Education and Labour Earnings Inequality in Tanzania: Evidence from Quantile Regression Analysis

Mlacha, Cornel J. and Ndanshau, Michael O.A

Mkwawa University College of Education, of University of Dar es Salaam, Tanzania, University of Dar es Salaam, Tanzania

15 September 2018

Education and Labour Earnings Inequality in Tanzania: Evidence from Quantile Regression Analysis

Cornel J. Mlacha
University of Dar es Salaam-MUCE

and

Michael O.A. Ndanshau
University of Dar es Salaam

Abstract

This paper aims to investigate the relationship between education and labour earning inequalities by using 2014 Integrated Labour Force Survey data for Tanzania. The quantile regression method is applied to compute returns to education at different points of earnings distribution. The estimation result reveals that there is significant variation in the coefficients of marginal returns to education across earning distributions; and, the estimated coefficients are higher at the top of earning distribution. This finding suggests education could contribute to widening of earnings dispersion in Tanzania. Accordingly, it is important to have policy in Tanzania to reduce disparities in the levels of education attained between the least and the most educated individuals.

Department of Economics Working Paper Series
University of Dar es Salaam.

Key Words: Earning Inequality, Returns to Education, Quantile Regression, Tanzania.

JEL Classification: I24, I26.

Education and Labour Earnings Inequality in Tanzania: Evidence from Quantile Regression Analysis

Cornel J. Mlacha
University of Dar es Salaam-MUCE

Michael O.A. Ndanshau
University of Dar es Salaam

Outline

1. INTRODUCTION 1
2. REVIEW OF RELATED LITERATURE 3
3. METHODOLOGY 6
3.1 Baseline Earning Equation 6
3.2 Quantile Estimations Technique 8
4. DATA SOURCES AND DESCRIPTIVE STATISTICS 11
Education 14
Potential Experiences and Training 16
Union Membership 17
Locality 17
Weekly Working Hours 17
Sectors of Employment 18
5. CONCLUSION 18
References 19

The Authors are respectively academic staff of the Department of Economics of at Mkwawa University College of Education (MUCE), a constituent College of the University of Dar es Salaam (UDSM), and the Mwalimu J.K. Nyerere Campus of the UDSM. Correspondence E-mail: cjmlacha@gmail.com.

First Draft

Education and Labour Earnings Inequality in Tanzania: Evidence from Quantile Regression Analysis

1. INTRODUCTION

Education plays a big role in economic transformation. Evidences show that many developing countries have used education as a policy tool for reducing poverty, addressing inequality and promoting standard of living (Heckman *et al.,* 2003; Wang, 2013). Given an understanding of its importance, Tanzania has implemented various educational policies, programmes and plans, including adoption of Universal Primary Education (UPE) programme in 1977; a launch of Primary Education Development Plan (PEDP) for the period 2002-2006; and, implementation of Secondary Education Development Plan (SEDP) during the period between 2004 and 2009. The trio policies, programmes and plans expanded significantly the education opportunities in Tanzania leading to increase in the supply of educated labour. The arising critical questions for research and of policy interest are: can education reduce earnings inequality *while* increasing individuals' earnings? Who benefits from education most? To answer these questions, we need to understand how education affects the earnings distribution. Specifically, we need to know whether education affects individuals differently across the earnings distribution.

Previous empirical studies typically relied on regression analysis based on standard linear specification, thereby focusing mainly on *average* effects of schooling (Söderbom *et al.,* 2006; Quinn and Teal, 2008; Islam *et al.,* 2015). However, the OLS assumes that individuals are homogeneous and give an estimate for an average effect, but in reality marginal returns to education vary across individuals because they are heterogeneous (Card, 2001; Kingdon and Söderbom, 2007; Kavuma, 2014). The fact that returns to education can be heterogeneous across individuals has implications for inequality reducing role of education. While the findings of such studies are of interest to note, the evidence on *average* effects of schooling may mask much important information in the earnings distribution; and, besides, may not be informative as to the inequality-reducing effects of education (Wang, 2013). For example, if the effects are more pronounced in the upper than in the lower tail of the earnings distribution, education increases rather than decreasing inequality. In order for education to necessarily promote equality, it should increase earnings more for individuals in the lower tail of the earnings distribution. If the average effects of schooling were the only information available, it would not be clear whether or not expanded educational opportunities will increase or decrease inequality.

The objective of this paper is to investigate the effects of education on labour earning in Tanzania by using quantile regression technique. Specifically, the paper tries to answer one main question: how does educational composition of the workforce in Tanzania influence the distribution of labour earnings? The findings of the paper, which are based on the Tanzania Integrated Labour Force Survey (ILFS) dataset of 2014, adds value to existing literature on labour earnings and education in Tanzania, first, by applying quantile regression (QR) technique to investigate returns to education across the earnings spectrum. Such findings serve to establish whether some workers benefit more from education; and, therefore, implication of education on inequality. Second, the QR technique is somehow superior to the OLS technique used in some of the previous studies to capture the effect of education and other covariates on mean labour earnings. The technique serves establishment of the heterogeneity of returns to education and, in relation, the arising inequality implications of education. As Buchinsky (1998) informs the technique is important in that it helps establish the differential effects of education on earnings among individuals with implications on income distribution and inequality. In this regard, the QR technique help shed light on whether premiums to education and other earnings determinants are identical for low and high earning workers, in addition to allowing establishment of whether education ameliorates or worsens existing inequalities. Equally important, the QR technique is considered a useful technique in the presence of heteroskedasticity and, even most useful for analysis of the behavior of the dependent variable at multiple locations of the earnings distribution (Fournier and Koske, 2013). The test for robustness of QR results over the OLS presented in this paper is expected to help policymakers to better understand the role played by education in determining labor earnings in Tanzania.

The rest of the paper is organised as follows: Section 2 briefly reviews the related literature; Section 3 presents the empirical methods employed; Section 4 describes the data; Section 5 presents and discusses the empirical results; and Section 6 concludes.

2. REVIEW OF RELATED LITERATURE

Studies on examine returns to education are mostly based on human capital theory. The theoretical and empirical foundations of human capital are underpinned by Mincer (1974), Schultz (1961) and Becker (1964). The theory highlights importance of education in enhancing productivity of an individual. The basic argument in the theory is that an individual invests in education in order to acquire necessary skills demanded in the labour market. As a result, the wage paid to an individual in the labour market is determined by expected marginal contribution to the output (Schultz, 1961). In this context, Spence (1973) proposes a signaling model in which education is a signal for higher ability and, therefore, productivity of a worker.

Empirical evidence on developing countries so far shows existence of positive effects of education on earnings, implying the returns to schooling are convex (Schultz, 2003; Psacharopoulos, 2004). However, the size of the effects is variable across studies that exist in the literature. For example, study by Söderbom *et al.* (2006) that examine returns to education in Kenya and Tanzania by using data on manufacturing employees for the period 1993-2001 established existence of convex returns to schooling. Also, study by Kifle (2007) that estimated the private rate of returns to education by using a sample of data from formal sector employees in Eritrea, found the marginal returns to education increased with the level of education. Moreover, Sackey (2008) in a study on private returns to schooling in Ghana by using living standard surveys data for 1992 and 1999 that was fitted by using Ordinary Least Squares (OLS) technique. The study found private returns to schooling at higher levels of education had increased for both female and male workers.

Kahyarara (2013) examined the extent to which levels of education of a wage employee account for wage difference in a selected sample of workers in Kenya, Tanzania, Uganda, Madagascar, Ghana, Niger, Guinea Conakry, Rwanda, Benin and Togo. The study found existence of positive correlation between education and wages and the marginal return to education was greater in higher levels of education. Islam *et al.* (2015) examine determinants of labour income in Tanzania by using a Mincerian human capital model. The study used Tanzania National Panel Survey (NPS) data wave two of 2011/12. The findings showed that education and experience exerted positive influence on earnings for both male and female.

Twumasi-Baffour (2013) used quantile and OLS regression methods to examine the role of education in determination of earnings in Ghana and Tanzania by using all three rounds of the Urban Worker Surveys of 2004-2006 for both countries. The quantile regressions for both

Tanzania and Ghana suggested that primary and secondary levels of education were inequality-reducing among workers in Tanzania but not in Ghana. Moreover, the study found tertiary education widens earnings inequality in both Tanzania and Ghana. On the other hand, by using three rounds of the Urban Worker Survey in Ghana for the period 2004-2006, Twumasi-Baffour (2015) examined the role of education in earnings determination in Ghana. The OLS and QR techniques were applied, the findings showed that all levels of education were associated with earnings premiums across quantiles with larger returns to higher levels of education.

Likewise, Twumasi-Baffour (2016) used QR technique to investigate effect of education on earnings distribution of urban workers in the labour market in Ghana over the period between 1998/99 and 2005/6. The findings showed that in 1998/99, with the exception of secondary education, premiums to post-secondary and university education relative to primary were highest at the second quantile (median) of the conditional earnings distribution. Whilst the returns to post-secondary and university education were lowest at the top quartile of the earnings distribution, secondary education had lowest returns at the bottom quartile. However by using 2005/06 sample, the results revealed the consistent pattern with higher premiums to all levels of education at the top quantile (75^{th}) of the earnings distribution.

Leyaro *et al.* (2014) investigate the determinants of earnings of urban workers in Tanzania by using two dataset: Integrated Labour Force Survey (ILFS) for 2000/01 and 2006 and the Urban Household Worker Survey (UHWS) for 2004, 2005 and 2006. The findings showed returns to education increased with level and years of education. Based on QR, the result suggested existence of differential returns to education across the earnings distribution: primary and secondary educations were inequality-reducing, implying were more beneficial to those on lower earnings whereas tertiary education was inequality-increasing. Moreover, Kavuma (2015) examine the private marginal returns to education between wage-employees and the self-employed in Uganda by using a Mincerian framework with pooled regression models. The study used data two waves of UNHS panel data (2005/06 and 2009/10). The result revealed existence of a convexity between returns and levels of educational attained. In addition, by using QR technique to investigate the heterogeneous returns to education, Kavuma (2015) found returns to education were decreasing with quantile for all employment types examined.

Generally, the survey of literature revealed the most recent empirical studies have been on the causal average effects of education on earnings. Consequently, very little is known about how education affects the earnings distribution, particularly so in the case of Tanzania.

3. METHODOLOGY

3.1 Baseline Earning Equation

On the basis of human capital theory, a Mincerian model is used to establish the link between returns and education. Thus, private rate of return to education is estimated, first, by using the basic earnings function developed by Mincer (1974) that reads as:

$$ln\,E = \beta_0 + \beta_1 S + \beta_2 EX + \beta_3 EX^2 + \mu_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (1)$$

where *ln E* is natural logarithms of monthly earnings, *S* is number of years of schooling of an individual and both *EX* and EX^2 are respectively potential years of experience (age –school–age started school) and its square. The EX^2 captures the declining effects of experience as individuals' age increases, μ_i is a well behaved stochastic error term.

Moreover, previous studies[1], have adopted the extended version of Mincerian wage equation specified as follows:

$$ln\, E = \beta_0 + \beta_1 S + \beta_2 EX + \beta_3 EX^2 + Z_i\beta + \mu_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots ...(2)$$

where Z_i is a vector of control variables, including, sex (takes the value of 1 if is a male, 0 otherwise), training (takes a value of 1 if an individual attended any training for at least a month, and zero otherwise), regional or location dummies (Dar es Salaam, rural and other urban areas), dummies for the sectors of employment (public, private, non-agricultural self-employment with and without employees and self-employment in agriculture), weekly working hours (in natural logarithms), a dummy for marital status (takes a value of 1 if the respondent was married and zero otherwise), union (if an individual is a member of trade union or not), casual worker (takes the value of 1 if individual worked for casual jobs , and zero otherwise).

The S in equation (1) is at the center of analysis. The coefficient on years of schooling (β_1) represents the average private rate of return to one additional year of schooling (marginal returns to education), regardless of the level of education. Specifically, the coefficient (β_1) of S should capture the percentage change in earnings given a one-unit increase in the years of education. *A prior* the rate of return to an additional year of education (β_1) should be constant across all levels of education. Noteworthy, however, is that available evidence from different parts of the world

[1] Among other, see Söderbom *et al.*, 2006; Comola and Mello, 2011; Kahyarara, 2013; Kavuma *et al.,* 2014; Falco *et al.*, 2014

suggests that different school years impart different skills to workers and bring different returns (Schultz and Mwabu, 1998b; Nasir, 2002). Therefore, it is misleading to maintain existence of constant rates of return (CCR) for all years of education. On this account the model has been re-casted, first, by converting the continuous years of schooling into a series of dummy variables; and, second, by including additional variables in the estimation model. By this approach, the slope of the earnings function changes with different levels of education if there are significant differences in returns to education for each level.

The re-casted model has converted continuous years of schooling variable *(S)* into dummy variables representing different levels of education:

$$lnE_i = \gamma + \alpha_1 D_{Pr} + \alpha_2 D_{Sec} + \alpha_3 D_{Ad} + \alpha_4 D_{Te} + \beta_1 EX + \beta_2 EX^2 + Z_i\beta + \mu_i \ldots (3)$$

where D_{Pr} is a dummy for primary school education; D_{Sec} is a dummy for lower secondary school education; D_{Ad} is a dummy for upper secondary education; and D_{Te} is a dummy for tertiary level of education. Other variables are as already defined.

3.2 Quantile Estimations Technique

It is quite inappropriate for the study of the relationship between education and labour earning across earning distribution to use OLS technique. This is mainly because the estimation under OLS technique is based on the mean of the dependent variable which is controlled by un-centered regressors (Buchinsky, 1994). Quantile Regression is considered superior and used here instead because it is based on the entire sample available and allows estimations of the return to education within different quantiles of the earnings distribution. Nonetheless, we must interpret cautiously the marginal returns to education from QR estimates, since they do not control for the problems of endogeneity (Schultz and Mwabu, 1998b; Twumasi-Baffour, 2016). According to Mwabu and Schultz (1996) the errors in the quantiles may be heteroscedastic because of ability and education or that other covariates may not be independent, thus making the quantile regression variances to be biased. Therefore, on this account the quantile regression understate the true standard errors (Kingdom and Soderbom, 2007; Twumasi-Baffour, 2015). We therefore utilize bootstrap estimates of the asymptotic variances of the quantile coefficients within 100 repetitions.

According to Koenker and Bassett (1978), quantile regression estimation is characterized by a minimization of an equation that reads as:

$$Min_{\beta \varepsilon R^k} \sum_{i:\varepsilon(y_t \geq x_t \beta)} \theta \, | \, y_t - x_t \beta \, | + \sum_{i:\varepsilon(y_t < x_t \beta)} (1-\theta) \, | \, y_t - x_t \beta \, | \qquad (4)$$

where y_t is dependent variable, x_t is k by 1 vector of explanatory variables, β is a vector of coefficients and i is the quantile to be estimated. Following Bushnisky (1998), the quantile regression model of earnings function is specified as follows:

$$ln\, w_i = x'_i \beta + \mu\theta_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (5)$$

$$Quant_\theta(ln\, w_i / x_i) = x'_i \beta_\theta ; Quant_\theta(\mu\theta_i | x_i) = 0 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. \dots. (6)$$

where *w* denotes monthly earnings, x is a vector of explanatory variables and $u\theta$ is a random error term. The *i=1,..........,n,* is an index for individual worker and *n* is number of workers in the sample.

The vector of parameters denoted by β_θ and $Quant_\theta$ ($lnw_i|x_i$) is the θ^{th}conditional quantile of lnw given x_i. Given that, quantile regression parameters minimize the absolute sum of the errors from a particular quantile of earnings across individuals, the problem is to obtain parameter estimates of the θ^{th} quantile regression in equation 6, which reads as:

$$Min\left\{\sum_{i:lnw_i \geq x'_i\beta_\theta} \theta|lnw_i - x'_i\beta_\theta| + \sum_{i:lnw_i < x'_i\beta_\theta} (1-\theta)|lnw_i - x'_i\beta_\theta\right\} \dots\dots\dots\dots (7)$$

The median regression or least absolute deviation (LAD) is when $\theta = 0.50$. Other quantile regressions are estimated through weighting of the absolute sum of the errors. On the one hand, if $lnwi \geq x'_i\beta_\theta$, then the deviation is positive and θ is the weight used. On the other hand, when $lnwi < x'_i\beta_\theta$, the deviation is negative and the weight used is $1-\theta$.

The quantile regression method was used to estimate earning functions at three different percentiles of earnings distribution: the first quantile, the median and the third quantile of log monthly earnings. Unlike, the OLS technique, which was also used to control for the robustness of results, the QR technique is based on the determinants of labour earnings at some other points of the earnings distribution, for example, the bottom or top quartile. The estimation of the model at different quantiles enables us to trace the entire conditional distribution of earnings, given a set of regressors. Thereafter, comparisons of the estimated returns (premiums) across the whole earnings distribution help establishment of the extent to which education exacerbates or reduces underlying inequalities. Another advantage of employing QR estimation method is that the vector of coefficients is not sensitive to outlying values of the dependent variable. This is mainly because the quantile regression objective function is a weighted sum of absolute deviations (Twumasi-Baffour, 2013).

4. DATA SOURCES AND DESCRIPTIVE STATISTICS

The study is based on the 2014 ILFS data for Tanzania collected by the Tanzania National Bureau of Statistics (NBS). The key information collected by the survey is of two types: the household and personal characteristics and employment-related information. That information has important implication on earning determination. During the survey, individuals were required to report earnings from both paid employment and self-employment such as business and agriculture; and, most of individuals even reported weekly or monthly earnings. For other individuals and/or households that reported earnings in ways other than paid or self-employments were dropped from the analysis. For those with weekly earnings, these were converted into monthly earnings so as to have a common measure for all individuals. Therefore, this study is based on monthly earnings, taking into account hours worked. In terms of number of hours worked, individuals reported the number of hours they worked in the previous week as well as the number of hours they usually work. Owing to data limitations, we were not able to control for quality of education in the analysis. Instead, analysis is based on the assumption that the quality of schooling is the same across individuals and across all levels of education.

Table 1 present a descriptive analysis of average monthly earnings of an individual respondent by sectors of employment and sex.

Table 1: Average Monthly Earnings by Employment Sector and Sex (Tshs)

Employment Sectors	Male	Female	All
Wage employment	454,617	335,087	409,793
Self-employment (nonagric)	443,944	203,717	321,834
Self-employment (agric)	170,445	133,007	158,172

Source: Computations based on ILFS data 2014.

Table 1 shows huge difference in earnings between wage employees and those in either self-employment or employed in agriculture. Average monthly earnings in formal wage sector are more than agricultural and non-agricultural self-employment earnings respectively. Disaggregation of earnings by gender shows males on average earn more in all sectors than females. However, since distribution of earnings is mostly skewed to the right in favour of wage employment, the mean can be a misleading measure of central tendency. Figure 1, which shows distribution of the natural logarithm of earnings, confirms the hierarchy in earnings across sectors where wage employees earn significant higher than employees in other sectors.

Figure 1: Sample Distribution of Monthly Earnings by Employment Categories

Source: Construction based on ILFS data 2014.

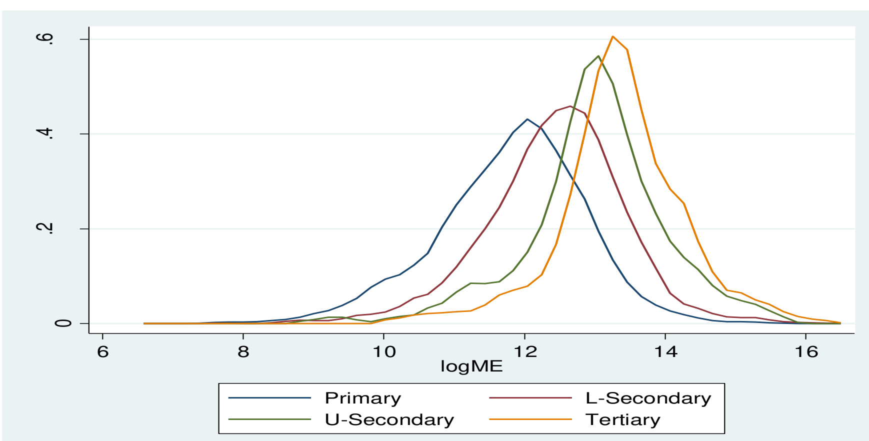
A further disaggregation of earnings by the level of education presented in Table 2 and Figure 3 indicate incremental returns by level of education is higher for individuals with tertiary levels of education than those with primary education. Individual with tertiary education earn approximately four times that worker who attained primary education. In the whole sample, those without education earned only 225, 225 Tshs, while those with tertiary education earn 957,441 Tshs. Thus, indicates that individuals with higher education were paid markedly better for their labour than those with lower education. We also observe that across all levels of education, males earn significant higher than females.

Table 2: Monthly Earnings by levels of Education (Tshs)

Levels of Education	Male	Female	All
Primary	273,493	162,357	225,225
Lower Secondary	468,487	310,034	402,254
Upper Secondary	746,372	539993	691484
Tertiary	1,090,065	751,009	957,441

Source: Computations based on ILFS data 2014.

Figure 2: Sample Distribution of Monthly Earnings by Levels of Education



Source: Construction based on ILFS data 2014.

5. Empirical Results

Table 3 presents quantile regression (QR) estimates of the earnings function for the 1st, 2nd and 3rd quantile. The OLS results are presented in the last column for comparisons purpose.

Education

The regression results presented in Table 3 suggests the marginal returns to education increased considerably over the quantiles of the conditional distribution of earnings. This finding is consistent with that obtained by some of the previous studies, for example Mwabu and Schultz (1996), Twumasi-Baffour (2013), Leyaro *et al.* (2014) and Twumasi-Baffour (2016).

Evidence of convex relationship between labour earnings and education levels are found at all quantiles of the earnings distribution. Moreover, the results suggest that on average, lower secondary, upper-secondary or tertiary education is associated with labour earnings premium across all quantiles, relative to a primary education. This variation in the rates of return across quantiles can be interpreted as the composition effect of a change in the educational composition of the workforce. The highest premiums to all levels of education are largest at the 3rd quantile of the conditional earnings distribution. This suggests that over time education reduce inequality of earnings. Thus individuals earn more from additional investment in education. Table 3 shows further that the magnitudes of coefficients of education levels for QR estimates are larger than that of the OLS estimates at the highest quantile.

Table 3: Quantile Regression Estimates

Variables	1st Quantile(25th)	2nd Quantile(50th)	3rd Quantile (75th)	OLS
Levels of education-reference category is Primary education				
Lower secondary	0.374***	0.349***	0.389***	0.398***
	(0.026)	(0.024)	(0.029)	(0.022)
Upper secondary	0.598***	0.614***	0.741***	0.690***
	(0.052)	(0.061)	(0.090)	(0.066)
Tertiary	0.986***	0.999***	1.136***	1.076***
	(0.041)	(0.039)	(0.045)	(0.039)
Tvet	0.096***	0.090***	0.127***	0.090***
	(0.023)	(0.023)	(0.022)	(0.020)
Exper	0.026***	0.028***	0.032***	0.026***
	(0.004)	(0.004)	(0.004)	(0.004)
Expersq	-0.047***	-0.046***	-0.053***	-0.043***
	(0.007)	(0.007)	(0.008)	(0.007)
Sex	0.368***	0.347***	0.355***	0.373***
	(0.019)	(0.020)	(0.020)	(0.017)
Married	0.090***	0.122***	0.121***	0.124***
	(0.026)	(0.021)	(0.022)	(0.023)
Union	0.482***	0.414***	0.367***	0.416***
	(0.035)	(0.033)	(0.040)	(0.029)
Logwwh	0.365***	0.326***	0.269***	0.353***
	(0.028)	(0.028)	(0.034)	(0.025)
Casual	-0.110***	-0.180***	-0.215***	-0.172***
	(0.028)	(0.024)	(0.028)	(0.020)
Youth	-0.227***	-0.081**	0.012	-0.104***
	(0.040)	(0.038)	(0.034)	(0.033)
Regional dummies-reference category is Dar es Salaam				
Other urban	-0.295***	-0.291***	-0.298***	-0.322***
	(0.023)	(0.020)	(0.022)	(0.018)
Rural	-0.643***	-0.589***	-0.508***	-0.600***
	(0.044)	(0.035)	(0.039)	(0.030)
Status in employment-reference category is Agriculture				
Public	0.519***	0.445***	0.324***	0.391***
	(0.059)	(0.046)	(0.048)	(0.043)
Private	0.992***	0.640***	0.357***	0.662***
	(0.044)	(0.037)	(0.039)	(0.034)
Self-employedwith	0.969***	0.815***	0.785***	0.861***
	(0.052)	(0.046)	(0.061)	(0.044)
Self-employedwithout	0.410***	0.257***	0.193***	0.273***
	(0.043)	(0.038)	(0.035)	(0.032)
Constant	8.969***	9.798***	10.562***	9.653***
	(0.120)	(0.110)	(0.143)	(0.108)
Observations	11,724	11,724	11,724	11,724
R-squared	0.401			

Notes: Dependent variable is the logarithm of monthly earnings. For OLS regressions robust standard errors in parentheses and for quantile regressions bootstrapped standard errors using 100 replications in parentheses , *** p<0.01, ** p<0.05, * p<0.1 .
Source: Calculation based on ILFS data 2014.

Potential Experiences and Training

Potential experiences and training influenced positively the monthly earning (in natural logarithm) across quantiles. Table 3 indicates that potential labour market experiences and training are positively correlated with monthly earning (in natural logarithm); and, magnitudes of its effect increases as quantile increases. The returns to experience and training are larger at the upper end of the earnings distribution. This suggests training and potential experiences have key roles in explaining variation between individuals that are in highly paid jobs and that are on lower paid occupations. The QR estimates are consistent with that obtained by OLS method. As in OLS results, experience and training have positive influence on the labour earning. Notabble, however, the coefficients of training and potential labour market experiences in QR estimates are larger than that of OLS estimates.

Sex

The Quantile Regression (QR) estimates for all coefficients of sex are positive; and their magnitude of the coefficients is increasing over the quantiles (Table 3). This finding suggests the effect of sex on monthly earning is positive. However, the coefficients of the QR estimates are less than the OLS estimate. This finding confirms existence of discrimination where women earn less than men in labour market.

Marital Status

The QR results indicate that marital status (married) has a positive effect on monthly earning. The result also shows that the effect is increasing over the quantile; and, the largest effect is realized in the 3rd quantile (Table 3). Again, the result shows that the estimated coefficient by OLS technique is 0.124; and this is larger than QR estimates across quantiles regressions (Table 3).

Union Membership

Result in Table 3 shows that membership in union has a positive and statistically significant impact on labour earnings. However, earnings benefits from membership in union are disproportionately skewed toward lower wage earners. Notable, the QR estimate is higher than OLS estimates in the lower quantile. This implies that unionized workers have higher labour earning benefits at lower tail of the earnings distribution. This suggests bargaining power of workers is much stronger and realized by workers on low paid jobs. The results are consistent with the findings of Schultz and Mwabu (1998a) in South Africa.

Locality

Table 3 shows further that living in rural and urban areas, other than Dar es Salaam, has a negative impact on monthly earning; and, the magnitudes of the effect is decreasing over the quantiles. As evident, the effect is much stronger in the case of workers on low paid occupations. Nevertheless, when compared with Dar es Salaam, both OLS and QR estimates are lower for rural and other urban areas; and while the magnitude of the coefficient for other urban areas is larger in OLS estimates, that of rural areas is much larger in lower quantile.

Weekly Working Hours

An important determinant of earnings inequality among the working population is the number of hours worked (generally captured by the number of hours worked per week in all jobs). The magnitude of the weekly working hour's coefficients is much higher in the lower quantile than in the OLS estimate. This suggests reward for working more is highest for workers at the lower end of the earnings distribution (Tables 3). This finding could be attributed to differences in the extent to which time spent at work is recorded, such as lower-income earners may be more likely to benefit from overtime pay whereas extra work hours by middle and high-income earners may be compensated as part of the basic remuneration package (Fourier and Koske, 2013). The results suggest that a general decrease in the number of hours worked, triggered, for example, by an economic recession, would thus particularly hurt more the lower income workers through a fall in overtime pay (Fourier and Koske, 2013).

Sectors of Employment

The monthly earning results based on QR and use of sectorial dummies provide robust evidence that employees on public, private, and non-agricultural self-employment earn more relative to those on agriculture sector (Tables 3). The difference in earnings is particularly large for workers at the bottom of the earnings distribution. The magnitude of this earnings gap at the 3rd quantile is rather small (relative to the gap at the 1st quantile) in all employment types. Similarly, the premiums of working in casual jobs are reduced along the earnings distribution. When, compared with OLS estimates, the magnitude of the coefficients obtained by QR technique for specific sectors of employment are larger in lower quantile regressions (Tables 3).

5. CONCLUSION

Quantile regression (QR) technique was used applied to analyse the effects of education on earnings along different quantiles of earnings distribution in Tanzania. The estimation results have shown that there is much heterogeneity in returns to education, since the marginal returns to education increased considerably over the quantiles of the conditional distribution of labour earnings. The finding suggests that returns to education are higher for individuals/households in the top quantile of income distribution. Furthermore, the findings revealed that all levels of education increased with earnings along the conditional earnings distribution. Consequently, this was evidenced by a convex relationship between earnings and education at all quantiles of earnings distribution where the highest premium to all levels of education was at the 3rd quantile of the conditional earnings distribution. The main policy implication of the finding is that investment in education, *ceteris peribus*, may contribute to increase in inequality among individuals and across regions. Thus better designed education policies to promote equality and support disadvantaged population and areas could avert and even reverse inequality in the country. Further research is on the link (s) between education, its returns and inequality is called for to better inform policy.

References

Becker, G. S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education.* New York: Columbia University Press.

Buchinsky, M. (1998). Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research. *Journal of Human Resources*, pp. 88-126.

Card, D. (2001).Estimating the Returns to Schooling: Progress on Some Persistent Econometric Problems. *Econometrica,* Vol. 69(5), pp. 1127–1160.

Comola, M., & De Mello, L. (2011). How Does Decentralized Minimum Wage Setting Affect Employment and Informality? The case of Indonesia. *Review of Income and Wealth*, Vol.*57*, pp. S79-S99.

Falco, P., Kerr, A., Pierella, P., Paci, P., and Rijkers, B. (2014).Working Toward Better Pay: Earnings Dynamics in Ghana and Tanzania. World Bank Publications.

Fournier, J. M., & Koske, I. (2013). The Determinants of Earnings Inequality. *OECD Journal: Economic Studies*, Vol. 2012(1), pp. 7-36.

Heckman, J. J., Lochner, L. J., & Todd, P. E. (2003). *Fifty Years of Mincer Earnings Regressions*. National Bureau of Economic Research. No. w9732

Kahyarara, G. (2013). Education and Wage in East and West Africa. Revue d'Economie Théoriqueet Appliquée, Vol. 3, No.1, pp. 49-70.

Kavuma, S. N., Morrissey, O., and Upward, R. (2015). Private Returns to Education for Wage-Employees and the Self-Employed in Uganda . WIDER Working Paper, (No. 2015/021).

Kifle, T. (2007). The Private Rate of Return to Schooling: Evidence from Eritrea. *Essays in Education*, *21*, pp. 77-99.

Kingdon, G. and Söderbom, M. (2007) Education, Skills, and Labour Market Outcomes: Evidence from Ghana. World Bank Human Development Network, Washington DC.

Koenker, R. (2005). *Quantile Regression*. Cambdrige University Press.

Koenker, R., & Bassett Jr, G. (1978). Regression Quantiles. *Econometrica:* Vol.46, pp. 33-50.

Koenker, R., & Hallock, K. F. (2001). Quantile Regression. *Journal of Economic Perspectives*, Vol. 15, No. 4, pp. 143-156.

Leyaro, V., Twumasi-Baffour, P., Morrissey, O., and Owens, T. (2014). Determinants of Urban Labour Earnings in Tanzania. CREDIT Research Paper, *2000/01-06,* No. 14/03.

Mincer, J. (1974). Schooling, Experience, and Earnings.Human Behavior & Social Institutions No. 2.

Mwabu, G., and Schultz, T. P. (1996). Education Returns across Quantiles of the Wage Function: Alternative Explanations for Returns to Education by Race in South Africa. *The American Economic Review*, *86*(2), pp. 335-339.

Nasir, Z. M. (2002). Returns to Human Capital in Pakistan: A Gender Disaggregated Analysis. *The Pakistan Development Review*, pp. 1-28.

Psacharopoulos, G. (1994). Returns to Investment in Education: A Global Update. *World Development*, *22*(9), pp. 1325-1343.

Psacharopoulos, G., & Patrinos, H. A. (2004). Returns to Investment in Education: A Further Update. *Education Economics*, *12*(2), pp. 111-134.

Quinn, S., & Teal, F. (2008). *Private Sector Development and Income Dynamics: A Panel Study of the Tanzanian Labour Market*. Centre for the Study of African Economies, No. 2008-09, University of Oxford.

Sackey, H. A. (2008). *Private Returns to Education in Ghana: Implications for Investments in Schooling and Migration*. African Economic Research Consortium, Research Paper No.174.

Schultz, T. P. (2003). Human Capital, Schooling and Health. *Economics and Human Biology*, *1*(2), pp. 207-221.

Schultz, T. P., & Mwabu, G. (1998a).Labor Unions and the Distribution of Wages and Employment in South Africa. *ILR Review*, *51*(4), pp. 680-703.

Schultz, T. P., & Mwabu, G. (1998b). *Wage Premia for Education and Location, by Gender and Race in South Africa*. Center Discussion Paper, No. 785.

Schultz, T. W. (1961). Investment in Human Capital. *The American Economic Review*, *51*(1), pp.1-17.

Soderbom, M., Teal, F., Wambugu, A., and Kahyarara, G. (2006).The Dynamics of Returns to Education in Kenyan and Tanzanian Manufacturing. .*Oxford Bulletin of Economics and Statistics*, *68*(3), pp. 261-288.

Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics*, *87*(3), pp.355-374.

Twumasi-Baffour, P. (2013). Determinants of Urban Worker Earnings in Ghana and Tanzania: The Role of Education. CREDIT Research Paper, No 13/01.

Twumasi-Baffour, P. (2015). Determinants of Urban Worker Earnings in Ghana: The Role of Education. *Modern Economy*, 6, pp. 1240-1252.

Twumasi-Baffour, P.(2016). Education and Earnings Inequality in Ghana. *Modern Economy, 7, pp. 456-469.*

Wang, L. (2013). How Does Education Affect the Earnings Distribution in Urban China?. *Oxford Bulletin of Economics and Statistics*, *75*(3), pp. 435-454.