.343**	-0.181***	-0.148*	-0.215***
	(0.137)	(0.217)	(0.128)	(0.129)	(0.0860)	(0.0836)	(0.123)	(0.0531)	(0.0642)	(0.0614)
Religion:										
Muslim	0.0753*	0.115	0.0866**	0.112**	0.0707**	0.0998***	0.0338	0.121***	0.0592*	0.112*
	(0.0369)	(0.0602)	(0.0276)	(0.0343)	(0.0268)	(0.0296)	(0.0217)	(0.0319)	(0.0266)	(0.0456)
Marital Status:										
Unmarried and Others	-0.224	-0.0635	-0.381*	-0.213	-0.289**	-0.206*	-0.165*	-0.183*	-0.146	0.0160
	(0.191)	(0.231)	(0.189)	(0.170)	(0.0993)	(0.0876)	(0.0838)	(0.0761)	(0.0954)	(0.122)
Field of Economic Activity:										
Non-Agriculture	0.324***	0.331**	0.245***	0.166	0.233***	0.0588	0.238***	0.156*	0.239***	0.159
	(0.0587)	(0.104)	(0.0470)	(0.177)	(0.0274)	(0.118)	(0.0233)	(0.0653)	(0.0409)	(0.160)
Occupation:										
Agricultural Sector	-0.0638	-0.359**	-0.138**	-0.420***	-0.157***	-0.352***	-0.164***	-0.192*	-0.189***	-0.208*
	(0.0522)	(0.117)	(0.0520)	(0.107)	(0.0368)	(0.0941)	(0.0258)	(0.0906)	(0.0403)	(0.0884)
Industrial Sector	0.155***	0.0339	0.0426*	-0.00445	-0.0287	-0.0472*	-0.0804***	-0.0974***	-0.114**	-0.148***
	(0.0463)	(0.0354)	(0.0198)	(0.0242)	(0.0266)	(0.0193)	(0.0209)	(0.0219)	(0.0365)	(0.0250)
Constant	7.586***	7.599***	8.056***	7.947***	8.262***	8.187***	8.504***	8.275***	8.677***	8.465***
	(0.211)	(0.177)	(0.0952)	(0.203)	(0.101)	(0.138)	(0.0679)	(0.113)	(0.0884)	(0.164)
N	5764	4068	5764	4068	5764	4068	5764	4068	5764	4068
R-squared										
Adjusted R-squared										
Root MSE										

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

5. Conclusion

This study examined the returns to education and work experience in Bangladesh using nationally representative HIES 2016–2017 data and an Instrumental Variable Quantile Regression (IVQR) framework. By explicitly addressing endogeneity and distributional heterogeneity, the analysis provides a nuanced and policy-relevant understanding of how human capital translates into earnings across different segments of the labor market.

The empirical results consistently show that both education and work experience have a positive and statistically significant impact on wages in Bangladesh. Estimates that correct for endogeneity reveal higher returns to education than conventional OLS results, confirming that standard mean-based models underestimate the actual causal effect of schooling. The IVQR results further demonstrate substantial heterogeneity: returns to education rise monotonically across the wage distribution, indicating that higher-wage earners benefit more from additional schooling than lower-wage earners. Work experience also yields positive but diminishing returns, consistent with the concave earnings–experience profile predicted by human capital theory.

Persistent disparities are evident across gender and location. Female workers earn substantially less than male workers across all quantiles, despite experiencing higher marginal returns to education, particularly at the lower end of the wage distribution. Similarly, urban workers enjoy significantly higher returns to both education and experience than their rural counterparts, reflecting structural differences in labor demand, job composition, and access to quality education and productive employment opportunities.

This study makes several important contributions to the literature on returns to education in developing countries. First, it is among the few studies to apply an IVQR approach to nationally representative Bangladeshi data, allowing for simultaneous correction of endogeneity and exploration of distributional heterogeneity. Second, by jointly analyzing education and work experience across the entire wage distribution, the study moves beyond average effects and provides richer insights into how human capital contributes to wage inequality. Third, the findings update and extend existing evidence for Bangladesh using recent data, offering robust and methodologically rigorous estimates that are directly relevant for contemporary policy debates on education, inequality, and labor market transformation.

Despite its strengths, the study has several limitations. First, the analysis relies on cross-sectional data, which limits the ability to capture dynamic effects of education and experience over the life cycle or to fully control for unobserved individual heterogeneity. Second, although parental education is a widely used and theoretically justified instrument, it may not completely eliminate all sources of endogeneity if intergenerational factors affect wages through channels other than education. Third, the sample of female wage earners is relatively small, reflecting low female labor force participation, which may reduce the precision of gender-specific estimates. Finally, the study focuses on years of schooling rather than the quality or field of education, which may also play an important role in determining earnings.

6. Prospects for Future Research

While this study provides robust evidence on the causal and distributional effects of education and work experience on wages in Bangladesh, several avenues remain for future research to deepen understanding and inform policy design.

1. **Dynamic Analysis Using Longitudinal Data:** The current analysis relies on cross-sectional data, which limits the ability to capture wage trajectories and the long-term impact of education and experience. Future research should employ longitudinal or panel datasets to examine how returns evolve over the life cycle, account for career interruptions, and identify causal mechanisms over time.

2. **Education Quality, Field of Study, and Skills Mismatch:** This study focuses on years of schooling as a proxy for human capital, but education quality and specialization are critical determinants of labor market outcomes. Incorporating measures such as standardized test scores, institutional rankings, and field of study would provide richer insights into why returns differ across individuals and sectors. Additionally, exploring skills mismatches between education and job requirements could shed light on inefficiencies in the labor market.

3. **Technology Adoption and Structural Transformation:** Bangladesh's economy is undergoing rapid digitalization and industrial restructuring. Future research should investigate how technological change interacts with education to influence wage inequality. Questions around skill-biased technological change, automation, and the demand for digital competencies are particularly relevant for understanding future labor market dynamics.

4. **Gender and Informal Sector Employment:** The persistent gender wage gap and low female labor force participation warrant more focused analysis. Future studies could explore barriers to women's entry into formal employment, the role of social norms, and the impact of childcare and workplace policies. Similarly, examining returns to education within the informal sector—where a large share of Bangladesh's workforce is concentrated—would provide a more comprehensive picture of human capital returns.

5. **Regional and Sectoral Disparities:** Further research could delve deeper into spatial heterogeneity by analyzing returns across different regions and sectors, including emerging industries such as ICT and services. Understanding how regional development policies and sectoral shifts influence returns to education will be crucial for designing inclusive growth strategies.

6. **Policy Simulation and Impact Evaluation:** Finally, future work could employ microsimulation models or randomized controlled trials to evaluate the effectiveness of education and labor market interventions. This would help policymakers identify which strategies—such as vocational training, digital literacy programs, or gender-targeted incentives—yield the highest returns in reducing inequality and promoting inclusive development.

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