Returns to schooling in Bangladesh revisited: An instrumental variable quantile regression approach

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Abstract

The paper focuses on estimation of returns to schooling in the Bangladesh context. Earlier articles which tried to quantify the returns were constrained by a number of limitations including measurement techniques that were deployed. The present article revisits the issue and makes an attempt to build on the earlier studies by making use of quantile regression and instrumental variable quantile regression methods. The paper finds that endogeneity problem leads to underestimation of the returns to schooling and the returns tend to vary along the wage distribution, which mean regression models fail to capture. The analysis shows that average returns to schooling for female is higher than that of male. The analysis also shows that returns to schooling tends to be higher as one moves along higher percentiles of wage distribution and this is true for both male and female.

Keywords: Returns to Schooling; Instrumental Variable Regression; Quantile Regression

JEL Classification: C21, C26, I26, J01

1. Introduction

Schooling has important implications for improving human productivity and earnings capabilities in later life and this nexus has been well established and documented in relevant global literature. On the other hand, only a few studies have attempted to estimate the returns to schooling in the context of the Bangladeshi labour market[1]. However, these have two important limitations which undermine the veracity and robustness of the results. These relate to the followings: (i) earlier studies have not addressed the endogeneity problem concerning schooling and ability to earn; (ii) these studies have focused exclusively on average returns and did not deal with distributional aspects of returns to schooling at different quantiles of wage distribution. A widely cited study which estimates returns to schooling for the Bangladesh labour market is Asadullah (2006). The study makes the following observation: "in the absence of credible instruments for the schooling variable in our data set, we have eschewed the IV strategy". More recently, Sen and Rahman (2016) observed that OLS tends to underestimate the returns to schooling due to the presence of endogeneity bias. In this article the authors make an attempt to address the endogeneity issue by using credible instrument and has tried to estimate the returns to schooling for the different quantiles of the wage distribution by deploying Quantile Regression (QR) tool developed by Koenker and Bassett (1978) and Instrumental Variable Quantile Regression (IVQR) method developed by Chernozhukov and Hansen (2008) and Powell (2016).

Estimation of returns to schooling is a critically important subject particularly because schooling impacts on the level of human productivity which consequently leads to higher efficiency in economic activities, resulting in higher wages and earnings (Psacharopoulos,

[1] These include Hossain (1990); Hussain (2000); Asadullah (2006); Shafiq (2007); Sen and Rahman (2016.)

1984). It is evident from relevant literature that, individuals with higher educational attainment earn higher wages than their less educated cohorts and schooling has a positive causal relationship with economic development (Meulemeester and Rochat, 1995). To estimate returns to schooling, studies have traditionally used Mincer's (1974) human capital earnings function. However, the model's fundamental problem is the existence of correlation between innate ability and regression disturbance in the earnings function. According to the signalling theory, more educated individuals receive higher wages because schooling acts as a signal for higher ability. Although schooling does not increase the individual's earnings capacity, there is a correlation between wage and schooling because both variables are influenced by unobserved ability. Schooling provides a more reliable signal to the employers in absence of complete information about individual's ability to perform a task in a competitive labour market. This is one of the key reasons why higher educational attainment yields a higher return (Spence, 1973; Wolpin, 1977; Borjas and Bronars, 1989; Parker, 2009).

It is argued that, studies that did not address the issue of ability and regression disturbance have been subjected to measurement errors in estimating returns to schooling because of model/functional form misspecification. Card (1999), and Heckman and Polachek (1974) have argued that, though the Mincerian model specification has a seminal contribution to the literature it also has serious shortcomings. The model fails to address endogeneity, omitted variable bias, sample selection bias and non-linearity in the relationship between wages and schooling. Various methodologies have been developed and used to address the aforementioned limitations. To address endogeneity problem Harmon et al., (2003), and Belzil and Hansen (2002) have suggested inclusion of explanatory variables such as IQ test or Armed Forces qualification tests that can capture innate ability of an individual. However, this approach did not gain much popularity as data on the relevant variables is not easily available. Instead, Instrumental Variable (IV) is more widely used to deal with the endogeneity problem. A distinctive feature of IV is that it correlates with the years of schooling variable but is uncorrelated with regression disturbance (i.e. ability).

A number of studies have used the IV method and introduced different instruments to estimate returns to schooling. For instances, Griliches (1976) have used the IQ score; Angrist and Kruger (1991) used the instrument of the quarter of birth; Kane and Rouse (1993) have used college tuition; Card (1995) have used schooling of parents while Card (1999) have used college proximity; Ashenfelter and Zimmerman (1997) have used brother's schooling and/or father's schooling as an instrument. A recent study by Angrist et al., (2006) used quantile regression to capture the distributional aspects of returns to schooling. In assessing different studies, Card (1999) observes that, results by using father's education as an instrument were remarkably consistent in Ashenfelter and Zimmerman (1997) study. Use of family background in wage equation as an instrument for schooling has also been widely prevalent among social scientists (see, for instance, Card, 1995; Card, 1999; Conneely and Uusitalo, 1997; Ashenfelter and Zimmerman, 1997; Miller et al., 1995; Ashenfelter and Rouse, 1998). A comprehensive review of the literature on returns to schooling can be found in Card (1999). Taking cue from global literature, in this study the authors have used father's schooling as the instrument for measuring returns to schooling.

The Reminder of this article is organized as follows. Section 2 deals with estimation methodology. Section 3 presents the data and some descriptive elements of returns to schooling. Section 4 discusses results of the analysis on returns to schooling. Section 5 concludes.

2. Estimation Methodology

The econometric analysis involves quantification of the magnitude of male-female returns to schooling by using OLS and Generalized Methods of Moment (GMM) by estimating the average returns to schooling. QR and IVQR estimate the returns to schooling at different quantiles of the wage distribution.

To estimate the average returns to schooling we can write the regression model as $Ln(Wage) = \beta_0 + \beta_1 Education + \beta_{i+1}\boldsymbol{X}_i + \varepsilon - -(1)$, where β_1 gives the average returns to schooling ($\boldsymbol{X}_i$ is other variables in equation). However, ability is unobserved in the equation which is correlated with schooling as higher schooling is associated with higher ability; however, this is in the error term (ε). Thus, the equation violates the assumption of $E(Education, \varepsilon) = 0$. This causes endogeneity problem in equation (1) which results in ambiguity in the economic interpretation. The concerned issue has been mentioned in several studies which made an attempt to estimate the economic returns to schooling. To address this omitted variable problem, social scientists uses several methods one of which is the IV method. The optimal general estimator is the GMM which can be written as $\hat{\beta}_{GMM} = (\boldsymbol{X}'\boldsymbol{Z}\boldsymbol{W}\boldsymbol{Z}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{Z}\boldsymbol{W}\boldsymbol{Z}'\boldsymbol{y}$**,** where $\mathbf{W}$ is any full-rank symmetric-weighted matrix. In general, the weights in $\mathbf{W}$ may depend both on unknown parameters and the data. For just-identified models, all choices of $\mathbf{W}$ lead to the same estimator which minimizes the objective function $Q(\beta) = \left\{\frac{1}{N}\,(\boldsymbol{y} - \boldsymbol{X\beta})'\boldsymbol{Z}\right\}\mathbf{W}\left\{\frac{1}{N}\boldsymbol{Z}'(\boldsymbol{y} - \boldsymbol{X\beta})\right\}$ which is a matrix quadratic form in $\boldsymbol{Z}'(\boldsymbol{y} - \boldsymbol{XB})$**.** The 2SLS estimator is obtained with weighting matrix $\boldsymbol{W} = (\boldsymbol{Z}'\boldsymbol{Z})^{-\mathbf{1}}$**.** The optimal GMM estimator uses $\boldsymbol{W} = \widehat{\boldsymbol{S}}^{-\mathbf{1}}$**,** so $\widehat{\boldsymbol{\beta}}_{\boldsymbol{OGMM}} = (\boldsymbol{X}'\boldsymbol{Z}\widehat{\boldsymbol{S}}^{-\mathbf{1}}\boldsymbol{Z}'\boldsymbol{X})^{-\mathbf{1}}\boldsymbol{X}'\boldsymbol{Z}\widehat{\boldsymbol{S}}^{-\mathbf{1}}\boldsymbol{Z}'\boldsymbol{y}$**.** The estimator reduces to $\widehat{\boldsymbol{\beta}}_{\boldsymbol{IV}} = (\boldsymbol{Z}'\boldsymbol{X})^{-\mathbf{1}}\boldsymbol{Z}'\boldsymbol{y}$ in the just-identified case (Cameron and Trivedi, 2010). A more comprehensive treatment of GMM can be found in Hayashi (2000).

The statistical model of QR specifies the τ^{th} quantile of the conditional distribution of $Wage\ (w_i)$ given $regression\ (\boldsymbol{x}_i)$ as a linear function of the covariates: $Q_{\tau}(w_i|X_i) = F_w^{-1}(\tau|X_i)$, where $F_w^{-1}(\tau|X_i)$ is the distribution function for w_i conditional on X_i. τ = 0.1, $Q_{\tau}(w_i|X_i)$ describes the lower decile of w_i given X_i, while τ = 0.5 gives us conditional median. By considering at the conditional quantile distribution of wage as a function of schooling, we can capture the returns to schooling across the wage distribution. As shown by Koenker and Bassett (1978), the quantile regression coefficient β_{τ} is estimated as the solution of the following minimization problem: $Q_{\tau}(w_i|X_i) = \arg\min_{q(x)} \mathrm{E}\ [\rho_{\tau}(w_i - q(X_i))]$.

The estimated quantile regression coefficient, β_{τ}, is interpreted as the estimated returns to schooling at the τ^{th} quantile of the log wage distribution. The IVQR (Chernozhukov and Hansen, 2008) can be defined as follows: for a given $(\left(\hat{\beta}(\alpha,\tau), \hat{\gamma}\ (\alpha,\tau)\right) := \arg\min_{\beta,\gamma} Q_n(\tau,\alpha,\beta,\gamma)$. To find an estimate for $\alpha(\tau)$ we look for a value α that makes the coefficient on the instrumental variable $\hat{\gamma}\ (\alpha,\tau)$ as close to zero as possible. Let $\alpha(\tau) = \arg\inf_{\alpha \in \mathcal{A}} [W_n(\alpha)]$, $W_n(\alpha) = n[\hat{\gamma}(\alpha,\tau)']\hat{A}(\alpha)[\hat{\gamma}(\alpha,\tau)]$, where $\hat{A}(\alpha) = A(\alpha) + o_p(1)$ and $A(\alpha)$ is positive definite, uniformly in $\alpha \in \mathcal{A}$. The parameter estimates are given by $\hat{\theta}(\tau) := (\hat{\alpha}(\tau), \hat{\beta}(\tau) := (\hat{\alpha}(\tau), \hat{\beta}(\hat{\alpha}(\tau),\tau)$ ----(2). Equation 2 is the finite sample IVQR which estimates the population parameter values for α and β. This estimator is consistent and asymptotically normal under appropriate regularity and identification conditions.

3. Data and Variables

The study uses the Quarterly Labour Force Survey (QLFS) 2015-2016 data of Bangladesh Bureau of Statistics (BBS). This is a cross-section dataset and is nationally representative. The survey collects quarterly information for about 30 thousand households (about 126 thousand individuals). The dataset captures various productivity characteristics of an individual and industry, and the different occupational characteristics of the labour force. The survey collects data for the household domain. The data does not contain information on the IQ score, birth cohort, or college proximity but has rich information on family background (such as father's schooling, mother's schooling and sibling's schooling). We have taken the cue from Card (1999) which has argued that father's schooling was a relatively more strong instrument (p. 1842). Consideration of sibling's schooling makes the data generation process complex and reduces the sample size. Since we are using father's schooling as an instrument, we have dropped father's and mother's wages from the analysis. Accordingly, the estimated results only apply to son/daughter. The sample selection based on independent variables (exogenous sample selection) does not cause any statistical problem and provide reliable results (see, Wooldridge, 2013, p. 315). The sample in this study includes employed individuals between 15 to 60 years of age who had wage earnings in the reference period of the survey.

In addition to schooling, authors have also considered various productivity and occupational characteristics such as age, age square, rural-urban dummy, regional dummy and occupational status in the wage equation as explanatory variables in undertaking the exercise to estimate returns to schooling. The justification of including these variables in wage equations may be found in several studies (Mincer, 1954; Oaxaca, 1973; Blinder, 1973; Angrist and Kruger, 1991; Ashenfelter and Kruger, 1994; Card, 1995; Griliches, 1977; Card, 1999). Table 1 presents a summary of the descriptive statistic for some of the key relevant variables.

Table 1: Summary Statistics

	Male				Female			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Log (Hourly wage)	3.87	0.51	1.19	6.84	3.82	0.54	2.33	5.83
Schooling	6.7	3.8	0.0	15.0	6.5	4.1	0.0	15.0
Father's Schooling	2.8	4.0	0.0	15.0	3.0	4.3	0.0	14.0
Sample Size	3953				565			

Source: Authors' calculation using QLFS 2015-16

Average schooling in Bangladesh is found to be 6.7 years and 6.5 years for male and female respectively (Table 1). As may be noted, Asadullah (2006) found the average schooling to be 3.52 years based on HIES 1999 data set. Average log hourly wages were BDT 3.87 for male and BDT 3.82 for female respectively for the 2015-16 LFS data.

4. Results and Discussion

In this section we discuss returns to schooling for male and female, estimated by using four estimation procedures which were presented in section 2 of the paper. We compare the IV and without IV results. We also investigate the urban-rural variations in the context of returns to schooling. Table 2 shows the effect of father's schooling on the schooling of children. Average returns to schooling is given in Table 3. Table 4 present the QR and IVQR estimates of returns to schooling both for male and female.

Table 2: Effect of Father's Schooling on Completion of Schooling by Child

Dependent Variable: Highest class passed by an individual

Children	Father's Schooling	R^2	F
Male	0.46	0.23	1147.14
Female	0.51	0.25	190.82

Source: Authors' calculation using QLFS 2015-16

The reason behind using father's schooling as an instrument is because a child's schooling is highly correlated with his/her parent's schooling (Siebert, 1985). The strength of this correlation is illustrated in Table 2. Results show that each additional year of father's schooling raises the male (female) child’s schooling by 0.46 (0.51) years. About 25 per cent of the observed variations in schooling among Bangladeshi adults is explained by father’s schooling.

Table 3: Average Returns to Schooling by Gender[2]

Dependent Variable: Log (Hourly Wage)

Variables	Male		Female	
	OLS (1)	IV GMM (2)	OLS (3)	IV GMM (4)
Schooling	0.027*** (0.003)	0.073*** (0.0101)	0.025*** (0.00674)	0.081*** (0.0305)
Others variable Included?	Yes	Yes	Yes	Yes
Instrument:				
Father’s Schooling	No	Yes	No	Yes
Constant	3.94*** (0.153)	3.92*** (0.157)	3.86*** (0.258)	3.74*** (0.608)
Obs.	3,954	3,954	565	565
R-squared	0.29	0.29	0.28	0.11

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Authors’ calculation using QLFS 2015-16
Note: Others variable includes Age and age square, economic sector, rural dummy, regional dummy, marital status, occupational dummy.

Table 3 shows that, ceteris paribus, the average rate of returns to schooling for male is 2.7 per cent. However, the OLS estimates suffer from endogeneity. To address this problem, we applied the IVGMM techniques and find that the average returns to schooling is 7.3 per cent. For female, the average returns to schooling is found to be 2.5 per cent as is seen from the OLS exercise. In case of female, IVGMM shows the returns to schooling to be 8.1 per cent which is about one percentage point higher than that of male. That the returns to schooling is higher for female is not new. For instance, Dougherty (2005), using U.S. NLSY data, found that returns to schooling for female was 1.96 percentage point

[2] First stage IV regression is associated with F value is 204.45 for male and 107.25 for female. The associate p-value is 0.000 for both male and female. Sargen statistics show exact identification and validity of instrument.

higher than that of the male. Using Household Income and Expenditure Survey (HIES) 2000 data, Asadullah (2005) had earlier found that returns to schooling for female was 13.2 per cent while that for the male was 6.2 per cent (P. 459). However, the magnitude of this returns for female (7 per cent age point higher than that of male) found in the study is significantly higher than what appears to be the average case. As is seen from a review of relevant literature, this difference is less than happen to be of two percentage points[3]. Whilst women earn less than that of men, the double effects of schooling, (it increases skills and productivity for women as well as men) and schooling leading to reduction in discrimination against women, (and the resultant improved circumstances) explain the high returns on schooling for women (Dougherty, 2005).

Averages portray the returns to schooling only partially; estimates are likely to be significantly different for different quantiles of the wage distribution. We address the issue of distributional effects by applying the IVQR estimates both for male and female. This is presented in Table 4.

Table 4: QR and IVQR of Returns to Schooling by Gender

Dependent Variable: Log (Hourly Wage)

Quantiles	Male		Female	
	QR (1)	IVQR (2)	QR (3)	IVQR (4)
$\tau(15)$	0.029***	0.029***	0.014**	0.027
	(0.003)	(0.009)	(0.006)	(0.017)
$\tau(25)$	0.029***	0.055***	0.017***	0.030***
	(0.002)	(0.009)	(0.005)	(0.009)
$\tau(50)$	0.033***	0.052***	0.044***	0.069***
	(0.002)	(0.007)	(0.004)	(0.014)
$\tau(75)$	0.040***	0.057***	0.042***	0.069***
	(0.002)	(0.005)	(0.006)	(0.010)
$\tau(85)$	0.040***	0.071***	0.045***	0.071***
	(0.00313)	(0.003)	(0.009)	(0.004)
Other variables included?	Yes	Yes	Yes	Yes

[3] See Dougherty (2005), appendix 1, for a summary of 27 studies.

Instrument:				
Father's Schooling	No	Yes	No	Yes
Obs.	3953	3953	565	565

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' calculation using QLFS 2015-16
Other variable includes Age and age square, economic sector, rural dummy, regional dummy, marital status, occupational dummy. IVQR results based on 10,000 replications.

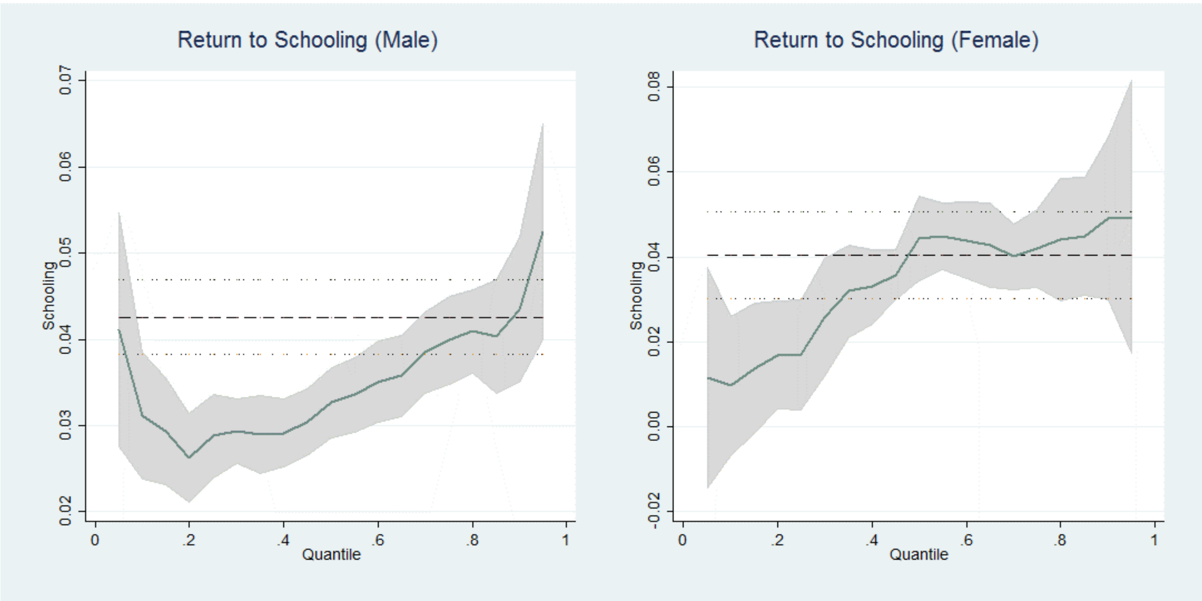
The joint significance test validates our point that returns to schooling may change significantly at different quantiles of the wage distribution. Both for male and female we reject the null hypothesis of coefficient equality at a level of 0.01 (F = 6.68 with associated p-value is 0.0000 and F = 4.72 with associated p-value is 0.0009 for male and female respectively).

IVQR shows that, at 15 percentile, the returns to schooling is 2.9 per cent (same as QR) for male and for female the returns to schooling is 2.7 per cent (but statistically insignificant as shown in the 4th column in Table 4). The returns are 5.5 (3.0) per cent at 25th percentile for male (female), 5.2 (6.9) per cent at 50th percentile for male (female), and 5.7 (6.9) per cent at 75th percentile for male (female) and 7.1 (7.1) per cent at 85th percentile for male (female) (in 2nd and 4th column in Table 4).

While the average returns to schooling is higher for female, we observe mixed results of the returns by using quantile estimates. Comparing the IVQR results only, at the 15th percentile, the returns to schooling for male is 2.9 per cent whilst that for females is statistically insignificant. A female earns 2.5 percentage point lower than that of male at the 25th percentile. On the contrary, returns to schooling for female are 1.7 and 1.2 percentage points higher at 50th and 75th percentile respectively. At the 85th percentile we observe that returns to schooling for both male and female are similar. This shows that previous studies relating to the Bangladesh labour market which have relied exclusively on average returns provides only a partial picture with respect to returns to schooling.

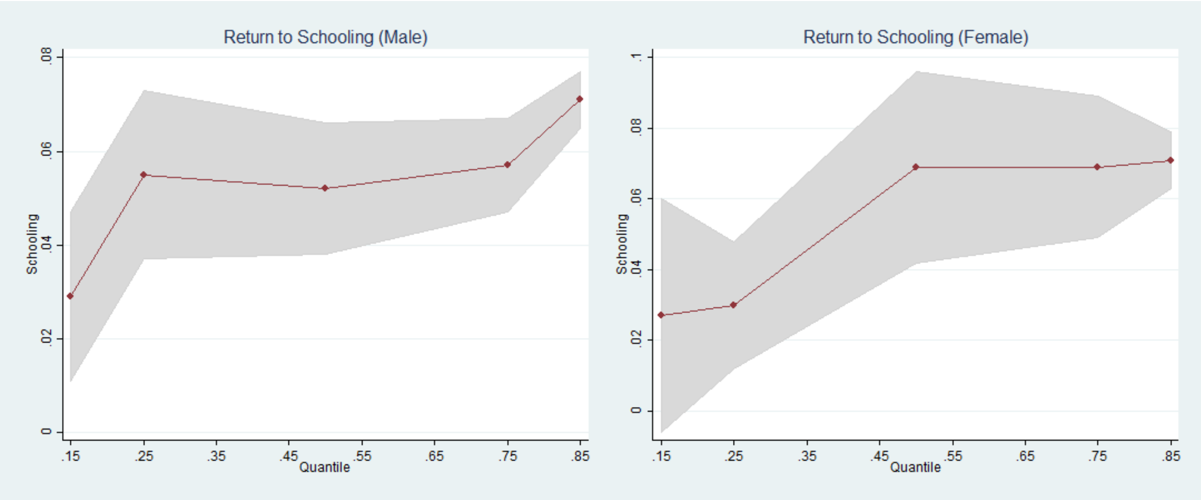
Despite the changed slope of schooling along the wage distribution, in absence of IV, both the OLS and QR underestimate the returns to schooling. For instance, for the male (female) using OLS it is found that the average returns to schooling is 2.7 (2.5) per cent. In contrast, IVGMM estimates show returns to schooling to be 7.3 (8.1) per cent. Graphical presentation of QR and OLS coefficients and their confidence intervals are presented in Figure 1 and IVQR coefficients and their confidence intervals are given in Figure 2.

Figure 1: QR and OLS coefficients and confidence intervals for Schooling



Source: Authors' calculation

Figure 2: IVQREG coefficients and confidence intervals for schooling



Source: Authors' calculation

The study extends our understanding of returns to schooling both in the urban and rural labour market (see appendix 1, Table 6). We find that an average returns to schooling in the urban labour market is 9.8 per cent for male (compared to 7.3 per cent for the male full sample). In the rural labour market, the rate is found to be 4.9 per cent (only IV results are discussed). Female returns to schooling is found to be 13.0 per cent in the rural labour market (compared to 8.1 per cent for the full sample for female). The figure is 7.2 per cent in the urban labour market. It is found that women earn more in rural areas compared to the urban areas, but male earns relatively more in the urban areas. The QR and IVQR also show similar results conditional at different quantiles (see appendix 1, Table 7). One possible explanation for this could be the higher gender segregation in various occupations observed in the urban labour market of Bangladesh (see, Rahman and Al-Hasan, 2018).

5. Conclusion

The study found that the presence of endogeneity in wage equation underestimates the returns estimated both by OLS and QR methods. The study finds that the average returns to schooling is higher for female compared to that for male. Our study found that the returns to schooling is not uniform throughout the wage distribution and that mean regression models fail to capture the distributional effects. The returns to schooling tends to be low at the lower percentiles (2.9 per cent for male and 2.7 per cent for a female at the 15th percentile) and high as we move to the higher percentiles of wage distribution (7.1 per cent both for male and female at 85th percentile). The need for indepth analysis of the various issues related to returns to schooling in the Bangladesh context, observed in Sen and Rahman (2016) continues to remain valid today. Our understanding about returns to schooling can also be further enriched by a deeper understanding about the social returns to schooling. More research is called for in this particular area.

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Appendix 1:

Table 5: Average Returns to Schooling by Gender and Urban-Rural Divide

Dependent Variable: Log (Hourly Wage)

	Urban Bangladesh				Rural Bangladesh			
	Male		Female		Male		Female	
Variables	OLS (1)	IV GMM (2)	OLS (3)	IV GMM (4)	OLS (5)	IV GMM (6)	OLS (7)	IV GMM (8)
Schooling	0.032***	0.098***	0.025***	0.072*	0.023***	0.049***	0.021*	0.13*
	(0.004)	(0.016)	(0.008)	(0.039)	(0.00326)	(0.012)	(0.011)	(0.069)
Others variable Included?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instrument:								
Father's Schooling	No	Yes	No	Yes	No	Yes	No	Yes
Constant	3.83***	3.83***	4.03***	4.08***	3.99***	3.94***	3.38***	3.55***
	(0.240)	(0.261)	(0.322)	(0.36)	(0.163)	(0.165)	(0.426)	(0.548)
Obs.	1,919	1,919	399	399	2,034	1,919	166	166
R-squared	0.30	0.19	0.33	0.13	0.25	0.22	0.40	--

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculation using QLFS 2015-16

Note: Other variables include age and age square, economic sector, rural dummy, regional dummy, marital status, occupational dummy.

Table 6: IV Quantile Estimates of Returns to Schooling by Gender and Urban-Rural Divide

Dependent Variable: Log (Hourly Wage)

	Urban				Rural			
	Male		Female		Male		Female	
Quantiles	QR (1)	IVQREG (2)	QR (3)	IVQREG (4)	QR (1)	IVQREG (2)	QR (3)	IVQREG (4)
$\tau(15)$	0.022***	0.036***	0.015*	-0.000	0.027***	0.039***	0.006	0.068***
	(0.004)	(0.002)	(0.008)	(0.008)	(0.004)	(0.006)	(0.010)	(0.013)
$\tau(25)$	0.026***	0.069***	0.022***	0.027**	0.027***	0.051***	0.022***	0.091***
	(0.003)	(0.015)	(0.005)	(0.013)	(0.003)	(0.013)	(0.008)	(0.016)
$\tau(50)$	0.031***	0.062***	0.035***	0.062***	0.029***	0.051***	0.035***	0.577
	(0.002)	(0.022)	(0.006)	(0.016)	(0.003)	(0.007)	(0.008)	(1.189)
$\tau(75)$	0.041***	0.062***	0.039***	0.052***	0.037***	0.046***	0.051***	0.061***
	(0.004)	(0.013)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.005)
$\tau(85)$	0.048***	0.066***	0.048***	0.053***	0.034***	0.049***	0.052***	0.086***
	(0.004)	(0.011)	(0.009)	(0.009)	(0.004)	(0.008)	(0.011)	(0.009)
Others variable included?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instrument:								
Father's Schooling	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Obs.	1,919	1,919	399	399	2,034	2,034	166	166

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculation using QLFS 2015

Note: Other variables include age and age square, economic sector, rural dummy, regional dummy, marital status, occupational dummy. IVQR results based on 10,000 replications.