Returns to Education in the Philippines

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Abstract: Current developments in education policy in the Philippines raise questions on the true effectiveness of our education structure in improving individuals' private returns. Luo and Terada (2009), for example, report that the unemployment rate is considerably higher for better-educated Filipinos. Various studies have estimated coefficients that capture the effect of education on earnings on the average; however, the returns to education may also differ across the wage distribution. Evidence based on Quantile Regression methods suggest that the returns are higher for those in the top decile of the wage distribution compared to those in the bottom decile (Harmon, Oosterbeek, and Walker, 2003). Punongbayan (2012), using Quantile Regression, finds that returns to education in the Philippines are higher for individuals who receive lower wages, but without accounting for sample selection bias. Hence, in this paper, by applying the Heckman Selection Procedure and a Quantile Regression Analysis, we investigate the level of private returns to education and how it varies across the wage distribution in the Philippines, while accounting for selection bias and using more recent data. Results show that, across all quantiles, college level returns are higher than those for elementary and high school levels. We also find that returns are higher for individuals receiving higher wages, which may imply an inconsistency between education and earnings.

Key Words: returns to education; sample selection bias; quantile regression; Philippines

1. INTRODUCTION

In 2016, the Philippine government implemented the K-12 education policy in the country, adding two more years of schooling in the high school level. This implies an improvement in the education system brought about by an increase in the years of schooling. However, this also implies an increase in the cost of education. This then raises questions on the value of investing in education and the effectiveness of our education system in improving households' private returns.

In the Philippines, Luo and Terada (2009) report that Filipinos with a higher level of educational attainment face a considerably higher unemployment rate than those with a lower level of education attainment. They attribute 30 percent of the differences in wages across the country to education – highlighting that education is a determinant of wage inequality. An earlier study by Paqueo and Tan (1989) also highlights the role of education. They find that an additional year of education leads to an increase in private returns by 8.1 percent. Schady (2002) also finds similar results for the male population: even if costs to acquiring a college education are very high, the highest returns are also experienced by those who complete a college degree.

It is also important to note that in terms of income inequality, in 2009, the average per capita income for the poorest 20 percent was PHP 14,022.00 while for the richest 20 percent, it was PHP 176,863.00 (Albert, Dumagan, and Martinez, 2015). This highlights the need to understand how investments in education may or may not help in reducing wage differentials in the Philippines, especially in light of recent policy regarding education.

Staneva, Arabsheibani, and Murphy (2010) note the importance of assessing returns to education across the conditional earnings distribution through the Quantile Regression method (QR, hereafter). Relatively, the use of QR in estimating returns to education is still quite unexplored in the literature. In the Philippines, Punongbayan (2012) studies this aspect of returns to education and finds that returns are higher for low-wage individuals.

In this paper, we aim to investigate the level of private returns to education further and how it varies among individuals across the wage distribution in the Philippines. We would like to do this by using more recent data as well as accounting for sample selection bias.

In Section 2, we discuss our methodology and the data used. In Section 3, we present our results and a discussion of the results. And Section 4 concludes the paper.

2. DATA AND METHODOLOGY

2.1 Data

The raw data are from the October rounds of the Philippine Labor Force Survey (LFS, hereafter) from 2008 to 2012; this is the only quarterly round where wages are reported. Based on the non-missing data on wages and highest educational attainment, the 5-year sample is reduced to 176,203 observations or household members.

The survey has information on the following variables of interest for this study: wages (in the form of the basic pay per day for individuals 15 years old and above), highest educational attainment (created as a dummy with "no grade completed" as a reference category), experience (which takes on the usual Mincerian form of age less years of schooling less six) (Mincer, 1974). On the other hand, the following variables were used from the same survey for the participation equation: household size, number of children below 18 years of age, gender, origin (created as a dummy variable with a value of 1 if living in an urban area), marital status (created as a dummy with "married" as a reference status).

2.2 Methodology

The private rates of returns of investing in education are estimated via the earnings function method (Psacharopoulos, 1981; 1994) which most studies on returns to education are based on. The earnings (wage) function or the "Mincerian" method of Mincer (1974) is an approximation of the human capital theoretical framework, which has a similar function equation, expressed as:

$$\ln y_i = \alpha + \beta S_i + \gamma_1 X_i + \gamma_2 X_I^2 + u_i \qquad \text{(Eq.1)}$$

where:

y_i = earnings per day for individual i
S_i = highest educational attainment
X_i = measure of experience
X_i^2 = experienced squared to capture the possibility of a non-linear relationship between earnings and experience, and
u_i = disturbance term representing other unobservable factors which are not explicitly measured.

One issue arises when regressing earnings on characteristics for those in employment, which is that we are not observing the equation for the population as a whole. This tends to result in a sample selection bias. Thus, to account for this potential bias, we use the Heckman (1979) two-step procedure wherein a labor participation equation estimates the probability of being employed, after which, the earnings equation is estimated.

2.2.1 First Stage Probit Estimation

The first stage estimation of the participation equation is given as

$$y_i = Z_i'\beta + \epsilon_i \quad \text{(Eq.2)}$$

where the dependent variable y_i takes a value of 1 if an individual is working and 0 if not. Z represents a set of human capital variables, demographic variables, and identifying variables represented as

$$Z_i = \begin{cases} 1 \text{ if}(HS, CH, G, O, MS_{1-5})_i * \beta + \epsilon_i > 0 \\ 0 \text{ otherwise} \end{cases} \quad \text{(Eq.3)}$$

where:
- HS = household or family size
- C = number of children under the age of 18
- G = gender, 1 if female, 0 if male
- O = 1 if urban area, 0 if rural area
- MS = marital status

From the estimated participation equation, a selection variable,λ, known as the inverse Mills ratio, is created. This ratio is defined as the ratio of the probability density function to the cumulative distribution function of a distribution. This estimate is then used as an additional independent variable in wage equation in the second stage.

2.2.2 Second Stage Earnings Equation

Adopted from Agrawal (2011), the second stage involves estimating the wage function by ordinary least squares. Since we are also interested in estimating returns for different levels of education and the existence of diminishing returns, an augmented wage function is used, as shown below.

$$\ln y_i = \alpha + \sum_k \beta_{i,k} S_{i,k} + \gamma_1 X_i + \gamma_2 X_I^2 + \theta \widehat{\lambda_i} + u_i \quad \text{(Eq. 4)}$$

where:
- $S_{i,k}$ = dummy variable for kth level of education
- $\widehat{\lambda_i}$ = estimated inverse Mills ratio

2.2.3 Quantile Regression

Similar to Buchinsky (1994) who examined the heterogenous returns to education, the distributional approach was based on the use of QR by Koenerr and Bassett (1978). The QR model can be written as

$$y_i = x_i'\beta_\theta + u_i \text{ with } \mathrm{Quant}_\theta(y_i|x_i) = x_i'\beta_\theta \quad \text{(Eq.5)}$$

where β_θ and x_i are K x 1 vectors and $\mathrm{Quant}_\theta(y_i|x_i)$ is the conditional quantile θ of y_i, conditional on the regressor vector x_i. The quantile θ represents how y splits the data into proportions θ below and $(1-\theta)$ above. The QR model is then able to provide an estimation of the effect of education on earnings at different points of the earnings distribution.

3. RESULTS AND DISCUSSION

In Tables 1 and 2, we present the descriptive statistics for the OLS Estimation and the Heckman Selection Estimation, respectively. Here, we note that there is a big change in mean years of education and experience. These differences may lead to the existence of a selection bias in the OLS estimates.

Table 1. Descriptive Statistics, OLS Estimation

Year	No. of Observations	Mean years, Education	Mean years, Experience	Mean log Daily Wage
2008	32,987	9.56	19.59	5.39
2009	33,749	9.63	19.55	5.43
2010	34,785	9.68	19.73	5.46
2011	36,940	9.56	19.70	5.48
2012	37,742	9.50	20.00	5.53

Table 2. Descriptive Statistics, Heckman Selection

Year	No. of Observations	Mean years, Education	Mean years, Experience	Mean log Daily Wage
2008	202,083	6.47	15.49	5.39
2009	201,478	6.56	15.70	5.43
2010	201,695	6.64	15.87	5.46
2011	203,011	6.68	16.05	5.48
2012	206,020	6.64	16.18	5.53

We derive the Heckman estimates of the augmented wage equation to determine if a sample selection bias may exist. The estimates show that there is evidence in favor of a sample selection as the rho (ρ) for years 2008 to 2012 are not zero and significant in terms of the Wald's test.

Table 3 shows the private rates of return to education based on the Heckman estimation separately for the years 2008 to 2012. The private returns to education are the average rates of return per year to each education level, as based on Agrawal (2011).

Table 3. Private Rates of Return to Education (%)

Educ Level	2008	2009	2010	2011	2012
Elem	-3.243	-3.746	-3.506	-3.298	-2.443
HS	5.705	6.205	5.377	5.307	7.240
College	20.66	21.17	22.21	22.98	21.80

We find that rates of return to education increase with educational attainment, i.e. returns are lower for elementary level and higher for the college level. These values are the rates of return for one additional year of schooling at that particular level. As cited in Agrawal (2011), lower returns for elementary level education is echoed in studies of Duraisamy (2002), Dutta (2006, and Moll (1996).

These results indicate that there is an incentive for individuals to achieve higher levels of education. This also implies that poorer households need to invest more in education in order to reap its benefits, which may be very relatively more costly. As a result, poorer households may be less motivated to invest in their children's education and inequality may continue to persist (Schultz, 2004).

Below, we show the estimates of the QR for each year (from 2008 to 2012) and from there, we show the estimated returns to HS and College Education across quantiles from 2008 to 2012. For Tables 4 to 8, we only show the QR estimates for deciles Q10, Q50, and Q90.

Table 4. QR Estimates for 2008

	Q10	Q50	Q90
Elementary	-.0733*	-.1532*	-.2889*
High School	.0702*	.0939*	-.0459*
College	.9043*	.8853*	.7615*
Experience	.0275*	.0270*	.0185*
Experience^2	-.0004*	-.0004*	-.0002*
Inverse Mills	-.7421*	-.8297*	-.6321*

*indicates significance at 1% level

Table 5. QR Estimates for 2009

	Q10	Q50	Q90
Elementary	-.1330*	-.1916*	-.3172*
High School	.0359*	.0643*	-.0670*
College	.8833*	.8897*	.7730*
Experience	.0282*	.0281*	.0175*
Experience^2	-.0005*	-.0005*	-.0002*
Inverse Mills	-.8062*	-.8684*	-.6097*

*indicates significance at 1% level

Table 6. QR Estimates for 2010

	Q10	Q50	Q90
Elementary	-.0609*	-.1821*	-.3072*
High School	.0606*	.0533*	-.0821*
College	.9412*	.9043*	.8185*
Experience	.0261*	.0268*	.0182*
Experience^2	-.0005*	-.0005*	-.0003*
Inverse Mills	-.7617*	-.8449*	-.6267*

*indicates significance at 1% level

Table 7. QR Estimates for 2011

	Q10	Q50	Q90
Elementary	-.0644*	-.1606*	-.3114*
High School	.0636*	.0679*	-.0706*
College	.9155*	.9613*	.8682*
Experience	.0238*	.0271*	.0199*
Experience^2	-.0004*	-.0004*	-.0003*
Inverse Mills	-.7344*	-.8443*	-.5831*

*indicates significance at 1% level

Table 8. QR Estimates for 2012

	Q10	Q50	Q90
Elementary	-.0753*	-.1117*	-.2406*
High School	.1378*	.1875*	.0555*
College	.9439*	1.012*	.9775*
Experience	.0211*	.0254*	.0209*
Experience^2	-.0004*	-.0004*	-.0003*
Inverse Mills	-.7744*	-.7860*	-.5645*

*indicates significance at 1% level

The results from Tables 4 to 8 are then compounded with the results from selectivity corrected Heckman estimates. In Figure 1, we show the rates of return to education across different wage quantiles (QR) and across the mean (OLS) over time.

Figure 1. Returns to HS and College Educ, Quantiles

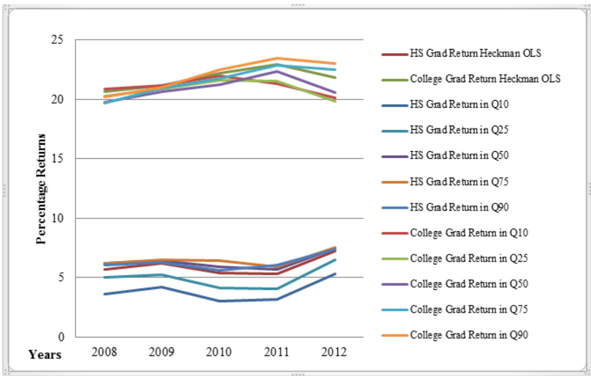

Figure 1 highlights the difference in the returns to education for high school and for college. Attaining a college level of education is higher across the whole wage distribution (around 20 percent) compared to a high school level of education (around 5 percent). According to Duraisamy (2002) and Madheswaran & Attewell (2007), returns to education may be increasing due to the introduction of new technologies, which promotes the demand for skilled labor especially those with more specialized education. This implies that a college level education still results into the highest possible private returns for households. From this, we can infer that investing in a college education eventually leads to higher wages, more than simply investing in a high school education.

We also note that at different quantiles, the returns to education are positive, implying that a high school and college education leads to positive returns, regardless of the level of wages received by the household. Again, this implies that investing further in education leads to positive gains.

An important result from the QR method is that there is a large gap between the returns of the 10th and 90th deciles, which is more notable for high school education. The effect is smaller at lower quantiles, and is larger at higher quantiles at the high school level. For example for 2012, there is a 38.94% gap between Q=0.10 and Q=0.90. At the college level, the gap is not as large as that of the high school level. In 2012, there is a 14.37% gap between Q=0.10 and Q=.90. This implies that richer households, or households that earn higher wages, have even more to gain if either a high school or a college education is attained. This may reduce the incentive to invest in education for poorer households and may also imply wage inequalities due to education.

We also compare OLS and QR estimates and confirm that the QR estimates of each educational level lie outside the confidence intervals of the OLS regression. This means that the QR method captures a large disparity along the wage distribution and, in this manner, it is quite helpful over the OLS regression which assumes identical returns to education in the same education group, regardless of wage level.

We note, however, that in the literature, a potential endogeneity bias may exist for the Mincerian wage equation, wherein an individual's ability may both affect their potential to earn higher wages and their potential to improve their education levels. This ability bias may be solved through the use of an instrumental variable method, which may be done in future research.

4. CONCLUSIONS

Due to recent government efforts to align Philippine education with the international standard by enforcing two additional years through the K-12 program, questions regarding the private returns to education arise. Studies in the literature have also flourished, due to a renewed interest in this area because of an increase in particular enrolment rates as well as continuous improvements in the standard methodologies used in estimating returns to education. Previous studies in the Philippines have shed light on this issue; however, we would like to contribute to this literature by studying more recent data and by accounting for any selectivity bias present.

We revisit fundamental concepts introduced by Becker (1964) and Mincer (1974) in assessing the returns to education and run a two-stage Heckman process and Quantile Regression to correct for selection bias and to analyze returns to education across the wage distribution. We find that returns to education are highest when the university level is completed, supporting results of earlier studies, and emphasizing the importance of ensuring that the right incentives are in place for families to invest in completing education. Higher demand for labor with higher and more specialized education might also result in higher returns for university graduates. If we assess the returns to education across the wage distribution, even if we find that returns are higher upon completion of high school and college, the returns are higher for the higher quantiles, with the difference between the lowest and highest deciles being larger for the high school level. This raises the issue of wage inequality and the inconsistencies between education and earnings.

Further research may be done to control for endogeneity as other studies in the literature have discussed the potential for ability to cause endogeneity in the model. This may help us pinpoint further differences in returns to education across the wage distribution.

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