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THE EFFECTS OF HUMAN CAPITAL AND SOCIAL FACTORS ON THE HOUSEHOLD INCOME OF BANGLADESH: AN ECONOMETRIC ANALYSIS

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The study examined the effects of human capital (education and experience) and social factors (gender, marital status, spatial condition, and occupation) on the monthly income of the people of Bangladesh through OLS and quantile regression based on the data of 9943 sample of Household Income and Expenditure Survey (HIES). It appears that both human capital and social factors have significant explanatory power to explicate the monthly income of the household. The OLS and quantile regression suggest that the effects of social factors are superior to that of human capital on the monthly income. The estimates further reveal that urban people get 18% more wage than their rural counterparts, and people engaged in the non-agricultural sector received 25% higher wages than the agricultural sector. Besides, female workers receive 36% less wage than male workers. Nevertheless, there is a distinct effect of the human capital and social factors in the gender and rural-urban context. The study recommends, a reorient policy to properly address these gender wage gap, sectoral and area-specific issues of the labor market with a view to ensuring the fair income distribution and inequality reduction.

Keywords: HIES; Human Capital, Gender, Income Inequality, Econometric Analysis, Bangladesh
JEL Classification: E24, I26, J01, J24, O15, O50, R20

1. INTRODUCTION

Bangladesh is currently passing the transition period as it has seized the lower middle-income country status in 2015 and become eligible for graduating from the LDC group for the first time in 2018. In the last decade, the country has shown remarkable success in major social, economic, and human development indicators and maintained above 6% GDP growth. Bangladesh has achieved the highest-ever 7.86% GDP growth in the 2017-2018 fiscal year, broadly exceeding the estimated growth of 7.65% which is

also higher than the neighboring economic giant India. The World Bank projected that by 2020 Bangladesh will overhaul Pakistan on per capita GDP. The per capita income of the country has jumped to USD 1751 in FY 2017-2018 from USD 1610 in 2016-2017 FY. In 1991, 44% people of Bangladesh lived in poverty, but in 2017, only 14% people were living on USD 1.9 or less. In the juncture of Bangladesh's rapid development drive and future socio-economic steadiness, it is pertinent to examine the effects of human capital such as education, job experience, and relevant social factors such as age, sex, economic activities on the income of the people. Because human capital investments are associated with higher Gross Domestic Product and lower inequality and social factors are associated with the wellbeing and dignity of the people (Dorset et al., 2010). Much of the broader evidence base suggests that the higher the level of education, the greater are the cumulative returns and the relationship between education and income is robust (Ashenfelter, 1991; Conlon and Patrignani, 2013). In comparison to other OECD countries, the UK reports one of the largest differences in earnings between students who pass upper secondary schooling and those who do not (OECD, 2014). It also shows that an individual without upper secondary education in the UK earns only 70% of what someone with upper secondary education does. Psacharopoulos (1994) and Bhutoria (2016) disclosed the positive economic returns to formal education was consistently higher at the individual level. Returns vary with the type and level of the qualification obtained, by subject area, age, experience, and gender. Regarding academic qualifications, wage returns (marginal and accrued) are highest for completed tertiary education. Benhabib and Spiegel (1994) revealed that the increase in the number of those who attended secondary school had enjoyed a higher level of income. Further, Chowdhury et al. (2018), Alam (2009), and Sharif (2013) found a strong positive relationship between human capital development and economic growth in Bangladesh.

According to Scully (2002), human capital is directly related to economic growth, and the relationship can be measured by how much is invested in people's educations. Boxmen et al. (1991) revealed using multivariate analysis of a sample of 1359 managers of larger companies in the Netherlands that social capital has a substantial independent influence on income, net of human capital, and position level. Human and social capital can act as substitutes for each other, and social capital helps at any level of human capital, but human capital does not make a difference at the highest levels of social capital. Shahpari and Davoudi (2014) suggested that a rise in human and physical capital can reduce inequality and make income distribution fairer. Su and Heshmati (2013) found in China, education and occupation are essential determinants of households' income in urban areas, education is more valued for high-income earners, while for rural areas, specialized or tertiary education is more beneficial for the poorer households. Their study also suggested that migration sometimes plays a notable role in income determination. Keller and Nabil (2002) concluded that improvements in human capital, including education and skill, contributed to economic growth, better income distribution, and less poverty in many regions across the world. They revealed that the Middle East and North Africa (MENA) region is experiencing an improved level of the

quantity and quality of human capital as it invested heavily in education over the past few decades. Researchers also found an insignificant relationship between income and education. Ning (2010) discovered that there is evidence of inferior returns for educational investment for the low-income group in China. Leeuwen and Foldvari (2011) revealed no significant association between education and income inequality for different OECD and non-OECD countries. Appleton (2000) similarly found that return to investment in education is reverse.

As there are a good number of studies found to have analyzed effects of education on income and income inequality in Bangladesh, there are no studies that had dwelled on the effects of human capital (education, experience) and social factors (age, gender, location, economic activity) on the income. To bridge the current knowledge, gap the study endeavors to inspect the following questions.

(i) Which factors are the major determinants of income in Bangladesh?
(ii) How do social factors such as gender, age, marital status, rural-urban, and non-social factors (human capital) such as education and income, affect the income?
(iii) Have does improvements in human capital and social factors contributed to better income distribution and inclusive growth in Bangladesh?

Though the per capita income has increased in Bangladesh in the last few decades, income inequality has not seen much progress over this period. Thus, the causes behind the income inequality situation in Bangladesh require intense investigation. In this backdrop, this study will generate robust evidence and scientific knowledge of the factors affecting the level of income as well as inequality. It is anticipated that the findings of the study will guide necessary policy intervention in relevant sectors and issues to mitigate income inequality and advance fair income distribution and inclusive growth in Bangladesh.

2. METHODOLOGY AND DATA

2.1. OLS Regression

The ordinary least squares (OLS) regression method has been adopted in the study to estimate the unknown effect of changing one variable over another (Stock and Watson, 2003).[1] The OLS minimizes the sum of squared errors $\sum_i e_i^2$ for choosing the parameters of a linear function from a set of covariates. However, the extension of the Mincerian earning function[2] has been taken to estimate the income equation (Mincer,

[1] The OLS regression shows how much dependent variable changes when independent variable/ variables change one unit. The OLS regression assumes the linear relationship between two variables, and this relationship is additive (Torres-Reyna, 2017).

[2] The basic Mincerian income function is: $\ln Y = \alpha + \beta_1 S_i + \beta_2 E_i + \beta_3 E_i^2 + \varepsilon_i$, where Y is individual

1958). The general income function is estimated using the following equation:

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

where I denoted the individuals, Y denoted the log of monthly income, X is the vector of independent variables (set of individual characteristics), and β is the intercept and the slope parameters of the income equation. Similar to equation 1, the monthly income equations can be written for the males ($\ln Y_{iM} = X'_{iM}\beta_{iM}$) and females ($\ln Y_{iF} = X'_{iF}\beta_{iF}$), as well as for the rural ($\ln Y_{iR} = X'_{iR}\beta_{iR}$) and urban ($\ln Y_{iU} = X'_{iU}\beta_{iU}$) areas separately to estimate the income determinants and their gap.

2.2. Quantile Regression

The OLS regression is often used to estimate the conditional mean value of a dependent variable given the specific value of the independent variables, but the quantile regression is used to estimate the conditional value of different quantiles of interest of the dependent variable. The quantile regression is nothing but an extended version of OLS regression. However, this study has used the quantile regression of Koenker and Bassett (1978) to estimate the conditional income distribution of different quantiles. Based on the extension of the Mincerian earnings function, the quantile regression function can be written as:

$$Q_q(Y_i|X_i) = X'_i\beta_q, \text{ for each } q \in (0,1), \text{ and } i = 1,2,3,\dots,n \tag{2}$$

where $Q_q(Y_i|X_i)$ denotes the conditional quantile of Y_i; X_i is the vector of covariates for each i; Y_i denotes the log of monthly income and β_q is the vector of unknown parameters associated with the qth quantile. Similar to OLS regression, Equation 2 also can be rewritten for the males ($Q_q(Y_{iM}|X_{iM}) = X'_{iM}\beta_{qM}$) and females ($Q_q(Y_{iF}|X_{iF}) = X'_{iF}\beta_{qF}$), as well as for the rural ($Q_q(Y_{iR}|X_{iR}) = X'_{iR}\beta_{qR}$) and urban ($Q_q(Y_{iU}|X_{iU}) = X'_{iU}\beta_{qU}$) areas independently.

2.3. Specification of the Econometric Model

However, the overall monthly income equation can be estimated as in Equation 1 where X'_i equals the vector of the mean value of independent variables of the earning groups, and β_i equals the corresponding vectors of the estimated coefficient. With incorporating the variables, the income equation is specified as follows:

income; S is years of schooling or education; E is years of work experience, and ε is the error term with zero mean and constant variance.

$$\begin{aligned}\ln Income_i \;=\; & \alpha + \beta_2 Education_i + \beta_3 Experience_i + \beta_4 Experience_i^2 \\ & + \beta_5 Gender_i + \beta_6 MaritalStatus_i + \beta_7 Area_i \\ & + \beta_8 FieldofEconomicActivity_i + \beta_9 Occupation_i + \varepsilon_i, \end{aligned} \quad (3)$$

However, Equation 3 is similarly used for the males-females, and rural-urban to estimate the separate income function. The parameters of the models are estimated through OLS regression where the error terms ε_i are normally distributed, and the variances are homogeneous.

As the regression model always has a risk of endogeneity, variables such as age, level of education, and ability have not included for explaining the monthly income but included in a more precise way, i.e., experience variable included as a year of experience and education variable included as a year of education. When the regression model possesses the endogeneity problem, the OLS estimation becomes inconsistent and biased, and the estimator may not be appropriate (Verbeek, 2008). By choosing the right variables, this study minimizes the endogeneity problem.

Since the OLS regression only estimates the mean value of the response variable, the study considers quantile regression to estimate the monthly income indifferent distributions of interest such as 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} quantile. However, the overall monthly income equation for the quantile regression is specified by Equation 2 as follows.

$$\begin{aligned}\ln Income_i = \; & \alpha_q + \beta_{q2} Education_i + \beta_{q3} Experience_i + \beta_{q4}\, Experience_i^2 \\ & + \beta_{q5} Gender_i + \beta_{q6} MaritalStatus_i + \beta_{q7} Area_i \\ & + \beta_{q8} FieldofEconomicActivity_i + \beta_{q9} Occupation_i + \varepsilon_i\,, \end{aligned} \quad (4)$$

Equation 4 is also considered for males-females, and rural-urban to estimate the magnitude of income determinants for different income distribution of interest with the gaps among them. In the case of quantile regression, the standard errors are obtainable by bootstrapping methods. In this study, the quantiles are obtained by $q = 0.10, 0.25, 0.50, 0.75, 0.90$, where $q = 0.50$ is the median regression or least absolute deviation (LAD).

The OLS and quantile regression both are used to estimate the unknown parameters with minimization of the errors, but the difference arises between two models because the OLS minimizes the sum of squared errors $\sum_i e_i^2$ and quantile regression minimizes the sum of the weighted[3] value of the error, $\sum_i q|e_i| + \sum_i (1-q)|e_i|$. The q^{th} estimator for quantile regression β is given as:

[3] Weights are the percentiles taking different values of the interest to the researchers.

$$Q(\beta_q) = min\beta \sum_{i:Y_i \geq x_i'\beta}^{N} q|Y_i - x_i'\beta_q| + \sum_{i:Y_i < x_i'\beta}^{N} (1-q)|Y_i - x_i'\beta_q|, \quad (5)$$

where $0 < q < 1$.

Equation 5 can be considered for the males-females, and rural-urban separately. However, the quantile regression is more robust to outliers than least squares regression and is semi-parametric as it avoids assumptions about the parametric distribution of the error process. Quantile regressions provide pictures of the different conditional distribution of interest. Therefore, they established a frugal way of describing the whole distribution and added significant value if the relationship between the explained variable and predictors evolves across its conditional distribution (Martins and Pereira, 2004).

2.4. Data Source

This study is conducted based on the data of the Household Income and Expenditure Survey (HIES) of Bangladesh. The survey has been carried out by the Bangladesh Bureau of Statistics (BBS) from February 2010 to January 2011. The dataset has covered 12,240 households from 16 strata (6 rural, 6 urban, and 4 statistical metropolitan areas), which has drawn from 612 Primary Sampling Units (PSUs). The two-stage stratified random sampling method was adopted for sampling wherein the first stage primary sampling units (PSU) were selected from all divisions and in the second stage, households were selected randomly from each PSU (BBS, 2011). However, the HIES dataset has divided into nine sections, and each section provides different information about the individual household.[4] This study has considered monthly wage as the dependent variable and year of education, job experience, gender dummy, marital status dummy (married, and unmarried and others), area dummy (rural and urban), field of economic activities dummy (agriculture and non-agriculture), and occupation dummy (service sector, agricultural sector, and industrial sector) as explanatory variables.

The HIES 2010 has covered 12,240 households and 55,580 individuals. After considering all earner groups from the dataset, the sample size has reduced to 15,968 observations. This study has considered the age limit between 15 to 60 years[5], which

[4] In more details, section one provides the information roster of household, the second section includes educational information, and the third section offers health information of the individuals. Similarly, fourth to ninth section supply the information about economic activities and wage employment, non-agricultural enterprises, housing, agricultural enterprises, others income and assets and finally consumption information respectively.

[5] Below 15 years of age has not been considered because age between 5-14 years consider as child labor in Bangladesh (BBS-UNICEF, 2017). On the other hand, above 60 years also not considered in this study due to the retirement age is 59 years in Bangladesh, according to the Public Service Retirement Act 1974b.

again reduced the sample size to 14,566 observations. After taking all the variables from a different section and dropping the missing data from the dataset, the sample size finally reduced to 9,943 observations. However, the final sample dataset has contained a total of 8,535 males and 1,408 females; and 5,367 rural people and 4,576 urban people.

3. RESULTS AND DISCUSSION

Table 1 demonstrates the summary statistics of all the variables used in the study. It appears that the mean monthly wage of the sample population is BDT 5,323.36 (US$ 65), where the mean monthly wage of the male and female workers is BDT 5434.59 (US$ 66) and BDT. 4665.05 (US$ 57), respectively. Though there are 0.14 years of education and 0.24 years of experience gap exists between the male and female, the wage differential emerges at BDT. 707 (US$ 8.5) between males and females, which is not negligible in the context of Bangladesh. There is moreover a spatial difference found in the mean wage of the respondents which is 4044.78 and 6829.21 respectively for the rural and urban areas. Besides, the average years of schooling have estimated at 4.79 years for the respondents which are slightly behind from the national average (4.9 years) in 2010 (UNDP, 2018). Besides, the average experience of the earning groups is found to be 24.02 years indicating the earners have an extensive period of job experience.

In the gender category, among the total sample, 86% are males, and 14% are females, which indicates the lower participation rate of females' in the workforce. Further, among the total sample, 75% of respondents are married, and 25% are single including others (widowed, divorced, and separated). It is clear from the dataset that married peoples are mostly involved in the workforce due to their financial responsibilities to the families or people marry after getting the job. The average number of married male is a bit higher than the female, and the average number of rural male people are somewhat higher than that of urban areas. Among the respondents, 54% people work in rural areas, and the rest of 46% works in urban areas. Whereas 73% respondents are engaged in the non-agricultural[6] sector for economic activity and 27% people are involved with the agricultural field. The sample dataset denotes that the non-agriculture sector generates more than double employment in Bangladesh than the agriculture sector. The occupation of wage earners shows that the service sector is mostly superior (50%) compared to the agricultural sector (27%) and the industrial sector (23%). Here, the share of the agriculture and industrial sector is nearly the same and collectively, they are equal to the contribution of the service sector in Bangladesh.

[6] The nonagricultural income of the households came from business and commerce, professional wages and salary, housing services, gift and remittance, and other sectors.

Table 1. Summary Statistics

	Full	SD	Male	SD	Female	SD	Rural	SD	Urban	SD
Monthly Income	5323.36	5642.67	5434.59	5564.90	4665.05	6061.69	4044.78	3639.34	6829.21	7037.46
Year of Education	4.79	5.56	4.80	5.48	4.66	6.06	3.46	4.82	6.34	5.98
Experience	24.02	13.09	24.02	12.99	23.78	13.61	25.33	13.17	22.40	12.80
Gender:										
Male	0.86	0.35	---	---	---	---	0.87	0.34	0.84	0.36
Female	0.14	0.35	---	---	---	---	0.13	0.34	0.16	0.36
Marital Status:										
Married	0.75	0.43	0.78	0.42	0.64	0.48	0.77	0.42	0.75	0.44
Unmarried and Others	0.25	0.43	0.22	0.42	0.36	0.48	0.23	0.42	0.25	0.44
Area:										
Rural	0.54	0.50	0.55	0.50	0.50	0.50	---	---	---	---
Urban	0.46	0.50	0.45	0.50	0.50	0.50	---	---	---	---
Field of Economic Activity:										
Agriculture	0.27	0.44	0.28	0.45	0.19	0.39	0.45	0.50	0.05	0.23
Non-Agriculture	0.73	0.44	0.72	0.45	0.81	0.39	0.55	0.50	0.95	0.23
Occupation:										
Service Sector	0.50	0.50	0.49	0.50	0.53	0.50	0.36	0.48	0.66	0.48
Agricultural Sector	0.27	0.45	0.29	0.45	0.18	0.38	0.46	0.50	0.06	0.24
Industrial Sector	0.23	0.42	0.22	0.41	0.29	0.45	0.18	0.38	0.28	0.45
Observations	9943		8535		1408		5367		4576	

3.1. Estimates of the OLS and Quantile Regression

Table 2 exhibits the results of the regression where the log monthly income function has been estimated using both OLS and quantile regression.[7] The coefficient of determination of OLS is 0.3, and all the explanatory variables are significant at 1% level except marital status and occupational category. It appears that the mean return to the additional year of education obtained for the sample size is 6%, which is statistically significant at a 1% level, and it is also found to be increasing at an increasing rate from lower to upper quantile. Besides, returns to an additional year of experience have a 1% significance level at the mean (3%) as well as at all the estimated quantiles, which are also heading to the increasing trend. This study has also considered the quadratic form of experience for the robust estimation, which follows the same pattern as experience.[8] However, the positive effect of experience and the negative effect of experience-squared indicates that as much as the person gets to experience, the effect of experience is lessened. As Mincer (1958) showed, the year of education and experience have a considerable positive impact on a person's income; similarly, this study also found the same result.

The estimates indicate that the females are remarkably earning less than the males at the mean (36%), and every quantile. Interestingly, the income gaps are decreasing at a decreasing rate from lower to upper quartile for the females. Besides, the unmarried and others (including widowed/ divorced/ separated) have been earning 6% less than the married people.

Usually, urban workers earn higher compared to their rural counterparts (Asadullah, 2005). Our study found the same result, which is not only at mean but also in different quantiles. The OLS estimates suggest that the urban people get 17% more monthly wage than the rural people. Similarly, the non-agriculture field has a positive impact on the income level of the people. It appears that people from the non-agricultural sector earn 25% more than the agricultural sector, and in each quantile, the wage of non-agricultural sectors is higher. The mean wage of the agricultural sector is 7% higher than the service sector. In the different quantiles, the wage of the agricultural sector also higher than the service sector, except for the 90th quantile. Surprisingly, the mean wage of the industrial sector is slightly negative than the service sector, which is only 3% also low in each quantile but quantile 10.

[7] The assumption of homogeneity has tested by the Breusch-Pagan heteroscedasticity test. This study uses heteroscedasticity-robust standard errors to correct the detected heteroscedasticity. This study also tests multicollinearity and omitted-variable test by using the variance information factor (VIF) and Ramsey RESET test.

[8] This study has taken the explanatory variable experience-squared to estimate the effect of experience more accurately, which may have a non-linear relationship with the independent variable. If you have a positive effect of experience and the negative effect of experience-squared, that means that as a person get experienced the effect of experience is lessened and vice versa.

Table 2. OLS and Quantile Regression of Log Monthly Income

	OLS	Q10	Q25	Q50	Q75	Q90
Year of Education	0.06***	0.04***	0.05***	0.06***	0.07***	0.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience	0.03***	0.02***	0.03***	0.03***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience Square	-0.05***	-0.04***	-0.04***	-0.05***	-0.05***	-0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gender:						
Female	-0.36***	-0.67***	-0.53***	-0.34***	-0.25***	-0.18***
	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)
Marital Status:						
Unmarried and Others	-0.06**	-0.14**	-0.1***	-0.06*	-0.01	0.04
	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)
Area:						
Urban	0.18***	0.17***	0.17***	0.17***	0.15***	0.14***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Field of Economic Activity:						
Non-Agriculture	0.25***	0.15*	0.20***	0.25***	0.33***	0.31***
	(0.04)	(0.07)	(0.05)	(0.04)	(0.04)	(0.05)
Occupation:						
Agricultural Sector	0.07*	0.15	0.11*	0.08*	0.03	-0.03
	(0.04)	(0.08)	(0.05)	(0.04)	(0.04)	(0.05)
Industrial Sector	-0.03*	0.04	-0.00	-0.03	-0.08***	-0.06**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)
Constant	7.36***	6.96***	7.16***	7.39***	7.62***	7.87***
	(0.05)	(0.11)	(0.07)	(0.06)	(0.05)	(0.07)
N	9943	9943	9943	9943	9943	9943
R-squared	0.3					
Adjusted R-squared	0.28					
Root MSE	0.67					

Note: Robust standard errors in the parentheses.

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

Table 3. OLS and Quantile Regression of Log Monthly Income for Male and Female

	OLS		Q10		Q25		Q50		Q75		Q90	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Year of Education	0.06***	0.1***	0.03***	0.09***	0.05***	0.11***	0.06***	0.1***	0.067***	0.1***	0.07***	0.08***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Experience	0.03***	0.05***	0.02***	0.05***	0.02***	0.06***	0.03***	0.04***	0.04***	0.04***	0.04***	0.04***
	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Experience Square	-0.05***	-0.07***	-0.05***	-0.06*	-0.05***	-0.1***	-0.05***	-0.07***	-0.06***	-0.07***	-0.06***	-0.073***
	(0.05)	(0.01)	(0.01)	(0.03)	(0.001)	(0.012)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Marital Status:												
Unmarried and Others	0.01	-0.11*	-0.12*	-0.28*	-0.05	-0.04	0.01	-0.1	0.08***	-0.09	0.12***	-0.1
	(0.023)	(0.05)	(0.05)	(0.11)	(0.03)	(0.07)	(0.02)	(0.06)	(0.02)	(0.05)	(0.03)	(0.06)
Area:												
Urban	0.16***	0.23***	0.17***	0.25*	0.18***	0.1	0.15***	0.2***	0.13***	0.27***	0.13***	0.26***
	(0.02)	(0.05)	(0.03)	(0.11)	(0.02)	(0.07)	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.06)
Field of Economic Activity												
Non-Agriculture	0.27***	0.05	0.13	-0.09	0.22***	0.16	0.26***	0.03	0.35***	-0.00	0.33***	0.16
	(0.04)	(0.14)	(0.08)	(0.3)	(0.05)	(0.18)	(0.04)	(0.14)	(0.04)	(0.13)	(0.05)	(0.16)
Occupation:												
Agricultural Sector	0.07	0.03	0.13	0.06	0.09	0.19	0.05	0.05	0.05	-0.06	-0.03	-0.15
	(0.04)	(0.14)	(0.08)	(0.31)	(0.05)	(0.19)	(0.04)	(0.14)	(0.04)	(0.14)	(0.05)	(0.16)
Industrial Sector	-0.06**	0.12*	0.02	0.24	-0.05*	0.25**	-0.05**	0.09	-0.08***	0.07	-0.07**	-0.04
	(0.02)	(0.05)	(0.04)	(0.13)	(0.03)	(0.08)	(0.02)	(0.06)	(0.02)	(0.06)	(0.02)	(0.06)
Constant	7.31***	6.77***	6.99***	5.69***	7.14***	6.02***	7.35***	6.99***	7.49***	7.33***	7.78***	7.76***
	(0.06)	(0.17)	(0.12)	(0.4)	(0.08)	(0.23)	(0.06)	(0.18)	(0.06)	(0.17)	(0.07)	(0.20)
N	8535	1408	8535	1408	8535	1408	8535	1408	8535	1408	8535	1408
R-squared	0.26	0.35										
Adjusted R-squared	0.26	0.35										
Root MSE	0.64	0.78										

Note: Robust standard errors in the parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001.

Table 4. OLS and Quantile Regression of Log Monthly Income for Rural and Urban Areas

	OLS		Q10		Q25		Q50		Q75		Q90	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Year of Education	0.04***	0.08***	0.02**	0.06***	0.02***	0.07***	0.04***	0.08***	0.05***	0.0830***	0.05***	0.09***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience	0.02***	0.04***	0.01	0.03***	0.02***	0.03***	0.02***	0.04***	0.02***	0.04***	0.03***	0.043***
	(0.004)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience Square	-0.03***	-0.05***	-0.03*	-0.06***	-0.03***	-0.06***	-0.04***	-0.06***	-0.04***	-0.05***	-0.03***	-0.06***
	(0.001)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.0)
Gender:												
Female	-0.43***	-0.29***	-0.67***	-0.65***	-0.57***	-0.48***	-0.43***	-0.24***	-0.32***	-0.13***	-0.23***	-0.09**
	(0.03)	(0.03)	(0.06)	(0.06)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Marital Status:												
Unmarried and Others	-0.03	-0.09**	-0.07	-0.3***	-0.07*	-0.15***	-0.04	-0.06	-0.02	-0.03	0.00	0.06
	(0.0273)	(0.0320)	(0.0611)	(0.0685)	(0.0355)	(0.0450)	(0.0277)	(0.0333)	(0.0267)	(0.0311)	(0.0384)	(0.0402)
Field of Economic Activity:												
Non-Agriculture	0.31***	0.11	0.17	-0.04	0.29***	0.16	0.28***	0.15	0.36***	0.36***	0.42***	0.32**
	(0.04)	(0.1)	(0.09)	(0.2)	(0.05)	(0.13)	(0.04)	(0.09)	(0.04)	(0.09)	(0.05)	(0.11)
Occupation:												
Agricultural Sector	0.09*	-0.13	0.16	-0.08	0.17***	0.04	0.07	-0.07	0.06	0.03	0.02	-0.16
	(0.04)	(0.11)	(0.09)	(0.19)	(0.05)	(0.13)	(0.04)	(0.09)	(0.04)	(0.09)	(0.06)	(0.11)
Industrial Sector	-0.04	-0.02	-0.03	0.09	-0.01	0.03	-0.01	-0.04	-0.07*	-0.07**	-0.07	-0.09**
	(0.023)	(0.02)	(0.06)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)
Constant	7.5***	7.54***	7.1***	7.21***	7.34***	7.19***	7.58***	7.46***	7.83***	7.58***	8.01***	7.86***
	(0.067)	(0.12)	(0.15)	(0.24)	(0.08)	(0.16)	(0.07)	(0.12)	(0.07)	(0.1)	(0.09)	(0.14)
N	5367	4576	5367	4576	5367	4576	5367	4576	5367	4576	5367	4576
R-squared	0.17	0.32										
Adjusted R-squared	0.17	0.32										
Root MSE	0.62	0.7										

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

3.2. Estimates of Gender-Specific OLS and Quantile Regression

This study estimates the income equation separately for the males and females using both OLS and quantile regression for in-depth assessment and evidence generation. This methodology helped us to identify the determinants of the income separately with the gap between the parameters. Table 3 illustrates the result of OLS and quantile regression, where the R-squared value of the OLS appears 0.26, and all the variables are significant at 1% level except marital status and occupation.

The return to an additional year of education has a remarkable positive impact on the mean monthly income for both males and females alongside all the estimated quantiles. The OLS result suggests that the rate of return to education is interestingly higher for the females compared to the males and at any level of the quantile. Here, the male worker received approximately 4% less wage than that of women. Similarly, the return to an additional year of experience is also superior for male and female in both OLS and every quantile, where females' earnings are considerably higher than that of the male. The estimates of OLS shows an average return of an additional year of experience for a male is 3% and 5% for female where the extent of the wage gap between them appears at 2%. There is also a visible wage disparity between urban male and female workers. Urban female earns an average 7% higher wage than that of the male. However, the quadratic form of experience shows a negative impact on the mean income and different quantiles. Using OLS and Heckman estimates, Asadullah (2005) found that both education and experience have a positive influence on income, and the mean wage of educated and experienced females is notably higher than that of males. This signifies educated and experienced females have an intense demand in the labor market in Bangladesh, and qualified females tend to receive a decent wage in the formal sector. It will encourage other females to be skilled and enter the job market. Consequently, the competency of male and female workers will be boosted, and women empowerment will be soared to a large extent in the country.

However, if we look at the spatial wage distribution, the females' earnings ratio is higher in the urban area than that of males at mean along with every quantile except 25th quantile. In contrast, the earnings of the males of the non-agriculture sector are 27% superior to the agriculture sector in OLS and also higher in each quantile.

Whereas, the earnings of females in 5% higher in OLS and lower in quantile 10 and 75. The males of the agricultural sector earn a 7% higher wage than that of the service sector, and males in the industrial sector earn 6% less wage than the service sector. Whereas, the females of the agriculture and industrial sector earn more than the wage of the service sector's worker.

3.3. Estimates of Area-Specific OLS and Quantile Regression

The study likewise estimated the monthly income equation for the rural and urban areas using the OLS and quantile regression. The estimation of income determinants

such as human capital and social factors at the mean and different quantile shown in Table 4. The R-squared value is found to be 0.17 and 0.32 for rural and urban areas, respectively. Except for marital status and occupation, all the explanatory variables are found significant at 1% level for rural areas. For urban areas, all the variables but marital status, the field of economic activities and occupation appear statistically significant at 1% level.

Table 5. The Effects of Human Capital and Social Factors on the Household Income: Global and Regional Evidence

Studies	Scale/Country	Major findings	The confidence level of the findings
Lee and Lee (2018)	Global	Educational expansion is a major contributor in the reduction of income inequality.	High
Jaumotte et al. (2013)	Global	Income is affected by the average years of schooling.	Medium
Földvári and van Leeuwen (2011)	OECD countries	Average years of schooling has an insignificant effect on income.	Low
Castelló-Climent and Doménech (2017)	Latin America	Human capital has a positive relationship with income distribution.	Medium
Zhang et al. (2005), Fang et al. (2012)	China	An additional year of schooling has a positive impact on income.	High
Lee and Wie (2015)	Indonesia	Higher education positively influences income.	High
WB (2019)	Global	Investment in human capital has a stronger influence on income than the investment in physical capital.	Medium
Cram (2017)	OECD countries	Human capital positively affects the income level.	Medium
Wolla and Sullivan (2017)	USA	Workers with more education enjoy higher income and wealth.	Medium
Liu et al. (2019), Bobbitt-Zeher (2007)	USA	Gender differences cause income inequality among workers.	High
Bobbitt-Zeher (2007)	USA	With the same level of education, the male-female wage gap is, on average, $4400/year.	Medium

Table 5. The Effects of Human Capital and Social Factors on the Household Income: Global and Regional Evidence (con't)

Studies	Scale/Country	Major findings	The confidence level of the findings
Bernadette et al. (2016)	USA	The total gender wage difference is about $799 billion annually, which is worse for black women and Latinas.	High
Oxfam (2018)	Global	Men are paid more for doing the same roles as women and men are concentrated in higher status jobs.	High
Baloch et al. (2018)	Global	Increasing equality between males and females will result in lower income inequality.	High
Herrera et al. (2019)	Nicaragua	Despite having higher average education levels, women still earn less than men.	High
Equitable Growth (2018)	USA	Regional differences affect women's wages relative to men's wages by 0.3%.	High
Klasen and Lamanna (2009)	Global	The aggregate costs of education and employment gaps in the Middle East, North Africa, and South Asia amount respectively to 0.9–1.7.	Medium
Waugh et al. (2016)	Bangladesh	Rural people receive a lower wage than that of urban areas.	High
Young (2013)	Global	Spatial factors affect the rural-urban wage gap.	High
Gollin et al. (2013)	Developing countries	The value-added and wage level is much higher in the nonagricultural sector than in agriculture.	High

Notes: Confidence level refers to the level of strength of the findings. If the study generates strong evidence against the findings, then the confidence level would be higher and vice versa.

It emerges in Table 4 that the effects of the return of an additional year of education are positive for both areas, which are also valid for all estimated quantiles. Here, the return of education is relatively higher in urban areas than that of rural areas due to the higher level of industrialization and economic advancement in the urban areas. The OLS and quantile estimates also provided similar results for the additional year of experience. The quadratic form of experience has a significantly negative impact on income. However, the gender variable explains that females earn significantly lower than the

males in both rural and urban areas, but the gap between genders' wages is higher in rural areas than the urban areas. Female of rural areas receive an average 43% less wage than their male counterpart and urban females earns 29% less than the urban males, appeared in the OLS. In addition, unmarried workers earn less in both rural and urban areas compared to the married workers, which are also applicable in each quantile except quantile 90. The wage of the non-agriculture sector is 31% higher in the rural areas compared to that of the agriculture sector, which is also higher in each quantile except quantile 10. Whereas, in the urban areas, the wage of the non-agriculture sector is 11% higher than the agriculture sector, which is also higher in each quantile. The OLS estimates depict that the wage of rural agricultural wage is 9% higher than the service sector and rural industrial wage is 4% inferior to that of the service sector.

The human capital and social factors affect household income and inequality differently in different scales around the world (Table 5). There is strong evidence that income inequality, rural-urban difference, gender, and education level play a determining role in the household income in developed, developing countries in transition. Table 5 further demonstrates that level of education and average years of schooling positively affects the HH income in USA, China, India, Latin America, OECD as well as global level (Lee and Lee, 2018; Jaumotte et al., 2013; Castelló-Climent and Doménech, 2017). Besides, investment in human capital can generate more returns than investment in physical capital (WB, 2019). Hence, human capital accumulation has a comparative advantage over the physical capital, where opportunity needs to be created for the disadvantaged people of the world to ensure the decent wage that will also accelerate the SDG 8 and associated targets globally. It appears that globally gender difference is a concern and causes significant wage inequality among male and female workers (Baloch et al., 2018; Oxfam, 2018). Studies strongly supported that among the counties' gender wage gap is unsatisfactory in the USA, which squeezes the welfare level of women (Liu et al., 2019; Bobbitt-Zeher, 2007). It is found that gender wage difference is about $799 billion annually in the USA (Bernadette et al., 2016). Table 5 postulates that spatial differences also influence the wage level of people globally. In the globalized world, rural people receive relatively fewer wages than urban settlers (Young, 2013). There is high confidence that the non-agricultural sector is adding more value and offering higher wages than the agriculture sector in developing countries (Gollin et al., 2013). As agriculture is the dominant sector and absorb a large number of the labor force in the developing countries, commercialization, technological advancement, promotion of farmers organization, micro-SME, and substantial private investment in processing, storage, transportation and market system development can contribute to the transformation of the agricultural sector and reduce food waste and food insecurity. It is now evident that human capital and social factors both are the critical determining factors of the income in Bangladesh and around the world. Hence, they need to be equally treated in global policy discourse and need to be addressed by the national and regional development agenda through a holistic approach.

4. CONCLUSION

The study reveals that both human capital (education and experience) and social factors (gender, marital status, spatial condition, and occupation) have significant explanatory power to explicate the monthly income of the people. Surprisingly, the OLS and quantile estimates suggest that the effects of social factors are relatively superior to the effect of human capital on the monthly income. It mostly happened because of having the mean education years of the sample size is 4.79 only. On the contrary, though the mean experience of the sample size is 24.02, its effects on the income are also very slight. It is found that an increase in an additional year of education and experience leads to raising the monthly income by 6% and 3%. In social factors, gender, spatial condition, and field of economic activities have a more significant role in determining the income level of the people as well as households. It appears in the OLS estimates that urban people get 18% more wage than their rural counterparts, and people engaged in the non-agricultural sector received 25% higher wages than the agricultural sector. Moreover, female workers receive substantially lower wages than male workers, which is 36%. Interestingly, there is a significant gender dimension in the income effects of females. It appears that human capital and social factors play a prominent role in determining the income of females. The study result suggests that if human capital increases, females will earn more income than the males and the females of urban areas earn more than male workers in urban areas. It suggests that human capital endowment, urbanization and economic migration in urban areas are economically beneficial for the females. Besides, it is evident that the spatial condition has a considerable effect on the income level. Alternatively, human capital and social factors have a distinctive impact in determining income. It is found that both education and experience have a comparatively higher positive impact on the income level of urban people than that of rural areas. Further, the non-agricultural wage is higher in rural areas than the urban areas. This is a bit less encouraging for labor working in the agriculture sector. If this trend continues, people may be discouraged from working in the agriculture sector and sectoral shift of labor, as well as a deficit in agricultural labor, will emerge in Bangladesh. Consequently, reduction in the agricultural labor force will also lead to an increase in the wage of the agriculture sector, and in the long run it will help to wipe out disguised unemployment from the agricultural sector as well as contribute to the commercialization of this sector.

Most essential findings that appeared from the study include education as the most critical human capital does not have any leading effects on income. The agriculture sector offers a lower wage than the non-agricultural sector, and the females get a lower wage than males. Besides, there is a distinguished effect of the human capital and social factors in the gender and rural-urban context. Hence, we need a reorient policy to appropriately address these essential issues of the labor market of Bangladesh. That will further contribute in the reduction of income inequality across the sectors, gender, and scales and ensure equal welfare for all.

At the global level, human capital and social factors deserve equal attention

regardless of the economic status of the country to ensure balanced household income and reduce income and wealth inequality. Here, equal right to human capital accumulation needs to be established everywhere, and social factors such as gender, rural-urban, experience, and occupation that leads income distortion required concentrated and collaborative efforts (south-south, north-south, multilateral and triangular cooperation) and long-term mitigation strategies with result-oriented action plan.

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