査読論文

Return to Education in Bangladesh:
At Different Levels of Education and Wage Distribution

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Abstract

The purpose of this study is to investigate the return to education in Bangladesh. Several previous studies found the rate of return to education was just above 7%, but these studies failed to account for sample selection bias and the endogeneity of education. Compared to the estimated results of other developing countries, the return to education in Bangladesh found to be relatively low.

This study uses the recently published Household Income and Expenditure (HIES) survey 2016 data. The dependent variable is wages received daily in kind, in cash and monthly wage. This study applies the 2 step Heckman method to correct sample selection bias. Considering the heterogeneity of return to education across the distribution of the sample, quantile regression method is used to check the return.

The ordinary least square estimate is that the rate of return to an additional year of schooling ranges from 4.9% to 9% with an average rate of return at 5.4% for the full sample. After taking sample selection bias into account, the rate of return to one more year of schooling increased to 7% for men and decreased to about 2% for females with an average of 2.2% for the full sample. Quantile regression result reveals that the rates of return increases at the higher quantile with the level of education for the male sample. The OLS and quantile regression show that the rates of return to TVET and to tertiary education are higher for female than the male. This study finds that the average rate of the return to education is lower than that of the previous studies in Bangladesh and lower

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rate of return to education in rural areas.

Keywords

return to education, 2-step Heckman, quantile regression

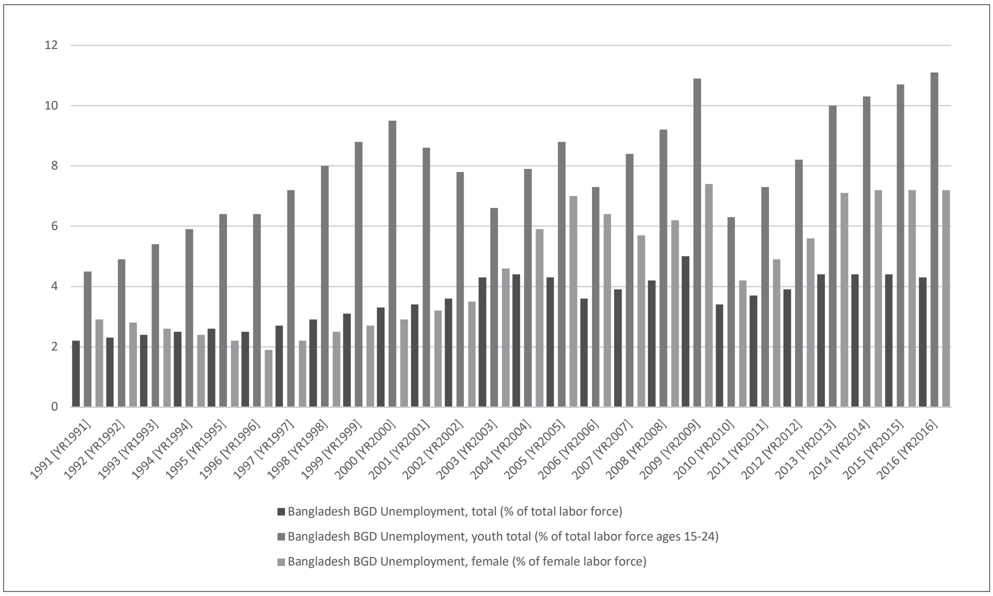
1. Introduction

Since Jacob Mincer proposed his famous Mincerian earning functions in 1974, numerous studies around the world have undertaken the task of finding the rates of return to education. The reasons behind the estimation of return to education is to justify the investment decision on education as resources are limited. In developing countries, households usually make the decision on which children should be invested in education and to what level, eyeing the prospective return on the investment.

This study examines return to education with the Household Income and Expenditure Survey (HIES) 2016 data. Prior to 2016, changes in labor market situation in Bangladesh may have affected the return to education. According to Quarterly report from the United Nations Development Program (2017), during 2003–2016 employment growth was higher than the growth of working age population. It was reported that during that period, more than a million net jobs were created with an annual growth rate of 2.4%. During this time real wages for the paid employees increased by about a 5% a year (UNDP, 2017). Despite these positive scenarios, according to UNDP Quarterly Development Updates (2017), about 40% of the working age population is out of the labor force and starting in 2010, job creation has slowed to 1.8% a year (Figure 1). The updates also raised question about the poor quality of jobs and the composition of the labor force with about 80% are engaged in informal, unpaid or agricultural work (Figure 2). Amidst slowed job creation, the 15–29 age group has the higher unemployment rate than the upper age groups (UNDP, 2017), and the likelihood of employment with a lower wage is higher.

The International Labor Organization (ILO) and the Bangladesh Bureau of Statistics (BBS) conducted survey to young people aged 15 to 29 years to monitor school to work transition. The School to Work Transition survey by the BBS found a higher rate of unemployment among the more educated individuals and labor market was highly affected by gender (Toufique, 2014). Toufique (2014) found that unemployment rates among people with no education, primary, secondary and tertiary education was 8.2%, 26.4%, 57.1% and 8.2%, respectively. He further found that about 80.8% of the women aged 15–29 were

Figure 1: Unemployment rates (as percent of labor force)



source: ILO, KLIM database

inactive or not in the labor market because of their responsibility to family and housework. A recent online survey by the Bangladesh Institute of Development Studies (BIDS) found that unemployment was lowest among the people with secondary and higher secondary education and highest among people with a bachelor's degree followed by postgraduates.

The gender gap in secondary and higher secondary education is converging in Bangladesh (Ileas and Inaba, 2020) and the women's labor force participation is in rising, though still low (UNDP, 2017). Since 2010, job creation in Bangladesh has slowed and the unemployment rate among the people aged 15–24 is increasing (Fig.1). Moreover, UNDP (2017) found a higher unemployment rate among people with tertiary education. Besides, Psacharopoulos and Patrinos (2018) found that the average rate of return to education (8.1%) in South Asia was similar to that of the advanced economies (8%). In these contexts, studying the return to education in Bangladesh can reveal how these changed situations impacted the rates of return to education in the last decade and of the labor market. This study also tries to provide policy suggestions to the government and households in order to make appropriate investment decisions.

The main objectives of this study are to investigate the following questions:

a) What is rate of return to education, and how do the findings compare previous studies in Bangladesh?

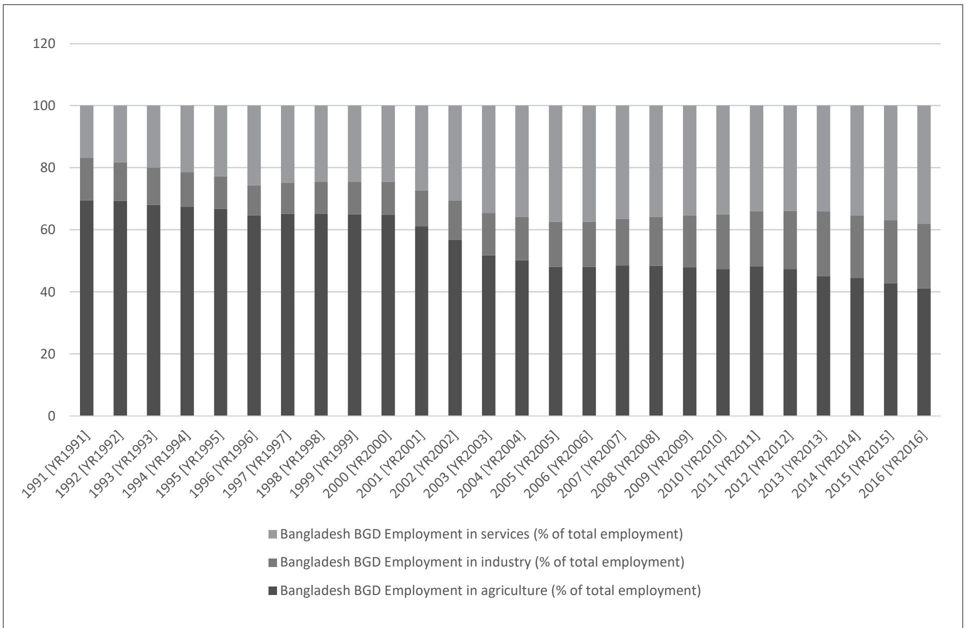
b) Are the returns different at different educational levels and wage distributions?

c) Are there any gender differences in the return to education?

This study is aware of the limitations of the HIES data and of the previous studies on the return to education in Bangladesh. This study tries to contribute to the existing literature. First, this study provides the latest estimates of the return to education. Since circumstances have changed as jobs creation has slowed, more and more women with increased education are entering into the labor market. Along with this, the prevalence of a higher rate of unemployment among people with tertiary education surely has an impact on the employability and wages in the labor market, and therefore impacts on the return to education in Bangladesh. Secondly, in terms of methodology this study adopts all feasible and available methods that are compatible with the data to estimate the return to education in Bangladesh. Thirdly, strengthening technical and vocational education and training (TVET) is suggested for Bangladesh for alleviating poverty and employment generation. Hence, this study incorporates technical and vocational education and training as another aspect of education and estimates the return to TVET compared to secondary and higher secondary education. Ultimately, this study attempts to complement and update the existing studies in Bangladesh.

This study has taken care of the sample selection bias with the 2-step Heckman method. The rates of return to education is heterogenous across the wage distribution. For

Figure 2: Employment by sector



source: ILO, KLIM database

this reason, people with the same education receive varied rates of return to education. To estimate the rates of return to education at different point of wage distribution, quantile regression method is used. This study finds that the average rate of return to an additional year of schooling compared to previous studies has decreased in Bangladesh. However, the return for women to primary and tertiary education is still higher than that of the other levels of education with significant wage difference between rural and urban areas.

This study is organized as follows; section 2 reviews the literature on the return to education, and section 3 provides the methodologies applied for the empirical analysis as well as the information of the data and variables used in the study. Section 4 analyze the results, provides a discussion of the findings with relevant policy suggestions. Section 5 concludes the study with limitations.

2. Literature Review

Household, family life and labor force surveys enabled to estimate the rate of return to education for many countries. Mincer (1974) proposed a semi-log type of earning function to examine the rate of return to education with the ordinary least square method. He used U.S. census data from the 1960s and found that the return was around 10%. His finding provided important investment information for the policy makers and helped individuals in their personal decision to invest in a certain amount of schooling.

Following Mincer (1974), George Psacharopoulos (1994) extensively examined the return to education. He found that in developing countries, primary education was a priority investment policy and educating women was more profitable than educating men. He also found that the return declined by the level of schooling and per capita income among countries and that the world average return to education was about 10% (Psacharopoulos, 1994; Psacharopoulos & Patrinos, 2004). In a recent review, the return to education was found to be about 9% and this estimate remained stable over the decades (Psacharopoulos & Patrinos, 2018). Patrinos and Montenegro (2014) studied 139 economies with 819 household surveys and also estimated the return to education with the same specification, estimation procedure and similar data. They found a similar pattern in the return to education with a 10% return to primary education and a 17% return to tertiary/ university education. Their findings were more robust than the preceding studies. Another study used 61 nationally representative household surveys from 25 developing countries during 1985 to 2012 (Peet, Fink, & Fawzi, 2015). This study also found the return to education was heterogenous with lower returns in rural areas, higher returns for females and Africans and Latin Americans had a higher return than the Asian and Eastern European. They modeled the effect of education on earnings with the standard Mincerian wage equation and found that the average rate of return was 7.6% in representative countries. On the other hand, Patrinos (2016) found that the private rate of return to an additional year of schooling ranged from 5%–8% per year and returns to tertiary education were highest followed by primary and secondary education. He also found that the return to education was higher in sub-Saharan Africa and high-income economies and it was about 13% and 10%, respectively. The return to primary, secondary and university education was about 10%, 7% and 17%, respectively (Patrinos, 2016).

The return to education is not the same for all countries and the rates differ by level of education. In developed countries, the return to all levels of educational attainment is lower and diminishing returns hold across countries (Dutt & Ros, 2008). In addition to education, one's family background, such as parents' education, plays an important role in determining wages. Individuals from less-educated parents have less wages but a higher rate of return (Gödde & Schnabel, 1998). Gödde and Schnabel, (1998) found in Germany that the average rate of return using Mincer equation was about 7.1% and when the wage was controled for parents' education, the rate of return decreased to 6.8%. In fixed model, wage regression with siblings data, the rate of return decreased to 1.68%. Average rate of return to schooling was lowest for the non-OECD European, Middle East and North African countries (Psacharopoulos & Patrinos, 2004). According to Patrinos and Montenegro (2014) the average rate of return to schooling in Middle East and North African (MENA) countries was about 7.3%. The low return to schooling in MENA countries may be explained by the religiosity, natural resource reliance, corruption and property rights issues (Kingsbury, 2018).

Since the above studies estimated the mean effect of education on wage, they assumed the return to schooling was uniform across wage distribution. The quantile regression method considers return to education at different wage distributions (Sakellariou, 2006) and therefore wage distribution accounts for different aspects of the return to education, including unobservable factors such as ability and social skill (Fiszbein, Giovagnoli and Patrinos, 2007). Fiszbein, Giovagnoli and Patrinos (2007) used the quantile regression approach as well as the ordinary least squares in Argentina for the 1992–2002 time period to estimate the changes of return to education over that 10–year period. They divided the sample into 0.10, 0.25, 0.50, 0.75 and 0.90 quantiles and found that the return increased from 8.6% in 1992 to 11.4% in 2002 in the OLS estimate. The quantile regression estimate showed that the men in the higher quantile had a higher rate of return to education and that the return ranged from 7.4% at the lowest quantile to 10.5% at the highest quantile. On the other hand, women at the lowest quantile had the highest rate of return, 8.5%. Dumauli, (2015) estimated the return to education with sibling data in Indonesia with OLS and household fixed effect method. Household fixed effect method applied to address the unobserved family background. She also adopted the 2SLS and the Heckman 2 step to correct the endogeneity and sample selection bias. She found that the rate of return to education in OLS estimate was between 10% to 12%. However, household fixed effect estimate with sibling data reduced the rate of return to education from 10.8% to 5% (Dumauli, 2015).

Academic literature on returns to schooling both in quality and quantity has increased and returns to schooling are not seen as prescriptive but rather as an indicator that suggest areas of concentration (Psacharopoulos & Patrinos, 2002). Most studies which estimated the rates of return to education in Bangladesh are from the middle of 2000s, with the exception of a few studies (Hossain, 1990; Asadullah, 2006; Shafiq, 2007 and Ribound et. al., 2007). However, studies of the return to education in Bangladesh are not routinely undertaken and the most recent study these authors have come across is of Ahmed and McGillivray (2015), who estimated return to education while studying the gender wage gap in Bangladesh with the labor force survey data from 1999 to 2009. Therefore, more than a decade has passed without any re-examination of the trend of rate of return to education in Bangladesh. If the findings of these studies are compared to other developing countries studied by Patrinos (2016), the rate of return for an additional year of schooling is low in Bangladesh, and the returns are the highest for females to primary education followed by tertiary education. The findings of the previous papers reinforced the earlier policy suggestion by the international development partners to invest in primary education.

The study on the return to education in Bangladesh started in the 1990s. Hossain (1990) was one of the earliest studies that examined the return to schooling in the rural areas in Bangladesh. He used data of 4006 members from 640 rural households surveyed by the Bangladesh Institute of Development Studies (BIDS) in 1982 and examined the return to education as well as the effect of education on the labor force supply to agriculture and nonagricultural activities. He estimated that the return to primary education and lower secondary education was 25% and 12%, respectively, and he also found that the higher level of education reduced labor supply in agricultural activities.

However, from subsequent studies it appears that the rates of return to primary and secondary education decreased. Asadullah (2006) used data of the Bangladesh Household Income and Expenditure (HIES) 1999–2000 and in addition to OLS, used Heckman selection correction method to estimate the rate of return to schooling. According to his estimate the average return to schooling was 7.1%. He did not find any significant sample selection bias in his analysis, though he did find that women had a higher rate of return to schooling (13.2%) than the men (6.2%). Later on, using the same data Ribound, Savchenko, and Tan, (2007) found that the return to primary, secondary, high and tertiary was 8.1%, 7.2%, 3.2% and 10.3%, respectively. They have found that the return to education for women was higher at all levels of education than the men. Shafiq (2007) estimated the returns to education for male children in rural households and took into account the cost of education and forewent child labor earnings. He also examined the HIES data for 1999–2000 and found the return was 13.5% for primary education, 7.8% for junior-secondary education, 12.9% for higher secondary education and 9.7% for tertiary education.

While the previous studies on the return to education in Bangladesh largely used the Mincerian earning functions, in most cases endogeneity and the sample selection problem were not discussed. Asadullah (2006) has applied the 2-step Heckman method to correct the sample selection bias. He did not find Inverse Mills ratio significant i.e. no sample selectivity or bias. Heckman method is sensitive to the choice of covariates included in the selection function (Briggs, 2004) and even if the Inverse Mills ratio / Lambda is insignificant, sample selection bias can still exist in the sample. Because high correlation between Inverse Mills ratio and the regressors in the substantive equation in the second stage is likely to results high standard errors which can make the Inverse Mills ratio insignificant (Bushway, Johnson, & Slocum, 2007). The high standard error is often used as a justification for not using the Heckman selection model. Asadullah (2006) used non-earned income and land holding of different sizes as the selection variable. OLS estimates suffer from sample selection bias because in OLS, the sample only observable in variable is selected and women who are not in waged labor market and new entrants in the labor market who do not earn wages are not included in the sample which violates the randomness of the data and does not represent the population. Failing to ensure the randomness of the data or presence of sample selection bias distorts the results that lead to erroneous conclusion. This study uses four exclusion restriction variables to correct for sample selection bias. Given the presence of endogeneity, this study argues that the endogeneity driven by cognitive ability will have a different effect on the return to education at the different wage distributions. Therefore, this study also tries the quantile regression method. In the presence of various unobserved variables like ability, quantile regressions are more useful, because ability influences the parameters of the conditional distribution of the dependent variable, rather than the mean (Patrinos, et. al., 2007). Though quantile regression has policy relevance to income distribution and education, since it examines the wage distribution at various quantile, the use of quantile regression has hardly received due attention in Bangladesh.

3. Research Methodology

3.1 Model Specification

The standard methodology to estimate the return to schooling is based on the human capital theory that uses Mincerian earnings functions (Psacharopoulos, 1994). The private rate of return to an additional year of schooling can be estimated from earnings of the individual's employment and different levels of educational attainment data. We assume individuals are paid according to their marginal product, which increases with the accumulation of more human capital. The basic Mincerian earnings function we have used is as follows:

$$log(W_i) = \alpha_0 + \alpha_1 S_i + \beta_1 EXP_i + \beta_2 EXP_i^2 + \sum\nolimits_{k=3}^{n} \beta_k Z_i + \varepsilon_i \quad \text{..(1)}$$

Where W is the observed wage, S is the number of years of formal schooling, EXP is the experience, Z_i is a vector of control variables and ε_i is the error term which accumulated the unobservable factors affecting wages for the individual i. The coefficient α_1 is interpreted as the private rate of return to schooling. Since the standard Mincerian model assumes the returns to education are equal regardless of the level of education, the basic model has been extended by incorporating categorical variables for education with respect to different levels of education completed by an individual. The extended model used in this study becomes:

$$log(W_i) = \alpha_0 + \sum_{l=1}^{6} \alpha_l EDC_{li} + \beta_1 EXP_i + \beta_2 EXP_i^2 + \sum_{k=3}^{m} \beta_k Z_{ki} + \varepsilon_i \quad \text{..(2)}$$

Where the variables are as they have been defined in equation (1) and EDC is a dummy variable that represents level of education l of the individual i. Therefore, the model to estimate the return to level of schooling is specified as follows:

$$log(W_i) = \alpha_0 + \alpha_1 PRIM_i + \alpha_2 JSC_i + \alpha_3 SSC_i + \alpha_4 TVET_i + \alpha_5 HSC_i + \alpha_6 TER_i + \beta_1 EXP_i + \beta_2 EXP_i^2 + \sum_{k=3}^{m} \beta_k Z_{ki} + \varepsilon_i \quad \text{.........................(3)}$$

This paper created dummy variables for six levels of education and people with no education or less than five years of schooling are treated as the reference group[1]. To account for the effect of the educational attainment on wage, we defined educational level as the minimum number of years taken to attain a certain level and the years pursued in school, but the next level was not completed. For example, primary education is of five years in Bangladesh. So, primary education may have at least five years and at most seven years of schooling. To calculate the rate of return, this study uses the average years of schooling in a particular level. Average years of education at primary is 5.7 years, at junior secondary is 8.5 years and at tertiary 15.4 years. For postgraduates, tertiary education is of 17 years[2]. The survey does not provide information about years required to acquire a degree in technical and vocational education and training (TVET). Considering the nature of education and on the job training / apprenticeship, this paper deemed TVET consists of 12 years of education.

The rate of return to the different levels of educational attainment is calculated following equations provided by Psacharopoulos (1981), using education coefficient α_l from equation (3):

$$\boldsymbol{RORE_l\left(educationalattainment, l\ against\ l-1\right) = \frac{\alpha_l - \alpha_{l-1}}{S_l - S_{l-1}}} \quad \text{..(4)}$$

Here, $RORE_l$ is the rate of return to educational level attained, α_l is the coefficient of the attained educational level and $\alpha_{l\text{-}1}$ is the coefficient of the immediately previous educational level. S_l *and* $S_{l\text{-}1}$ are years taken to attain the education level, l and l-1 *and* l=1, 2, 3, 4, 5 and 6.

Though a vast number of studies use the OLS method based on Mincerian earnings function, the estimates potentially suffer from endogeneity and sample selectivity issues. Endogeneity exists in an economic model when an explanatory variable is correlated with the error term.

3.2 Sample selection issue

In the OLS estimation, wage is observed only for the participants in the labor market. In the 1970s, this issue led the economists to realize that the sample selectivity in the OLS method systematically provided biased estimator. This is because a large number of people were unemployed, and information on non-waged workers or self-employed was not accounted for in the OLS method. The issue of missing earning data is particularly relevant for women because women participation in waged labor market is low in developing countries (Deschacht & Goeman, 2015). To resolve the selection bias, the "Heckit" model proposed by James Heckman is now often used (Heckman, 1976). He treated the unobserved selection factors as a problem of specification error or a problem of omitted variables and corrected the bias by using information acquired from model of sample selection (Shenyang & Fraser, 2015). A sample selection model involves two equations in two steps. According to Shenyang and Fraser (2010), the first equation considers the mechanism determining the outcome variable and in the second step, the second equation considers the portion of the sample whose outcome is observed and the mechanism that determine the selection process. In the first stage, we estimate the following equation with the probit model:

$$Y_2 = \gamma_i X + \delta_i Z + \xi \qquad (5)$$

Y_2 is the dichotomous dependent variable, and Y_2 =1 if wage, Y_1>0 and Y_2 =0 if wage $Y_1 \leq 0$ in the second step. X and Z are independent variables where Z is the vector of observable covariates and act as the exclusion restriction related to the probability that an individual is selected into the sample and ξ is the normally distributed error term. Independent variables this paper uses in the first step are years of schooling, experience, squared experience, religion, rural urban dummy along with covariates, number of children in a household, marital status, non-earned income and remittance received by the household as the exclusion restriction variables Z in equation 5. In the earnings function, the outcome variable wage is observed if Y_2>0 and it is censored or missing if $Y_2 \leq 0$. Equation (5) estimates the probability of selection into the sample for each observation. In the second step, earnings function is estimated with the correction of sample selectivity, known as the Inverse Mills ratio calculated from the first stage together with the other independent variables. If the Inverse Mills ratio is negative and statistically significant in the second step, then the sample suffers from selection bias in OLS.

3.3 Quantile regression

Quantile regression is based on the minimization of weighted absolute deviations to estimate the conditional quantile function (Koenker and Hallock, 2001). For the median quantile (q=0.5), symmetric weight is used and for other quantiles asymmetric weights are employed (Cameroon and Trivedi, page:85–87, 2005). Standard least squares regression models the conditional mean functions and unlike OLS, quantile regression can be employed to explain the determinants of the dependent variable at any point of the distribution of dependent variable. Quantile regression generalizes the idea of an unconditional quantile to a quantile conditioned on one or more variables. The OLS minimizes the sum of the squared residuals, *e*:

$$\sum_{i=1}^{N} L(e) = \sum_{i=1}^{N} e^2 = \sum_{i=1}^{N} (y_i - g(X_i, \beta))^2$$

If the conditional mean function, $g(X_i, \beta)$, is restricted to be linear in X and β, so that $E[y|X = X'\beta]$, then the optimal least square predictor is $\hat{y} = X'\hat{\beta}$. On the other hand, the quantile regression minimizes, $\Sigma_i |y_i - X'_i\beta_i|$ and *if* $L(e) = /e/$, then the optimal predictor is the conditional median, $med[y/X/$. If the conditional median function is linear, so the $med[y|X] = X'\beta$, then the optimal predictor is $\hat{y} = X'\hat{\beta}$ and here $\hat{\beta}$ is the least absolute estimator.

However, if $L(e) = \begin{cases} (1-\alpha)|e| \text{ } if \text{ } e < 0 \\ \alpha|e| \text{ } if \text{ } e \geq 0 \end{cases}$ (*i.e.* error is asymmetric), then the penalty is $(1-\alpha)|e|$ for overprediction, and a different penalty $\alpha|e|$ on under prediction. Asymmetric parameter α is specified over interval (0,1), with symmetry at α=0.5 and increasing asymmetry if α approaches to 0 or 1. The optimal predictor is at the conditional quantile, denoted as $q_\alpha[y|X]$.

In wage equation, the quantile regression model can be written (Buchinsky, 1994; Patrinos et. al., 2007) as follows:

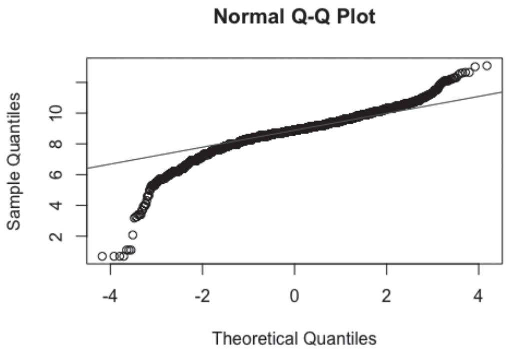
$$ln(W_i) = x_i\beta_\alpha + u_{\alpha i} \text{ with } Quant_\alpha(ln(W_i)|x_i) \quad \text{...(6)}$$

Here, x_i is a vector of exogeneous variables, β_α is a vector of parameters, $Quant_\alpha(ln(W_i)|X_i)$ is the α^{th} conditional quantile of log of wage given X_i. The α^{th} regression quantile is defined as a solution to the problem (Patrinos et. al., 2007):

$$\min_{\beta \in R^k} \left\{ \sum_{i:lnw_i \geq x_i\beta} \alpha \left| lnw_i - x_i\beta_\alpha \right| + \sum_{i:lnw_i < x_i\beta} (1-\alpha) \left| lnw_i - x_i\beta_\alpha \right| \right\} \quad \text{...(7)}$$

We have checked the normality of the data by the quantile plot. If the data were normally distributed, a normal quantile-quantile plot would have plotted most of the observation in a line, meaning both the data set and normal distribution has comparable quantile. Since a large number of observations is off the normal line, the sample used in this study is not normal. We have, approximately, $q_{0.3}$=8, $q_{0.5}$=9, $q_{0.75}$=10 and the distribution appears to be normal for 0.30<q<0.70. To capture the heterogeneity of the wage over the full distribution of the sample, we estimated .10 quantile, .25 quantile, .50 quantile, .75 quantile and .90 quantile.

Figure 3: Quantile-quantile plot for log of wage



3.4 Data and variables

This study uses the survey data from the Bangladesh Household Income and Expenditure Survey (HIES) conducted by the Bangladesh Bureau of Statistics (BBS) in 2016. BBS collected information of 186,078 individuals from 46,080 households. This study selects sample of individuals aged 15–65 years who are either employed or unemployed preceding the week of enumeration and excludes students and self-employed. An individual

Table 1: Distribution of Individuals Aged 15-65 years by work status

	Full sample		Male		Female	
	N	%	N	%	N	%
Unemployed	54,882	51.71	6,823	13.41	48,059	86.97
Daily wage earner	20,588	19.1	18,208	35.79	2,380	4.31
Self-employed	16,752	15.78	14,915	29.31	1,837	3.32
Monthly wage earner	13,918	13.11	10,933	21.49	2,985	5.40
Total	106,140	100	50,879	100	51,346	100

actively seeking employment is considered part of the labor force. Therefore, students who only concentrate on studies and are not actively seeking employment are not considered as a part of the labor force. Though, students work part time, there is no information on whether a student is working or seeking employment. For this reason, this study excludes students from the sample. After the exclusion of the students and people who are less than 15 years of age and self-employed, the sample size becomes of 90,808 individuals. Table 1 presents a glimpse of the work status of the individuals sampled in this study. Since this study focuses on the return on education in the labor market and considers only the waged laborer such as daily earners in kind and cash, and monthly wage earners. The survey provides information of daily average pay in cash and cash equivalent of in-kind pay. Previous studies translated all payment into hourly wages as there was information on how many hours an individual worked. This study translated the average daily payment into monthly wages by multiplying it with the number of days one has actually worked in the preceding month of enumeration and treated as monthly wage. We do this, because in

Table 2: Definition of variables used in the wage regressions

Variables	Definition
Sex	Sex=1 if Female
School Years	Number of years a person attended school
Experiences	Age-6-School years and treated as proxy of working experiences
Experience_squared	One's experience is multiplied by his/her experiences
Non_Muslim	Non_Muslim=1 if Muslim=0
Area_rural	Area_rural=1 if one works in rural area, 0 urban
wage_income	Monthly wages, and daily in kind and cash earn is translated to monthly wage in Taka, and other than monthly wage earners, calculated as average daily wage multiplied by number of days worked in a month.
Married	Married=1 if ever married
Nonearn_income	Interest, rent from land, other property, social and insurance, profit, dividend, lottery prize bond, gift, charity , gratuity,pension, alimony and other receipt
hh_remittance	Remittance received from relatives in one year and family member in two years
hh_children	Number of children in a household
L_dwelling asset	Market value of the homestead household residing
Education_PRIM	Completed at least 5 years of education
Education_JSEC	Completed at least 8 years of education
Education_SSC	Completed at least 10 years of education
Education_TVET	Completed technical and vocational education
Education_HSC	Completed 12 years of education
Education_TER	completed education beyond 12 years of education

Bangladesh the daily wage payment is dominantly prevalent for casual labors. For monthly wage earners, they receive monthly salary and allowances of different kinds. The translated monthly wages earned by daily earners and monthly wages earners are made dependent variable. Table 2 defines all the variables used in the regression analysis for this study.

This paper uses schooling as the proxy for education and reports the results. This study also reports the result using the level of education for the OLS, 2 step Heckman and quantile regression method. For level of education, this study created six dummy variables for six level of education: primary, junior secondary, secondary, technical and vocational education and training (TVET), higher secondary and tertiary education. Vocational education provides a number of education and training such as S.S.C (secondary) vocational, H.S.C (higher secondary) vocational. Technical and vocational institutions provide education and training in glass and ceramic, textiles, land survey, agriculture, marine, medical technology, etc. Individuals with no education or less than a primary education form the reference group for the regression of OLS and 2-step Heckman method adopted in this paper. Table 3 provides the descriptive statistics of the variables used in the wage functions for the full sample. The average monthly wage for the full sample is 9,288 Taka[3].

For males and females, the average wage is 9705 Taka and 6651 Taka, respectively. The mean year of schooling of the sample is, 4.58 years, excluded the individuals who are currently studying, aged under 15 and self-employed. Males and females have about 4.67 years and 4.15 average years of schooling, respectively. According to the Human Development Report (2019), the mean years of schooling in Bangladesh is 6.1 years and this figure is 6.8 years for male and 5.3 years for female. Male's experience is higher than that of the females. The male has about 14 years of average experience and for female, the average experience is 12 years. Female dominates the sample with no or less than a primary education[4]. More women with primary and junior secondary education enter the labor force than the men, and men are more in the labor market with education above the junior secondary level.

In Table 1 (sum of second and third row of column1), the number of waged labors calculated from the survey information is 34,506. When the wage, individual and household information was gathered for the wage earners the number of observations decreased to 32,823. Since many of the respondents are either unemployed or employed in family businesses or enterprises, they do not earn wages. For these reasons, the sample size for

Table 3: Descriptive statistics of the variables

Variables	Observation	Mean	Std. Dev
Sex	90,807	0.596595	0.4905834
School Years	90,808	4.579839	4.378402
Experiences	90,808	12.55114	14.09476
Experience_squared	90,808	356.1912	653.6533
Non_Muslim	90,808	0.1222469	0.3275726
Area_rural	90,808	0.8377015	0.3687264
Married	90,808	0.8850101	0.3190115
ln_wage	32,823	8.885031	0.7246149
wage_income (in Taka)	32,823	9275.491	9759.899
Nonearn_income (in Taka)	90,522	8473.843	37853.48
hh_remitt (in Taka)	90,808	26565.78	175933
hh_children	62,062	1.884567	0.9382666
Education_PRIM	90,808	0.2272487	0.4190569
Education_JSC	90,808	0.1389966	0.3459448
Education_SSC	90,808	0.0670536	0.2501161
Education_TVET	90,808	0.0042287	0.0648912
Education_HSC	90,808	0.0381684	0.1916038
Education_TER	90,808	0.0356246	0.1853534

OLS and quantile regression is 32,823. Since many of the respondents are either unemployed or employed in family businesses or enterprises, they do not earn wages. So, the sample is much lower than 90,808 and to address the sample selectivity, 2-step Heckman method is applied. For 2-step Heckman method, the full sample size is 90,808 individuals, among the sample 36,632 are males and 54,175 are females, and gender of an individual is missing.

4. Results

4.1 Estimated results

4.1.1 OLS estimation

The OLS estimates of the return to schooling is presented in Table 4. In columns 1, 3 and 5, estimates for the return to an additional year of schooling is reported. Columns 2,4 and 6 report the findings for educational levels. For the full sample, the returns to a year of schooling is reported in column 1 and 2 for levels of education. The average rate of return to an additional year of schooling is 5.4. Women receive higher rates of return than the men. The rate of return for an additional year of schooling for females' is about 9% while males receive a rate of return of 4.9%. The rates of return to different levels of education

Table 4: The OLS estimates of the wage functions: years of schooling and education level

	Full sample		Male		Female	
	Year	Level	Year	Level	Year	Level
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**l_wage**	**l_wage**	**l_wage**	**l_wage**	**l_wage**	**l_wage**
school_years	0.054***		0.049***		0.090***	
	(0.001)		(0.001)		(0.003)	
education_prim		0.032***		0.019*		0.187***
		(0.011)		(0.011)		(0.038)
education_jsc		0.141***		0.096***		0.427***
		(0.013)		(0.012)		(0.043)
education_ssc		0.312***		0.246***		0.695***
		(0.016)		(0.015)		(0.056)
education_hsc		0.471***		0.432***		0.806***
		(0.017)		(0.017)		(0.052)
education_tertiary		0.885***		0.802***		1.381***
		(0.015)		(0.015)		(0.045)
education_tvet		0.486***		0.377***		1.191***
		(0.044)		(0.042)		(0.134)
experience	0.000	0.014***	-0.002**	0.012***	-0.014***	0.005*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
experience_squared	0.000	-0.000***	0.000	-0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
married	0.197***	0.100***	0.274***	0.182***	0.136***	0.027
	(0.01)	(0.01)	(0.009)	(0.009)	(0.039)	(0.039)
non_muslim	-0.162***	-0.166***	-0.106***	-0.110***	-0.079***	-0.089***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.028)	(0.028)
area_rural	-0.265***	-0.268***	-0.293***	-0.295***	-0.342***	-0.355***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.023)	(0.023)
Constant	8.629***	8.743***	8.712***	8.818***	8.153***	8.292***
	(0.011)	(0.011)	(0.011)	(0.01)	(0.04)	(0.04)
Observations	32,823	32,823	27,713	27,713	5,110	5,110
R-squared	0.206	0.227	0.225	0.25	0.264	0.281

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

increases with the levels of education and they are positive and significant. Column 6 reports females' return to different levels of education and returns to primary, junior secondary, secondary, higher secondary, and tertiary education for female are about 19%, 24%, 27%, 11% and 58%, respectively. The returns to these levels of education for men are 2%, 7.7%, 15%, 18.6% and 37% (Table 7). These figures are returns to the respective education level calculated by subtracting the preceding return coefficient and using eq.(4). Compared to secondary education (SSC), the return to technical and vocational education for females is about 50% and for males is 13%. Females receive more from the TVET than they receive from secondary and higher secondary education. In wage regression with education level, the reference group is people with no education or with less than five years of schooling. Since primary education is significant, there is significant difference in wages earned by people in reference group and people with primary education.

Other personal characteristics that have an impact on wages are experience, squared experience, marriage, religion and geographic location of the working place. Table 4 shows that experience has positive and significant impacts on wages. *Ceteris paribus* other control variable, one more year of experience increases wages by about 1.4% in full sample. The negative coefficient of squared experience signaled that the return to experience is diminishing. Marriage is positive and significant in the males' sample, and negative and insignificant in females' sample. Marriage matters for employment or earnings in full sample and marriage has wage increasing effect. Non-Muslims and individuals working in the rural area earns significantly lower than the Muslims and individuals working in the urban area. People working in rural area earn 26% to 36% lower than the urban worker.

4.1.2 The 2-Step Heckman estimates

In Bangladesh, the labor force participation rate for male and female aged 15 years and over in 2017 was 80.7% and 35.86%, (www.worldbank.org) respectively. Like most other developing countries, the labor force participation for females is low in Bangladesh. Moreover, the unemployment rate for educated and skilled workers is high (Mahmud W.,2016). The OLS results using only the waged sample give rise to the sample selection bias. To overcome this issue, 2-step Heckman method is used. At the first step, the probability of labor force participation using probit model is estimated to obtain the sample-correcting Inverse Mills ratio or Lambda. In the estimation of Lambda, some exclusion variables (variables excluded in the second step) are used. These variables influence the probability of participation in the labor market and indirectly influence wages. The Inverse Mills ratio obtained from the first stage is included in the second step as an explanatory variable to estimate the wage function. If the coefficient of the Lambda is negative and statistically significant, the OLS estimated results suffer from the sample selection bias and 2-step Heckman would be effective in dealing with the sample selection.

Four exclusion variables included in the probit estimation are natural logarithm of non-earned income; remittances received from relatives during past 12 months from inside and outside the country and from family members abroad during last two years; number of children in the household; and marital status. Non-earned income as the exclusion variable plays as the proxy for the household asset of different kinds and may demotivate the men and women to participate in the waged work. Receipts of remittance tend to discourage women in the household to seek employment outside because the woman may have to take care of the household and the children. The number of children and marital status are particularly important for women because these two aspects influence whether they participate in the labor market. Marriage may discourage women to seek employment outside because in Bangladesh, women are usually in charge of the household. Having children in increasingly nuclear family[5] is another pull factor for women's participation in the waged work.

Table 5 and 6 report the results of 2-step Heckman estimates. Table 5 shows the results for years of schooling and levels of educational attainment for the full sample. The estimates with exclusion variables in the probit model are reported in columns titled "first step". All the exclusion variables except the number of children in the household included in the probit model have expected signs and statistically significant. Thus, the non-earned income, remittance, and marriage discourage participation in the waged labor market. In the second step, wage function is estimated with Lambda. The coefficient Lambda is negative and statistically significant for both years of schooling and levels of education in the full sample (Table 5). This indicates that the OLS estimates in Table 4 (columns 1 & 2) suffer from sample selection bias. After the correction of sample selection bias, the rate of return to an additional year of schooling decreased to 2.2% but retains statistical significance. The return to primary and junior secondary education is negative and primary education coefficient is statistically significant meaning people with primary and secondary education are likely to earn progressively less than the people with no education or less than primary education. However, returns to higher secondary and tertiary education from the 2-step Heckman estimates are higher than the OLS estimates in Table 4 and returns to secondary, higher secondary and tertiary education are 3%, 17% and 71%, respectively.

Table 5: The 2-step Heckman with school years and education level

Full sample	School Year		Education Level	
	1	2	1	2
VARIABLES	First step	Second step	First step	Second step
school_years	-0.031***	0.022***		
	(0.001)	(0.004)		
education_prim			-0.346***	-0.078**
			(0.015)	(0.038)
education_jsc			-0.520***	-0.024
			(0.017)	(0.047)
education_ssc			-0.515***	0.085
			(0.022)	(0.058)
education_tvet			-0.130*	0.330*
			(0.075)	(0.184)
education_hsc			-0.380***	0.197***
			(0.028)	(0.067)
education_tertiary			0.216***	0.908***
			(0.029)	(0.067)
experience	0.014***	-0.001	0.020***	0.008***
	(0.001)	(0.003)	(0.001)	(0.003)
experience_squared	-0.000***	0.000	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
non_muslim	0.158***	0.008	0.151***	-0.009
	(0.014)	(0.038)	(0.014)	(0.038)
area_rural	-2.044***	-2.415***	-2.016***	-2.373***
	(0.016)	(0.088)	(0.016)	(0.084)
married	-0.285***		-0.303***	
	(0.015)		(0.015)	
hh_children	0.038***		0.040***	
	(0.004)		(0.004)	
l_nonearnincome	-0.012***		-0.015***	
	(0.001)		(0.001)	
ln_hh_remitt	-0.053***		-0.051***	
	(0.002)		(0.002)	
lamda		-3.160***		-3.125***
		(0.072)		(0.069)
Constant	1.689***	8.512***	1.696***	8.473***
	(0.022)	(0.036)	(0.022)	(0.036)
Observations	90,808	90,808	90,808	90,808
R-squared		0.284		0.297

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6: The 2-Step Heckman estimates of wage function for males and females

	Male				Female			
	School Years		Education Level		School Years		Education Level	
VARIABLES	First step	Second step	First step	Second step	First step	Second step	First step	Second step
school_years	-0.032***	0.070***			-0.009***	0.019***		
	(0.002)	(0.006)			(0.003)	(0.002)		
education_prim			-0.130***	0.226***			-0.330***	-0.007
			(0.024)	(0.06)			(0.03)	(0.029)
education_jsc			-0.362***	0.286***			-0.486***	0.02
			(0.028)	(0.074)			(0.035)	(0.035)
education_ssc			-0.442***	0.450***			-0.408***	0.037
			(0.034)	(0.091)			(0.045)	(0.04)
education_tvet			-0.482***	0.666***			0.471***	0.769***
			(0.094)	(0.241)			(0.132)	(0.156)
education_hsc			-0.486***	0.664***			-0.06	0.195***
			(0.039)	(0.104)			(0.05)	(0.047)
education_tertiary			-0.222***	0.971***			0.511***	1.184***
			(0.038)	(0.09)			(0.053)	(0.063)
experience	0.036***	-0.062***	0.034***	-0.046***	-0.010***	-0.007***	0.004*	-0.001
	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
experience_squared	-0.001***	0.002***	-0.001***	0.001***	0.000*	0.000***	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
non_muslim	0.044*	-0.111*	0.043*	-0.102*	0.484***	0.256***	0.479***	0.259***
	(0.023)	(0.058)	(0.023)	(0.057)	(0.023)	(0.035)	(0.023)	(0.034)
area_rural	-0.887***	-0.238***	-0.894***	-0.299***	-3.149***	-5.748***	-3.138***	-5.742***
	(0.019)	(0.057)	(0.019)	(0.057)	(0.04)	(0.116)	(0.041)	(0.113)
married	0.633***		0.643***		0.026		0.008	
	(0.019)		(0.019)		(0.044)		(0.044)	
hh_children	0.071***		0.069***		-0.053***		-0.053***	
	(0.007)		(0.007)		(0.008)		(0.008)	
l_nonearnincome	-0.015***		-0.016***		0.006***		0.003	
	(0.002)		(0.002)		(0.002)		(0.002)	
ln_hh_remitt	-0.053***		-0.052***		-0.040***		-0.039***	
	(0.002)		(0.002)		(0.003)		(0.003)	
lamda		-6.069***		-5.901***		-0.745***		-0.700***
		(0.11)		(0.109)		(0.057)		(0.056)
Constant	0.901***	9.211***	0.898***	9.220***	1.653***	7.644***	1.684***	7.570***
	(0.026)	(0.049)	(0.026)	(0.048)	(0.057)	(0.039)	(0.057)	(0.038)
Observations	36,632	36,632	36,632	36,632	54,175	54,175	54,175	54,175
R-squared		0.181		0.187		0.407		0.416

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6 reports the estimates from the 2-step Heckman method for males and females. Unlike the first step estimates in Table 5, the exclusion restriction variables marriage and number of children have positive signs which indicates that the marital status and children increase the probability of men to participate in waged labor market and non-earned income and remittance receipts demotivate men to participate in waged labor and the coefficients are statistically significant. However, of all exclusion variablesnumber of children and receipts of remittance have negative influence on women's participation in the waged labor market. The number of children in the household and receipts of remittance coefficients are significant to 1% level. The Lambda coefficient included in the second step to correct sample selection bias is negative and significant for both male and female sample and for years of schooling and levels of education. Therefore, the OLS estimates of rates of return for male and female in Table 4 suffers from sample selection bias as well. After correction of the sample selection bias, the return to an additional year of schooling increases for men and decreases for female. The rate of return to one more year of schooling for men increases to 7% from 4.9% and decreases for women to 2% from 9% of OLS estimate.

The returns to education increase for men with education attainment. Men receive returns of 22.6% to primary, 6% to junior secondary, 16% to secondary, 21% to higher secondary and 31% to tertiary education. All these coefficients are statistically significant. However, for women return to primary, junior secondary and secondary education is insignificant and return to primary education is negative. Women receive most from tertiary education followed by technical education and vocational training. Women receive about 16% to higher secondary education and compared to higher secondary education, return to tertiary education is almost cent percent. If secondary education is considered as the reference group, return to technical and vocational education and training is about 73% and the return is more than it is to the higher secondary education and comparable to tertiary education.

Based on the estimates made in the Table 5 and 6 and equation 4, this study calculates the rate of return to different levels of education for men and women and for the full sample. These findings are compared to the findings from the quantile regression in Table 8, 9, Appendix A1 and A2.

The rate of return to primary education compared to reference group which is no education or less than 5 years education is 22.6% for male and negative, insignificant and less than 1% for female and for full sample return to primary education is negative and

Table 7: OLS Estimates vs. 2-step Heckman Estimates: Return to a year of schooling and educational level

Method	Sex	School years	PRIM	JSC	SSC	TVET	HSC	TER
OLS	**Full sample**	5.4	3.2	10.9	17.1	17.4	15.9	41.4
	M	4.9	1.9	7.7	15	13.1	18.6	37
	F	9	18.7	24	26.8	49.6	11.1	57.5
Heckman 2 step	**Full sample**	2.2	-7.8	5.4	3.1	21.5	16.6	71.1
	M	7	22.6	6	16.4	21.6	21.4	30.7
	F	1.9	-0.007	2	1.7	73.2	15.8	98.9

significant and this rate is 7.8% less than the return to the reference group. The rate of return to a year for women at junior secondary and secondary education is about 1%, to higher secondary education is about 8%. Rates of return is highest to the tertiary education and it is about 22% in the full sample and about 36% to a year for female. The rates of return for male to a year education in different educational level except technical and vocational education and training and tertiary education is higher for male then the female. The rates of return to a year of education at junior secondary, secondary, higher secondary and tertiary education for male are 2%, 11%, 10.7% and 9%. Compared to secondary education, rates of return to technical education and vocational training (TVET) is about 11% for full sample. The rates of return to TVET is higher for women than the men and for a year of technical and vocation education and training rates of return is about 11% for male and 37% for female[6].

4.1.3 Quantile Regression estimates

This section discusses the estimated results of the rates of return to education at different point of wage distribution. Examining the rates of return to education at different quantile reveals the nature of labor market and steepness of the slope of the education coefficients across the wage distribution for different levels of education. Besides, comparing the rates of return to schooling and levels of education among the quantiles in refences to OLS and 2-step Heckman estimates might help to determine the actual rate of return or bias in the estimates of rates of return to schooling and levels of education. Because, ability influences the distribution of wage, not the mean of wage.

Tables 8 represents the estimates of quantile rates of return to an additional year of education. It reports the return to a year of schooling for males and females participating in waged labor. The quantile rates of return for men to an addition year of schooling increases with the wage distribution and highest rate of return occurs at the .90 quantile

Table 8: Quantile Regression for School Year

	Male					Female				
	$q_{.10}$	$q_{.25}$	$q_{.5}$	$q_{.75}$	$q_{.9}$	$q_{.10}$	$q_{.25}$	$q_{.5}$	$q_{.75}$	$q_{.9}$
VARIABLES	l_wage	l_wage	l_wage	l_wage	l_wage	l_wage	l_wage	l_wage	l_wage	l_wage
school_years	0.027***	0.037***	0.049***	0.059***	0.065***	0.080***	0.081***	0.092***	0.098***	0.093***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.004)	(0.003)	(0.003)	(0.003)
experience	0.005***	0.002	-0.002***	-0.007***	-0.012***	-0.015**	-0.013***	-0.009***	-0.017***	-0.015***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.004)	(0.003)	(0.003)	(0.003)
experience_ squared	-0.000***	-0.000**	0.000**	0.000***	0.000***	0.000	0.000**	0.000*	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
married	0.333***	0.268***	0.235***	0.232***	0.236***	0.213**	0.106**	0.066	0.090**	0.109***
	(0.018)	(0.013)	(0.009)	(0.011)	(0.014)	(0.096)	(0.053)	(0.042)	(0.036)	(0.041)
non_muslim	-0.216***	-0.126***	-0.093***	-0.070***	-0.059***	0.127*	0.000	-0.128***	-0.172***	-0.117***
	(0.02)	(0.014)	(0.01)	(0.012)	(0.016)	(0.069)	(0.038)	(0.03)	(0.026)	(0.03)
area_rural	-0.315***	-0.281***	-0.278***	-0.267***	-0.292***	-0.470***	-0.511***	-0.348***	-0.208***	-0.130***
	(0.014)	(0.01)	(0.007)	(0.009)	(0.011)	(0.057)	(0.031)	(0.025)	(0.021)	(0.024)
Constant	8.164***	8.451***	8.758***	9.028***	9.306***	7.164***	7.901***	8.288***	8.610***	8.879***
	(0.02)	(0.015)	(0.011)	(0.013)	(0.016)	(0.098)	(0.054)	(0.042)	(0.037)	(0.042)
Observations	27,713	27,713	27,713	27,713	27,713	5,110	5,110	5,110	5,110	5,110

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

followed by 0.75 quantiles and the rates are 6.5% and 5.9%, respectively. The rates of return to an additional year of schooling is higher for women at higher quantiles and it is about 9%. The rate of return to an additional year of schooling for the full sample at the median quantile is about 5.4% which is the mean rate of return from the OLS estimates (Table A1 in the Appendix). The OLS estimate of the rate of return for male and female is 4.9% and 9%, respectively and occur at median quantile.

As Table 9 shows, the rate of return to primary education for male is highest at the highest quantile followed by the return at median quantile. The rates of return to primary education at 0.90 and 0.50 quantile is about 2.8%. However, for females, higher rates of return to primary education is received at lower quantiles and the rate of return is highest at the lowest quantile and it is around about 23.5%.

The rates of return to education for male increase within a quantile with the education levels and increase across the quantiles at higher wage distribution for secondary education and beyond. However, trends in the rate of return to education within and across quantile for women is heterogeneous. Across the quantiles, women receive the highest rate of return from technical and vocational and tertiary education and these rates are higher than that for men.

The mean wage distribution provided by the OLS estimates shadowed the important differences in the rates of return to education at different point of wage distribution which is revealed with the quantile regression method (Figure 4 & Figure F1 in Appendix). Figure 5 shows whether the quantile regression estimates are different from the OLS estimates at different wage distribution. It appears that except for the coefficients for primary (yet different at lower tail) and junior secondary education, all other coefficients are statistically different from the OLS estimates, and the quantile regression coefficients are statistically different from each other as well.

The rate of return to primary education for men is very high, about 22.6% in the

Table 9: Quantile Regression for Levels of Education

Education Level	Male					Female				
	$q_{.10}$	$q_{.25}$	$q_{.5}$	$q_{.75}$	$q_{.9}$	$q_{.10}$	$q_{.25}$	$q_{.5}$	$q_{.75}$	$q_{.9}$
VARIABLES	l_wage	l_wage	l_wage	l_wage	l_wage	l_wage	l_wage	l_wage	l_wage	l_wage
education_prim	0.013	0.025	0.028***	0.026**	0.029**	0.235**	0.225***	0.173***	0.164***	0.159***
	(0.021)	(0.016)	(0.011)	(0.012)	(0.015)	(0.101)	(0.061)	(0.042)	(0.033)	(0.047)
education_jsc	0.052**	0.094***	0.078***	0.156***	0.163***	0.686***	0.559***	0.319***	0.322***	0.386***
	(0.024)	(0.019)	(0.013)	(0.014)	(0.017)	(0.115)	(0.069)	(0.047)	(0.038)	(0.053)
education_ssc	0.100***	0.159***	0.224***	0.345***	0.423***	0.657***	0.568***	0.485***	0.830***	0.797***
	(0.03)	(0.023)	(0.016)	(0.017)	(0.021)	(0.149)	(0.09)	(0.062)	(0.049)	(0.069)
education_hsc	0.255***	0.335***	0.447***	0.542***	0.616***	0.675***	0.512***	0.804***	1.058***	1.007***
	(0.033)	(0.025)	(0.017)	(0.019)	(0.024)	(0.137)	(0.083)	(.057)	(0.045)	(0.064)
education_ tertiary	0.522***	0.775***	0.854***	0.911***	0.894***	1.328***	1.386***	1.435***	1.336***	1.261***
	(0.029)	(0.022)	(0.015)	(0.017)	(0.021)	(0.119)	(0.072)	(0.049)	(0.039)	(0.055)
education_tvet	0.058	0.130**	0.343***	0.628***	0.795***	0.931***	0.982***	1.504***	1.282***	1.212***
	(0.083)	(0.063)	(0.043)	(0.047)	(0.059)	(0.356)	(0.215)	(0.147)	(0.117)	(0.166)
experience	0.013***	0.012***	0.010***	0.009***	0.006***	0.000	0.000	0.014***	0.008***	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.005)	(0.003)	(0.003)	(0.004)
experience_ squared	-0.000***	-0.000***	-0.000***	-0.000***	0.000	0.000	0.000	-0.000***	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
married	0.289***	0.214***	0.140***	0.133***	0.133***	0.045	0.002	-0.039	-0.027	0.016
	(0.019)	(0.014)	(0.01)	(0.01)	(0.013)	(0.103)	(0.062)	(0.043)	(0.034)	(0.048)
non_muslim	-0.218***	-0.128***	-0.098***	-0.080***	-0.055***	0.118	0.015	-0.146***	-0.179***	-0.168***
	(0.02)	(0.015)	(0.01)	(0.011)	(0.014)	(0.073)	(0.044)	(0.03)	(0.024)	(0.034)
area_rural	-0.323***	-0.270***	-0.280***	-0.272***	-0.281***	-0.470***	-0.511***	-0.367***	-0.231***	-0.166***
	(0.014)	(0.011)	(0.007)	(0.008)	(0.01)	(0.061)	(0.037)	(0.025)	(0.02)	(0.028)
Constant	8.223***	8.526***	8.880***	9.141***	9.407***	7.333***	8.005***	8.453***	8.775***	9.032***
	(0.021)	(0.016)	(0.011)	(0.012)	(0.015)	(0.105)	(0.064)	(0.044)	(0.035)	(0.049)
Observations	27,713	27,713	27,713	27,713	27,713	5,110	5,110	5,110	5,110	5,110

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

2-step Heckman estimates which is not occurred in any of the wage distribution or in OLS estimate. Women at lower quantiles have rates of return range to about 5% to 16% to junior secondary education lower than the OLS but higher than the 2-step hackman estimates.

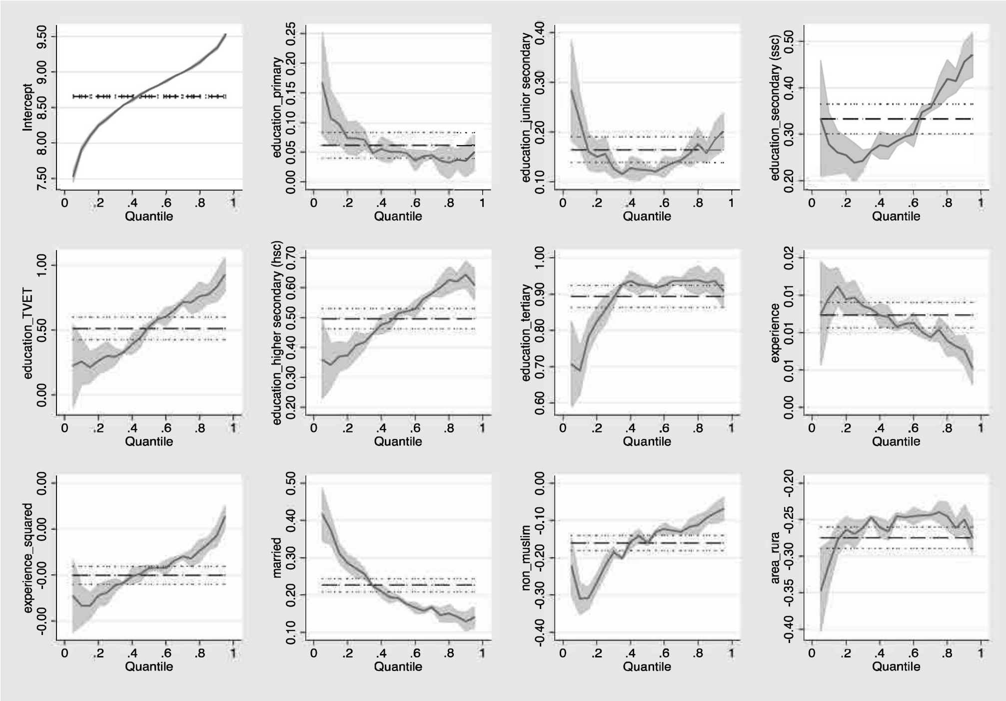
The quantile rates of return to secondary, higher secondary and tertiary education at median quantile for men is about 10%, 11% and 12%, respectively not much different from OLS and Heckman estimates. For women, these rates are 11%, 16%, and 19%. Quantile rate of return for women to secondary education at median quantile is higher than the 2-step Heckman and lower than the OLS estimates, to higher secondary education higher than both OLS and Heckman estimates and to tertiary education similar to the OLS but lower than the Heckman estimates.

The rate of return to primary education after the correction of sample selection bias for women is negative and insignificant but nearly zero but significant in full sample. Contrary to this, the rate of return to primary education at different wage distributions ranges from 16% to 23% for women which possibly explained by the family background and socioeconomic factors that plays a greater role in women employment and wage determination. In the case of TVET, the rate of return is higher at higher quantiles. This pattern is similar to that of the males although women receive higher rate of return than the men and these rates are for men, 6% and 51% for women. The rate of return to TVET for women is too high and demands for further investigation.

In addition to revealing varied rates of return to different educational levels, quantile regression signaled as well how the rates of return to education causes wage inequality

Figure 4: Schooling and Wage distribution of Male and Female:

Figure 5: Plot of OLS, Quantile regressions coefficients and their CI (Full sample)



and how unequal the rates of return are within and between quantiles. From Figure F1 in Appendix, it appears that return to education is higher at higher educational attainment within quantile and across the quantiles. Higher rates of return at higher quantiles with higher educational levels cause wage inequality within and between groups (quantiles) in case of male sample. Though the trend is not monotonic across the quantiles, it is also true for female wage earners.

4.2 Discussion of the results and Policy implications

In 1990s, different educational development policies were initiated around the world. Policies like education for all (EFA) and concerted effort from international organizations, government and non-government organizations (NGOs) greatly increased the education since 90s. For these, secondary school certificate (SSC) and higher secondary certificate (HSC) graduates are prevalent in increased number even in remote rural areas in Bangladesh (Kusakabe, 2012). The Fifth Five Year Plan 1997–2002 sought out to establish a knowledge-based society in Bangladesh with a special emphasis on establishment of technical and vocational education and training linked to job market. The National Educational policy 2010 as well provisioned for technical and vocational education and training to sensitize the children on its prospect in primary education and after completion secondary education, students in accordance to their ability pursue either higher education or vocational education. The Information Communication and Technology (ICT) policy 2009 and Education Policy 2010 perceived ICT as a means of development of the country.

Impacts of these policy initiatives related to ICT education is not reflected in our estimates because the HIES 2016 survey do not have information on ICT education. This study has incorporated technical and vocational education and training (TVET) to examine the return to it. Compared to secondary education, the rate of return to technical and vocational education and training (TVET) is higher for women than that of the men. For male, the rate of return to TVET is comparable to that of the higher secondary education. If time and expenses is taken into account for tertiary education, the return to technical and vocational education and training for women is more profitable and return to TVET is higher for women than the men.

Generally, the rates of return to education increases with the educational levels. The rates of return are higher to TVET and tertiary education. The rates of return to primary to secondary education estimated with OLS and 2-step Heckman method is lower than rates of return to other educational attainment in both male and female samples. Estimates of rate of return from 2-step Heckman to primary education in full sample and for female sample is negative and significant in full sample meaning that there is statistically no difference in rates of return to women with and without primary education and in full sample people with primary education earn about 8% less than the people with no education or less than primary education.

The average rate of return to an additional year of schooling compared to previous studies in Bangladesh has decreased. The decrease of rates of return is explained by the higher unemployment rate among the young and increased supply of educated people. However, after sample selectivity is addressed, the rates of return to an additional year of schooling increases for men and decreases for women from the OLS estimates. The findings from the quantile regression are consistent to the findings from the OLS estimates. Since, the average rates of return for full sample and for women decreases after sample correction, the OLS estimates is in full sample and for women are upward biased. The rate of return after sample correction for male sample to an additional year of schooling is higher than the estimates calculated with OLS and quantile regression method. In regard to full sample and female, 2-step Heckman removes sample selection bias, but rate of return decreased in both cases to about 2%.

Since private rate of return to education is in favor of higher education and increased supply of graduate with tertiary education will lower the rate of return to it amidst higher unemployment rate among the young with tertiary education. Moreover, given the socioeconomic situation in Bangladesh, realty is a good number of students is dropped out before passing the secondary education. Since, rates of return to the education below the secondary education is decreasing and investing in education below the secondary level is not profitable compared to TVET and tertiary education, government should aim to reap the social return to education below secondary education. For this, the government should formulate special policy to change behavioral pattern that will help people with less than secondary education to have better health outcomes, respect of law of the land and environment to mitigate climate change and ensure sustainable development and cultivate higher moral value. Besides, as TVET is more rewarding, post junior secondary education should be more emphasized on technical education and vocational training. Moreover, the varied rates of return to tertiary education revealed by quantile regression in Table 9 suggest that there exists difference in quality in higher education which also require appropriate policy intervention.

5. Conclusion and Limitations

This study finds that the average rate of return to one additional year of schooling is decreases to 2.2% from 5.4% after correcting the sample selection bias in OLS estimates. The average rates of return for one more year of schooling found in OLS and 2-step Heckman is lower than those of the previous estimates in Bangladesh and lower than the average rate of return in South Asia as Psacharopoulos and Patrinos (2018) found. Women receive a lower rate of return to an additional year of schooling than the men and the rate is about 2% after the sample selection bias is addressed and the rate of return for men increases to 7% from the OLS estimate of 4.9%. Since sample selection bias is addressed for full sample and for both male and female, this study sticks to the 2-step Heckman estimates.

The estimates of rates of return with OLS and 2-step Heckman to different educational attainment reveal that rates of return is higher to tertiary education and compared to time and expenses required for tertiary education, investing in technical education and vocational training (TVET) is rewarding. In Bangladesh, TVET is perceived as the inferior academic track and regarded as a fallback option after general educational courses (Nakata, Rahman, and Mokhlesur, 2018). Therefore, people, particularly women, are reluctant to pursue TVET although the rate of return to TVET for females (at median quantile and 2-step Heckman estimates) is higher than the return to secondary and higher secondary education. The rate of return to TVET from 2-step Heckman method is about 11% not different from the rate of return to the higher secondary education.Therefor investing in TVET specially for women could be an appropriate policy instrument for poverty reduction. The return to primary, junior secondary education in OLS, 2-step Heckman and quantile regression estimate in Appendix A2 suggest that return to these levels has decreased and earlier policy suggestion to invest in primary education is no longer viable for Bangladesh.

The rate of return to teriary education has increased compared to previous studies and quantile regression suggest higher rates reurn to teirtiary education at higher wage distribution. Females still demonstrate a higher rate of return to education in OLS and quantile regression. Therefore, investing in higher education as well as in TVET is profitable. Higher rates of return to higher education at higher quantile signaled the quality of education is not equal or comparable across the quantiles as the interquantile range is large. It also indicates that the ability does not determine decision to pursue higher education and therefore, demands level-wise education and employment policies for labor market participation and compensation.

Most of previous studies in Bangladesh did not deal with endogeneity and sample selection bias. Asadullah (2006) tried to address the sample selection bias and he did not find selection bias in his estimates. Endogeneity may arise from an omitted variable in the model specification and can give rise to measurement errors from misreport made by the respondents (Ashenfelter and Card, 1999). The most common cause of endogeneity is the presence of a two-way causal relationship between dependent and independent variables. Level of education or schooling varies with one's cognitive ability and social and household characteristics. These characteristics also determine one's earnings. Schooling variable thus becomes endogenous, and Mincerian earnings function cannot remove this endogeneity. The cognitive ability independent of education is nearly impossible to quantify and determine both educational attainment and earnings of an individual (Kenayathulla, 2013). The preceding studies tried to resolved endogeneity through the use of policy variables such as minimum school-leaving age as an instrument and IQ as a proxy for ability. Proxying ability lowers the estimated return to schooling signaling that the OLS estimates are upward biased (Kimenyi et.ai., 2006). Ability is affected by education as well and use of proxies for ability will cause downward biased estimates (Ashenfelter et. al., 1999).

Family background such as parental education also used as an instrument to account for endogeneity in literature. Siblings and twin data also used for controlling for endogeneity with the household fixed effect model. It is argued that since twins are born from the same pregnancy, they are supposed to have the same cognitive ability and family background (Makiko & Tomohiko, 2012). Unobserved ability and family background would have the equal effect on the same twin (Li et al., 2012). Sibling data can be applied to account for unobserved family characteristics as the unobserved heterogeneity is common to the members of the same family (Gödde and Schnabel, 1998). However, sibling data are not free of idiosyncratic differences among the siblings since they are born from different pregnancies.

The data constraints this study to use the instrument variable method (IV) to account for the endogeneity. HIES data does not include parental backgrounds that could be used as an instrument. If the information is gathered from the respondents other than the heads of the households, this paper could have used the information of the household heads as the instrument. However, since samples are different, we cannot compare the OLS estimates with the IV method estimates. For the same reason, this paper refrains from estimating sibling data with the household fixed effect model. We are aware of the presence of the endogeneity in Mincerian earning functions, but the presence of ability that caused endogeneity will not be equal across the distributions. The conventional mean regression model where it is assumed *ceteris paribus* other parameters, one more year of schooling only influences the mean of the conditional wage distribution, which is not helpful to examine the potential effects of schooling on wage distribution (Patrinos, et. al., 2007). On these premises, examining the rates of return to education at a different point of wage distribution with the quantile regression which reveal important information on labor market and help devise appropriate policies.

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Notes

1 Primary education is of five years, junior secondary is of eight years, Secondary education is of ten years, and Higher secondary education is of twelve years. Tertiary education can be 14 years, 15 years, 16 and 17 years.

2 For schooling and education in Bangladesh see, Ileas and Inaba (2020).

3 Currency of Bangladesh.

4 38.31% female and 33.29% male in the working age sample has less than primary education.

5 Average household size in HIES-2016 is 4.06 persons, from 4.53 in HIES-2010.

6 The difference between the average year of JSC and Primary is 2.8 years, SSC and JSC is 1.5 years; HSC and SSC and TVET and SSC is 2 years; Tertiary education and HSC 3.4 is years. The rates of return for a year spent in an education level can be calculated by dividing the returns to a level by the average difference between two successive educational attainment level.

References

Ahmed, S. & McGillivvray, M. (2015). Human capital, discrimination, and the gender wage gap in Bangladesh. World development, 67, 506–524. http://dx.doi.org/10.1016/j.worlddev.2014.10.017

Asadullah, M. N. (2006). Returns to education in Bangladesh. *Education Economics*, *14(4)*, 453–468. https://doi.org/10.1080/09645290600854144

Ashenfelter, O., Harmon, C., & Oosterbeek, H. (1999). A review of estimates of the schooling/earnings relationship, with tests for publication bias. *Labour Economics*, *6(4),* 453–470. https://doi.org/10.1016/S0927-5371(99)00041-X

Ashenfelter, O., Card, D. (1999). *Handbook of labor economics*. *1ed.,* 3Elsevier, 1339–1340 (Chap.23).

Briggs, D. C. (2004). Causal inference and the Heckman model. *Journal of Educational and*

Behavioral Statistics, *29(2),* 268. https://doi.org/10.3102/10769986029002268

Buchinsky, M. (1994). Changes in the U . S . wage structure 1963–1987: Application of quantile regression. *Econometrica, vol. 62*(2), 405–458.

Bushway, S., Johnson, B. D., & Slocum, L. A. (2007). Is the magic still there? The use of the Heckman two-step correction for selection bias in criminology. *Journal of Quantitative Criminology*, *23(2),* 151–178. https://doi.org/10.1007/s10940-007-9024-4

Cameron, A. C. & Trivedi, P. K. (2005). *Microeconometrics.* Cambridge University Press.

Deschacht, N., & Goeman, K. (2015). Selection bias in educational issues and the use of Heckman's sample selection model. *Contemporary Economic Perspectives in Education*, 35–51. https://doi.org/10.2307/j.ctt14jxsqg.5

Dumauli, M. T. (2015). Estimate of the private return on education in Indonesia: Evidence from sibling data. *International Journal of Educational Development*, *42*, 14–24. https://doi.org/10.1016/j.ijedudev.2015.02.012

Dutt, A. K., & Ros, J. (2008). *International Handbook of Development Economics, Volumes 1 & 2*. Edward Elgar Publishing.

Gödde, I., & Schnabel, R. (1998). Does family background matter? Returns to education and family characteristics in Germany. *SFB 504 Discussion Paper*, (May), 60–98. University of Mannheim

Fiszbein, A., Giovagnoli, P. & Patrinos, H. A. (2007). Estimating the returns to education in Argentina using quantile regression analysis:1992–2002. *Economica, Vol. LIII*, Nro.1-2

Hossain M. (1990) Returns from education in rural Bangladesh. In: Khan A.R., Sobhan R. (eds) *Trade, Planning and Rural Development*. Palgrave Macmillan, London

Li, H., Liu, P.W., Zhang, J. (2012). Estimating returns to education using twins in urban China. *Journal of Development Economics, 97(2),* 494–504.

Heckman, J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. *Annals of Economic and Social Measurement 5:* 475–492.

Ileas, M. M. & Inaba, K. (2020). (2020). Human capital in Bangladesh. *Ritsumeikan Economic Review, 61,* 19–35.

Ileas, M. M. & Inaba, K. (2020). Education, well-being, and healthier practices in Bangladesh. *Social System Studies, 40,* 85–107.

Kenayathulla, H. B. (2013). Higher levels of education for higher private returns: New evidence from Malaysia. *International Journal of Educational Development*, *33(4)*, 380–393. https://doi.org/10.1016/j.ijedudev.2012.05.008

Kimenyi, Mwangi S, Mwabu Germano, & Manda, D. K., (2006). Human capital externalities and private returns to education in Kenya. *Eastern Economic Association, vol. 32*(3), 493–513.

Kingsbury, I. (2018). Making sense of low private returns in MENA: A human capital approach. *International Journal of Educational Development*, *61*, 173–183. https://doi.org/10.1016/j.ijedudev.2018.01.001

Koenker, R. and Hallock, K.F. (2001). Quantile regression. *Journal of Economic Perspectives 15(4),* 143–156. Kusakabe, T. (2012). Impact of education expansion on Employability in Bangladesh: comparing two cases of villages in remote and suburban rural settings. *Journal of International Cooperation in Education, 15(2),* 53–68.

Mahmud, w. (2016, January 6). Education, jobs and economic development in Bangladesh. *Jobs and Development*. https://blogs.worldbank.org/jobs/education-jobs-and-economic-development-bangladesh

Makiko, N., & Tomohiko, I. (2012). Estimating the returns to education using a sample of twins-the case of Japan. *RIETI Discussion Paper Series 12-E-076.* Retrieved from https://www.rieti.go.jp/jp/publications/dp/12e076.pdf

Mincer, J. (1974). *Schooling, experience and earnings*. Columbia university press for National Bureau of Economic Research, New York.

Ministry of Education, Government of Bangladesh. (2010) *National education policy.* https://moedu.gov.bd/sites/default/files/files/moedu.portal.gov.bd/page/ad5cfca5_9b1e_4c0c_a4eb_fb1ded9e2fe5/National%20Education%20Policy%202010%20final.pdf

Ministry of Science and Information and Communication Technology, Government of Bangladesh. (2009). http://www.bcs.org.bd/img/upload/page/11.pdf

Nakata, S., Rahman, T., & Mokhlesur, R. M. (2018). Employability of post-secondary TVET in Bangladesh: Tracking survey of graduates of polytechnics. Washington, D.C.: World Bank Group. http://documents.worldbank.org/curated/en/718501528118077327/

Patrinos, H. A. (2016). Estimating the return to schooling using the Mincer equation. *IZA World of Labor*, (July), 1–11. https://doi.org/10.15185/izawol.278

Patrinos, H. A., & Montenegro, C. E. (2014). Comparable estimates of returns to schooling around the world. *Policy Research Working Paper no. 7020*, Education Global Practice Group, (September), 1–41. https://doi.org/10.1596/1813-9450-7020

Patrinos, H. A., Fiszbein A., & Giovagnoli P.I. (2007). Estimating the return to education in Argentina using quantile regression analysis: 1992–2002. *Económica, La Plata, Vol. LIII, Nro. 1-2, 2007*, *LIII*(2). https://doi.org/10.1080/15140326.2008.12040507

Peet, E. D., Fink, Gunther & Fawzi, W. (2015). Returns to education in developing countries :

Evidence from the living standards and measurement study surveys. *Economics of Education Review, Elsevier, vol. 49(C)*, 69–90.

Psacharopoulos, G. (1981). Returns to education: An updated international comparison. *Comparative Education*, *17*(3), 321–341. https://doi.org/10.1080/0305006810170308

Psacharopoulos, G. & Patrinos, H. A. (2002). Returns to investment in education:A further update. *Policy Research Working Paper no.2881.* The World Bank

Psacharopoulos, G. (1994). Returns to investment in education: A global update. *World Development, vol. 22*(9), 1325–1343. https://doi.org/10.1016/0305-750X(94)90007-8

Psacharopoulos, G., & Patrinos, H. A. (2004). Returns to investment in education : A further update. *Education Economics, vol. 12*(2). https://doi.org/10.1080/0964529042000239140

Psacharopoulos, G., & Patrinos, H. A. (2018). Returns to investment in education: a decennial review of the global literature. *Education Economics*, *26(5)*, 445–458. https://doi.org/10.1080/09645292.2018.1484426

Ribound, M., Savchenko, Y., & Tan, H. (2007). The knowledge economy and education and training in South Asia. *siteresources.worldbank.org*, World Bank

Sakellariou, C. (2006).Benefits of general vs vocational/technical education in Singapore using quantile regressions. *Interanational Journal of Manpower*, *27*, 358–376. https://doi.org/10.1108/01437720610679214

Shafiq, M. N. (2007). Household rates of return to education in rural Bangladesh: Accounting for direct costs, child labour, and option value. *Education Economics*, *15*(3), 343–358. https://doi.org/10.1080/09645290701306358

Shenyang, G. & Fraser, M. W. (2015). *Propensity score analysis: statistical methods and applications (2nd Ed).* SAGE Publication.

Toufique, K. A. (2014). Labour market transitions of young women and men in Bangladesh. *Work4Youth Publication Series no. 13*, ISSN: 2309-6780; 2309-6799 (web pdf). International Labor Organaization

United Nations Development Programme. (2017). *Bangladesh quarterly development update*. www.bd.undp.org/docs

United Nations Development Programme. (2019). *Human development report 2019.* http://hdr.undp.org/sites/default/files/hdr2019.pdf

Appendix: Quantile regression

A1: Full sample: years of schooling

Full Sample	School Years				
	q_{10}	q_{25}	q_{50}	q_{75}	q_{90}
VARIABLES	l_wage	l_wage	l_wage	l_wage	l_wage
school_years	0.040***	0.043***	0.054***	0.062***	0.067***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
experience	0.015***	0.005***	-0.003***	-0.008***	-0.012***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
experience_squared	-0.000***	-0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
married	0.126***	0.181***	0.205***	0.215***	0.211***
	(0.022)	(0.012)	(0.011)	(0.01)	(0.013)
non_muslim	-0.284***	-0.239***	-0.144***	-0.108***	-0.092***
	(0.023)	(0.013)	(0.011)	(0.011)	(0.013)
area_rural	-0.303***	-0.253***	-0.243***	-0.240***	-0.262***
	(0.016)	(0.009)	(0.008)	(0.008)	(0.01)
Constant	8.001***	8.366***	8.700***	8.987***	9.261***
	(0.024)	(0.014)	(0.012)	(0.012)	(0.014)
Observations	32,823	32,823	32,823	32,823	32,823

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

A2: Full sample: levels of education

Full sample	Education Level				
	q_{10}	q_{25}	q_{50}	q_{75}	q_{90}
VARIABLES	l_wage	l_wage	l_wage	l_wage	l_wage
education_prim	0.103***	0.035**	0.023**	0.028***	0.027**
	(0.028)	(0.015)	(0.011)	(0.011)	(0.013)
education_jsc	0.207***	0.134***	0.108***	0.150***	0.176***
	(0.033)	(0.017)	(0.013)	(0.012)	(0.016)
education_ssc	0.280***	0.219***	0.274***	0.383***	0.445***
	(0.041)	(0.021)	(0.016)	(0.015)	(0.02)
education_hsc	0.309***	0.378***	0.495***	0.587***	0.637***
	(0.044)	(0.023)	(0.017)	(0.016)	(0.021)
education_tertiary	0.690***	0.845***	0.916***	0.933***	0.929***
	(0.039)	(0.02)	(0.015)	(0.015)	(0.019)
education_tvet	0.226**	0.230***	0.511***	0.720***	0.826***
	(0.11)	(0.057)	(0.043)	(0.042)	(0.053)
experience	0.021***	0.019***	0.012***	0.010***	0.008***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
experience_squared	-0.000***	-0.000***	-0.000***	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
married	0.092***	0.099***	0.096***	0.104***	0.098***
	(0.025)	(0.013)	(0.01)	(0.01)	(0.012)
non_muslim	-0.279***	-0.245***	-0.163***	-0.117***	-0.081***
	(0.026)	(0.013)	(0.01)	(0.01)	(0.012)
area_rural	-0.300***	-0.261***	-0.242***	-0.248***	-0.260***
	(0.019)	(0.01)	(0.007)	(0.007)	(0.009)
Constant	8.063***	8.456***	8.826***	9.107***	9.373***
	(0.028)	(0.014)	(0.011)	(0.01)	(0.013)
Observations	32,823	32,823	32,823	32,823	32,823

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Figure F1: Returns to educational level for Males and Females over Wage distribution