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Determinants of Urban Worker Earnings in Ghana and Tanzania: The Role of Education

by

Priscilla Twumasi Baffour

Abstract

The paper examines the role of education in earnings determination by using all three rounds of the Urban Worker Surveys of Tanzania and Ghana for 2004-2006. We investigate and compare heterogeneity in earnings determinants among self-employed (informal), private and public sector workers. We examine the role education, individual and household characteristics play in facilitating entry into employment sectors in addition to analysing the pattern of returns to education along the earnings distribution. After addressing endogeneity and selectivity biases associated with estimating earnings equations, we find that education plays an important role in promoting access to formal sector jobs, particularly employment in the public sector, but has no direct impact on earnings within the sector in both countries. Results from quantile regressions indicate primary and secondary levels of education are inequality-reducing among workers in Tanzania but this is not the case in Ghana. Tertiary education on the other hand is found to widen earnings inequality in both Tanzania and Ghana.

JEL Classification:

Keywords: Education, Earnings, Employment Sector, Tanzania, Ghana

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1. Introduction

Human capital development (education) is fundamental to outcomes in modern labour markets. This is evident in various studies in different countries and time periods that undoubtedly confirm that better educated individuals earn higher wages, experience less unemployment and work in more prestigious occupations than their less educated counterparts. Psacharopoulos (1994) showed the significant and robust positive relationship between education and earnings is more or less universal (including middle and low income countries). Other studies that endorse the positive returns to education particularly at the primary level include Schultz (1999) and Psacharopoulos (2002). These have been in part, the justification for the prominent feature of policy in Sub-Saharan Africa (SSA) towards expanding primary education. All these findings are based on the numerous theoretical explanations such as Schultz (1961), Becker (1962; 1964) and Mincer (1974).

Recent empirical evidence on returns to education in Africa is mixed with some bias towards convexity (see Soderbom and Teal 2003, Kingdon and Soderbom 2007, Rankin et al 2010) which is a signal of skill shortage at high educational levels and calls to question policy prescriptions in the region tailored at primary education expansion. This therefore justifies the need for more research into returns to education particularly at higher levels of education.

Urban labour markets in developing countries are generally recognised as having two distinct sectors, a regulated/protected formal sector and an unregulated /unprotected informal sector (Pradhan and van Soest, 1995). Fields (1995) introduced the notion of the 'murky' sector by extending Harris and Todaro's (1970) model of labour market segmentation by the concurrent existence of an informal and a formal sector in urban labour markets. Here the formal sector sets wages above market clearing levels that leaves a large pool of unemployed. The informal sector therefore seems to absorb many job seekers who are unable to secure employment in the stagnant formal sector of employment. Recent empirical evidence on the other hand suggest the possibility of viewing the informal sector as an efficient outcome of the labour market that utilises technology intensive in unskilled labour that coexist with the formal sector with comparatively skilled labour at much higher wages. Maloney et al (2006) present evidence whereby small scale self-employment is a preferred outcome and not due to inability of such individuals to find rationed formal sector jobs.

In both Tanzania and Ghana, the self-employed outnumber wage employees by almost twice in the urban labour market and it is the fastest growing segment of the labour force across rural and urban areas, typical of most developing nations particularly in Africa. Among the enormous challenges that face governments in these countries as a result, is the need to identify development strategies that can generate new employment and income opportunities to reduce unemployment and under-employment. An understanding of the earnings determination process in the informal sector is as a consequence vital to understanding the labour market and income determination/distribution in these countries.

Studies which analyse returns to education (determinants of earnings) typically use the mincerian earnings model by relying on estimation methods such as Ordinary Least Squares (OLS) or Instrumental Variables (IV); this estimates the mean effect of schooling and other individual characteristic variables on earnings. The standard methodology estimates how 'on average' schooling and individual characteristics affect earnings; this yields straightforward interpretations but may miss crucial information for policy purposes. Recent empirical evidence by Bushnisky (1994, 1998), Mwabu and Schultz (1996), Fitzenberger and Kurz (1998), Machado and Mata (2000), Nielsen and Rosholm (2001), Kingdon and Soderbom (2007) indicate the level and change in returns to education in the Mincerian model can differ across the earnings distribution.

This paper consequently, aims to fill gaps in the earnings determination literature on Africa by investigating and comparing heterogeneity in earnings determinants across sectors (formal public and private sectors and the informal (self-employment) sector) for Tanzania and Ghana with particular attention on schooling. Firstly, we examine the role of education in the labour market in terms of earnings by sector of occupation. Secondly, we examine the role of education and individual and household characteristics in facilitating entry into employment sectors (state) in a multinomial logit model of occupational attainment and subsequently address selectivity bias in the earnings equation following Heckman (1979) and Lee (1983). This is necessitated by the important role education plays in labour market success by not only increasing earnings but by the indirect promotion of entry into well paid occupations. We further apply quantile regression to look at earnings determinants across quantiles of the conditional earnings distribution. This enables us to examine whether returns (premiums) to education and other earnings determinants for urban workers in both countries are identical for low and high earners and shed light on whether education ameliorates or worsens existing inequalities.

We utilise the Urban Household Worker Survey (UHWS) on Tanzania and Ghana. This data is suitable for this study because it provides information on imputed earnings figures for the self-employed (informal sector) in addition to the regulated formal sectors (public and private). This allows for comparison across occupations and shed more light on the importance of heterogeneity in earnings determination. The study uses all three rounds of the UHWS of 2004, 2005 and 2006 in pooled sample estimations with year dummies to capture all effects that are common at a particular point in time.

The following section presents our theoretical framework and empirical literature; this is followed by the methodology in section 3. Section 4 is on the data and empirical strategy for estimating earning determinants with emphasis on the role of education. Here we adopt two specifications of the earnings equation; one is a standard linear model with years of education and a second model with dummy variables for levels of education. Additional attempt is made to address the endogeneity bias by using instruments; sample selection bias due to estimation for sub samples is also addressed. Finally, earnings functions are estimated by quantile regressions to identify heterogeneities in earnings along the earnings distribution. Results are presented in section 5 and the final section concludes.

2. Literature/ Model

The estimation of the profitability of investment in education is arrived at using two different methods, the ‘full’ or ‘elaborate’ method and the ‘earnings function’ method, these in theory give very similar results. The method adopted in most studies is dictated by the nature of data available. The elaborate method uses detailed age-earnings profiles by level of education to find a discount rate that equates a stream of education benefits to a stream of education cost at a given point in time. The basic earnings function method is due to Mincer (1974) and involves the fitting of a semi-log ordinary least squares regression using the natural logarithm of earnings as the dependent variable and years of schooling and potential labour market experience and its square as independent variables. In this semi-log earnings function specification, the coefficient on years of schooling can be interpreted as the average private rate of return to an additional year of education, regardless of the educational level to which this year of schooling refers. The extended earnings function method is also used to estimate returns to education at different levels by converting the continuous years of schooling variable into a series of dummy variables that refer to the completion of the main schooling cycles (primary, secondary and tertiary education, or drop out of these levels or even different levels of curriculum (vocational versus general) within an educational level. The private rate of return to the different levels of education is consequently derived by comparing adjacent dummy variable coefficients.

Analysis of the demand for education has been driven by the concept of the human capital pioneered by Schultz (1961), Becker (1964) and Mincer (1974). Education in human capital theory is seen as an investment of current resources (the opportunity cost of the time involved as well as any direct costs) in exchange for future returns (expected higher earnings). The standard model for the development of empirical estimation of returns to education is based on the relationship derived by Mincer. The typical human capital theory (Becker, 1964) assumes level of education is chosen to maximise expected present value of the stream of future incomes net of the costs of education. The basic assumption in this model is that an individual’s earnings reflects labour productivity and that investment in human capital in the form of foregone earnings in the past pays off in higher wages in the future Card (1999). With this, Mincer developed a theoretical model from wage (earnings) equation. The Mincerian earning function has been used predominantly in many studies due to the increased availability of micro data. In the original study Mincer (1974) used 1960 US Census data and used an experience measure known as potential experience (*i.e.* current age *minus* age left full time schooling) and found that the returns to schooling were 10% with returns to experience of around 8%. Layard and Psacharopolous (1979) similarly found returns to schooling to be around 10% in Great Britain.

In the empirical application, the schooling measure is treated as exogenous, although education is an endogenous choice variable in the underlying human capital theory. In addition, the Mincer specification of the disturbance term captures unobserved individual effects such as ability or motivation which also influence the schooling decision and induce a correlation between schooling and the error term in the earnings function. If schooling is endogenous then estimation by least squares methods will yield biased estimates of the return to schooling.

A number of approaches have been proposed in the literature to deal with endogeneity problem. First of all, measures of ability have been incorporated to proxy for unobserved ability. Such studies include IQ and related tests as proxies (Grilches 1977, Griliches and Mason 1972). This is expected to reduce the estimated education coefficient if it acts as a proxy for ability, so that the coefficient on education captures the effect of education alone given that, ability is controlled for. Results of such studies suggest an upward bias in results that lack an ability measure. The method of adding ability proxies has however been criticised in literature because, it is very difficult to develop ability measures that are not determined by schooling. The second approach exploits a belief that siblings are more alike than a randomly selected pair of individuals, since they share common heredity, financial support, geographical influences and peer influence. The idea behind this strategy is that some of the unobserved differences that bias a cross-sectional comparison of education and earnings are reduced or eliminated within families.[1] This approach attempts to eliminate omitted variable bias by estimating the return to schooling from differences between siblings or twins in levels of schooling and earnings. It uses with-in twins or with-in sibling's differences in wages and education by accepting the assumption that unobserved effects are additive and common within twins. Given that siblings have the same level of ability (the omitted variable), any estimate of schooling from within family data is expected to eliminate this bias. This is a modification of a more general fixed effect framework in individual panel data, where unobserved individual effect is considered time-invariant. This approach however, has been criticised on two grounds. First, if ability has an individual component in addition to the family component, which is not independent of schooling variable, then the within-family approach may not yield estimates that are less biased than OLS estimates. Secondly, if schooling is measured with error, it will lead to a larger fraction of the differences between twins than across the population as a whole (Ashenfelter et al, 1999). Conclusions from within-twin studies suggest ability bias is relatively small when measurement error has been controlled for.

The final approach to deal with ability bias, exploits the natural variation in data caused by different influences in the schooling decision. The core of this natural experiment approach is to provide a suitable determinant (instrument) for schooling that is not correlated with the earnings residual. The treatment group is chosen (though not randomly) independently of individual characteristics. The treatment and the control groups should be identical in both observed and unobserved characteristics that affect earnings except for schooling. The construction of instruments that are uncorrelated with the earnings residual means instrumental variable (IV) approach will generate a consistent estimator of the return to schooling. The (IV) estimator proceeds in two stages; the effect of the instrumental variable on schooling is estimated first, and then the effect of the instrumental variable on earnings is estimated. By assumption, given that the instrument is correlated with earnings only because it influences schooling, the ratio of the effect of the instrument on

1 Within family estimator can be given an IV interpretation; the instrument for schooling is the deviation of an individual's schooling from the average for his or her family.

earnings to its effect on schooling provides an estimate of the causal effect of schooling on earnings. The main criticism of IV estimates is the concern that the instrument may not actually be truly independent of the earnings residual. IV studies however, differ in terms of results, a number of them indicate the presence of a downward bias in OLS estimates. Card (1998) proposed an explanation for this phenomenon that is based on the hypothesis of heterogeneous returns to schooling that declines at higher levels of schooling. IV estimates differ from OLS estimates by the extent to which the instrument influences schooling decisions at different levels. If the instrument influences decisions primarily at lower levels of schooling, the IV estimator may be higher than OLS estimator because it reflects the payoff to schooling at lower rather than higher schooling levels.

In instrumental variables estimation, the probability limit of the IV estimator is unaffected by measurement error in schooling[2]. This has the tendency for an IV estimator to exceed the corresponding OLS estimator of the effect of schooling on earnings. In addition, the validity of a given IV estimator critically depends on the assumption that the instruments are uncorrelated with other latent characteristics of individuals that may affect their earnings.

While recent research on schooling use institutional features of the educational system to identify causal effect of schooling, family background information such as mother's and father' s education have been used in most studies either directly to control for unobserved ability or as instrumental variables for completed education. The curiosity in family background is driven by the fact that children's schooling outcomes are very highly correlated with the characteristics of their parents, particularly with parents' education.

In spite of the strong intergenerational correlation in education, family background measures as instruments for completed education have been questioned, even if family background has no independent causal effect on earnings. However, due to data availability issues especially in Africa, family background measures continue to be used and considered to be legitimate instruments. Instrumental variables have been widely used in empirical work

2 Assumes the instrumental variable is uncorrelated with the measurement error in schooling

on schooling as a standard solution to the problem of causal inference. The landmark study by Angrist and Krueger (1991), employed a ‘natural experiment’ instrument strategy by assuming quarter of birth (interacted with year or state of birth in some specifications) is uncorrelated with earnings except through its effect on education through school-start age policy and compulsory school attainment laws. The study concluded subsequently that, men born from 1930 to 1959 with birth dates earlier in the year have slightly less schooling than men born later in the year. This was attributed to compulsory schooling laws where people born in the same calendar year typically start school at the same time. As such, individuals born earlier in the year reach the minimum school-leaving age at a lower grade than those born later in the year. This allows individuals who want to drop out as soon as it is legally possible, to leave school with less education. They found IV estimates of the return to education are on average higher than the corresponding OLS though the difference between the IV and OLS estimators were statistically insignificant. Their findings of little differences between OLS and IV estimates for the United States, suggested schooling endogeneity is not empirically an important source of parameter bias.

The findings of Angrist and Krueger have attracted a lot of interest and criticism in literature. Bound et al. (1995) indicate a problem of weak instruments in some of the specifications in Angrist and Krueger's IV models. Bound and Jaeger (1996), also criticised Angrist and Krueger's findings with the proposition that quarter of birth may be correlated with unobserved ability differences. Bound and Jaeger examined the schooling outcomes of earlier cohorts of men who were not subject to compulsory schooling institutions and found some evidence of seasonal patterns. They additionally discussed evidence from the socio-biology and psychobiology literature which suggests that season of birth is related to family background and the incidence of mental illness. This called to question, the explanatory power of the instruments used by Angrist and Krueger.[3] Staiger and Stock (1997), used a limited information maximum likelihood (LIML) approach with quarter of birth interacted with state of birth and year of birth as instruments to examined the same data used by Angrist and Krueger (the 1980 Census). They confirmed high IV estimates above corresponding OLS estimates can make one infer that asymptotically unbiased estimates of the causal effect of education are even higher.

Card (1999) compared the mean levels of parents' education by quarter of birth for children under one (1) year of age in a 1940 census in the United States. The comparison of the mean years of education for mothers and fathers of children born in each quarter by Card, led to the conclusion that, there is no indication children born in the first quarter come from relatively disadvantaged family backgrounds. This suggested the seasonality patterns identified by Angrist and Krueger are probably not caused by differences in family background.

A study by Kane and Rouse (1993) about the relative labour market valuation of credits from regular (4-year) and junior (2-year) colleges made findings that suggest credits awarded by the two types of colleges are interchangeable. Consequently, they measure schooling in terms of total college credit equivalents. Kane and Rouse compared OLS specifications against IV models that used distance to the nearest 2-year and 4-year colleges and state-specific tuition rates as instruments in the analysis of earnings effects of college credits. Their IV estimates were 15-50% above the corresponding OLS specifications. Card (1995b), examined schooling and earnings differentials associated with growing up near a college/university and found when college proximity is used as an instrument for schooling in the Young Men sample of a U.S. National Longitudinal Survey (NLS), the IV estimator subsequently, is considerably above the corresponding OLS estimator, though not very precise. This is consistent with the idea that accessibility matters more for individuals on the margin of continuing their education. College proximity is found in the study

3 Angrist and Krueger (1992) used the Vietnam-era draft lottery in conjunction with educational deferments to provide instruments for education in another natural experiment. They again find only a slight upward bias in the ordinary least squares estimated returns after showing that the instruments have strong explanatory power.

to have a bigger effect for children of less-educated parents and hence suggests an alternative specification that uses interactions of college proximity with family background variables as instruments for schooling, and includes college proximity as a direct control variable. The IV estimate from this interacted specification is to some extent lower than the estimate using college proximity alone, but about 30% above the OLS estimate.

Maluccio (1997) applied the school proximity idea on rural Philippines. The study combined education and earnings information for a sample of young adults with data for their parents' households which included the distance to the nearest high school and an indicator for the presence of a local private high school. The variables show a relatively strong effect on completed education in the sample and the OLS estimates and conventional IV models that used school proximity as an instrument, in addition to IV models that include a selectivity correction for employment status and location. Results from both IV estimates are considerably above corresponding OLS estimates. Other studies that have found high IV estimates over OLS include Conneely and Uusitalo (1997) and Ichino and Winter-Ebmer (1998).

The findings that emerge from the above studies on OLS and IV estimators lead to the conclusion that instrumental variables estimates of the return to schooling characteristically exceed the corresponding OLS estimates. With the assumption on a priori grounds that OLS methods lead to upward-biased estimates of the true return to education, then, larger IV estimates obtained in many current studies leads to a dilemma. Bound and Jaeger (1996), Griliches (1977) and Ashenfelter and Harmon (1998) have all offered hypothesis to explain this dilemma.

The above studies reviewed and others suggest the returns to education are biased downward in an ordinary least squares regression, even though it is unclear how to account for the results. In the case of developing countries, the evidence is mixed, mostly due to incomparability of results across studies. Behrman (1990) reviewed existing studies and concluded by citing several studies that, most standard estimates overstate the return to education. Few of the studies however simultaneously controlled for endogeneity and measurement error and others used earnings rather than wage data. Strauss and Thomas (1995) reviewed additional studies and suggests the evidence is inconclusive and warrant further studies. The study further proposed the use of an expanded set of instruments that include indicators of the availability of schooling and household resources measured contemporaneously with an individual's schooling decisions.

In Africa, numerous studies on schooling and earnings have used different methods and instruments to address problems of endogeneity. In a recent study on Tanzania by Soderbom et al. (2006), repeated cross-section surveys on Tanzanian and Kenyan manufacturing sectors were used in a control function approach to correct for endogenous education by instruments. Results generally, showed a pattern of upward biased OLS estimates contrary to the more recent studies reviewed for mainly developed countries. Subsequently, the conclusion from the study was contrary to the conventional view of concavity between earnings and education. The marginal return to education was found to increase with increased education in both Tanzania and Kenya, an indication of a convex earnings function with education.

In a study by Rankin, Sandefur and Teal (2010), the 2004 and 2005 rounds of the Tanzania and Ghana Household Worker survey were used in a pooled estimation to investigate the role of formal education and time spent in the labour market to explain labour market outcomes of urban workers in Ghana and Tanzania. The study adopted the standard Mincerian earnings function and controlled for endogenous education by education supply side variables in addition to family background in four models (self employment, public sector, small and large). After controlling for selection bias the paper concludes, the existence of a convex returns to education in self employment though average returns are low in this sector and a concave returns to education in large firms, this does not depend on how selection is modelled but depends on selection. In the public sector however, no returns to education is found in both countries.

A study by Quinn and Teal (2008), used three rounds (2004, 2005 and 2006) of the Tanzanian Household Worker survey in a panel study to examine determinants of earnings and earnings growth from 2004-2006. The study pooled all three rounds of the data in an OLS estimation of earnings equation. Results indicate a significant convex effect of education on earnings, with substantial heterogeneity between and within sectors. These results are shown to be robust to control of endogenous education with instruments.

Soderbom et al. (2007), in a study on education, skills and labour market outcomes in Ghana, used the Ghana Living Standards survey for 1998-99 in a three sector model of wage employment, self-employed and agricultural workers. Labour market returns to literacy and numeracy skills in addition to analysing the pattern of returns to education along the earnings distribution was examined. The study used household fixed effects earnings function to address endogeneity of schooling among wage workers and finds the fixed effects returns to education for men increases but that for women decreases though none of their estimates was statistically different from their OLS estimates. The study further corrected for sample selectivity bias by using Heckman (1979) and Lee (1983) selection correction method and concluded that, education raises earnings by indirectly helping individuals to gain entry into high paying occupations (wage employment) but has low direct effects on earnings. In addition, they found education to be inequality-reducing in wage employment in Ghana.

In Kenya, Wambugu (2002) used a survey of rural households 1994 to model employment sector choice in a five way multinomial logit model of agricultural sector, public sector, private sector, informal sector and unpaid family workers. The study found high levels of education to increase probability of participation in formal sector employment, specifically; men with more than primary education have low probability of entry into the informal sector whiles those with less than full secondary education have reduced chances of agricultural employment. Women in households with lands were found to be less likely to work off the farm. The study concluded that the highest returns to primary education is in the informal sector while that of secondary education is highest in the private sector and that correcting for sample selection bias does not to alter estimates except for women in the public sector.

Studies that have utilised quantile regression method within the Mincerian framework include Buchinsky (1994), who proves the returns to education in the U.S increase considerably over the quantiles of the conditional distribution of wages. Fitzenberger and Kurz (1998), Machado and Mata (2000), all found varying returns across quantiles of the wage distribution. Mwabu and Schultz (1996), in a similar manner used quantile regression on a sample of South African men and obtained varying returns across quantiles. Nielsen and Rosholm (2001), Kingdon and Soderbom (2007) all applied quantile method and obtained similar results that confirm heterogeneity in returns to education along the conditional wage distribution and the justification for quantile regression technique in returns to education studies. We as a result find it necessary to adopt this methodology in addition to using the standard methodologies and addressing the issues of endogeneity in returns to education estimates in a comparative study on existing data on Tanzania and Ghana.

Methodology

In this section, we discuss the estimation technique used and some of the econometric issues encountered. We adopt Mincer (1974) model based on the fundamental assumption that an individual's earnings reflect his labour productivity and that investment in human capital in the form of foregone earnings in the past pays off in higher wages in the future (Card 1999). This led to the development a theoretical model from which the following wage equation is derived

$$\log w_i = \beta_0 X_i + \beta_1 \mathrm{S_i} + \beta_2 x_\mathrm{i} + \beta_3 x_\mathrm{i}^2 + \mathrm{u_i} \quad \text{.........................(1)}$$

Where w_i is an earnings measure for individual *i* such as earnings per hour, week or month. S_i represents a measure of schooling, this proxy's human capital acquired through formal education, x_i is an experience measure (typically age – the age an individual left school), this captures human capital acquired on-the-job. X_i is a set of other variables assumed to affect earnings and u_i is the disturbance term which captures all factors other than schooling and labour market experience that affect wages. The derivation of the empirical model by Mincer implies, under the assumptions made (particularly of no tuition cost). β_1 can be considered the private financial return to schooling as well as the proportionate effect on wages of an increment in *S*.

In this study, OLS is used to estimate earnings equations as a baseline in the following model

$$lnw_i = \propto_i + \beta_i X_i + u_i \qquad (2.1)$$

Here, w_i is the monthly earnings of individual i, X_i is a vector of worker characteristics (list of explanatory variables) and u_i is the residual. According to Card (1999), the choice of time over which to measure earnings is mostly dictated by data availability. The explanatory variables include the log of hours of work, education (highest educational level completed), tenure (the duration on the job as a proxy for experience) and gender dummy to control for disparities in earnings by sex as well as occupational and firm level variables. Labour market tenure is included in linear and quadratic form to identify the shape of tenure earnings relationship. The estimated parameters $\hat{\beta}$, are computed by minimising the sample's sum of squared residuals;

$$\sum \hat{u}^2{}_i = \sum \left(Y_i - X_i{}'\hat{\beta}\right)^2 \qquad (2.2)$$

OLS estimators are the best linear unbiased estimators as suggested by the Gauss-Markov theorem with minimum variance in the class of all linear unbiased estimators, on condition that the OLS estimates comply with the assumptions of the classical linear regression. Violation of any of the assumptions makes OLS estimates inefficient, possibly biased and inconsistent (Greene, 2003). The presence of heteroskedasticity violates the assumption of the classical linear regression of constant conditional variance; this does not produce biased estimates but incorrect standard errors. We subsequently use robust standard errors.

Beneath the assumption of no other cost of education rather than foregone earnings, the estimated coefficient of the education (schooling) variable directly measures the returns to one additional year of education in terms of (log) earnings.

The use of years of schooling implicitly suggests that one additional year of schooling, regardless of the current level of education, yields the same return. This may not be the case if, for example, completed degrees rather than years of schooling itself are valued in the labour market. As a result, in addition to the quantitative specification, we allow education to affect earnings in a non-linear way by the inclusion of dummy variables for the highest completed educational level in the earnings function. Corresponding coefficients in this regard, represent the wage premium associated with the different education levels compared to the reference group (no education). Empirical analysis is carried out based on three labour market sub-sectors which are public sector, private sector, self-employment in addition to a pooled model.

Endogeneity bias

Two main sources of bias in OLS estimates of effects of education on earnings are endogeneity (omitted variable) bias and sample selectivity bias. The former relates to the concern in earnings literature that education may be positively correlated with unobserved ability which will lead to an upward bias of estimates of the returns to education.[4] Therefore, to be sure our findings are not due to the failure to allow for such endogeneity. Instrumental variables are used to control for endogenous education.

Endogeneity is caused by a correlation between explanatory variables and the disturbance term. This means;

$$Cov(x, u) \neq 0 \qquad (2.3)$$

This results in biased and inconsistent estimates; which is corrected by an identification of variable(s) that are not correlated with the residual but correlated with the endogenous variable. If we denote the instrumental variables as z, the following condition must hold:

4 Belzil and Hansen (2002) find a strong and positive correlation between unobserved ability and unobserved taste for schooling which leads to a substantial upward bias of OLS estimates of returns to schooling. However, recent findings in empirical literature indicate that estimated returns rise as a result of treating education as an endogenous variable, Card (2001).

$$Cov(z,u) = 0 \; and \; Cov(x,z) \neq 0 \quad (2.4)$$

A good instrument is highly correlated with the endogenous variable and uncorrelated with the residual. If condition 2.4 is satisfied, a two-stage least squares (2SLS) can produce consistent estimates.

If we assume in a reduced form, schooling is given by

$$s_i = \alpha . z_i + \delta_i \quad (2.5)$$

Where z_i is a vector of instruments independent of δ_i but uncorrelated with u_i in the structural equation. This requires valid exclusion restrictions (variables correlated with schooling but uncorrelated with the earnings residual). As a result, we use family background variables, specifically father and mother's education as instruments for education.

Sample Selection bias

OLS estimates are the best linear unbiased estimates if they comply with the assumptions of the classical linear regression. In this study, there is the possibility of violation of some of the assumptions for which reason, the disturbances are no longer normally distributed as expected as $\mu \sim N(0, \sigma^2)$. This suspicion is because in developing countries (Africa), having a job in the formal wage sector is typical of outcomes in the labour market (selection into different sectors of employment are correlated with the potential determinants of earnings). In addition, observations with no earnings information are excluded, if exclusion of such observations is not random (lower earners are less likely to work), such sample selection bias may bias OLS estimates. Estimation of equations over an endogenously selected population requires the implementation of selection correction methods following Heckman (1979). When selection is presumed to be over a large number of exclusive choices, the multinomial logit specification is applied Lee (1983) and Durbin and McFadden (1984).

We therefore model occupational outcomes by focusing on the way in which education and other individual and household characteristics influence people's decisions to participate in the formal public or private sectors and self-employment relative to unemployment for consistent estimates of the earning function.

Labour force Participation Model

Participation decision in the labour market is assumed to be a function of variables that influence a person's expected offer wage and reservation wage. An individual chooses to enter the labour market if the offer wage is greater than the reservation wage. Human capital variables are expected to influence the offer wage while household characteristics may influence the reservation wage by affecting productivity in the home and demand for leisure.

The multinomial logit model adopted, assumes each individual selects among four mutually exclusive alternatives in the labour market: working in the public sector (indexed p_u), working in the private sector (indexed p_r), self-employment in the informal sector (indexed s) and unemployment (indexed u). An individual compares the maximum utility attainable given each participation alternative and selects the alternative which yields the maximum utility.[5] Preferences are described by a well-behave utility function whose arguments include the household time of the individual, a Hicksian composite commodity and a vector of exogenous constraints on current decision making. Preferences are maximised subject to time and income constraints with no uncertainty.

If V_{ji} is the maximum utility attainable for individual i if he/she chooses participation status $j=p_u$, p_r, s, u and suppose this indirect utility function can be decomposed into a non-stochastic component (S) and a stochastic component (ϵ):

$$\mathrm{V}ji = Sji + \epsilon ji \qquad (3.1)$$

5 The specification does not allow the possibility of working concurrently in more than one sector. This restriction may be unreasonable if individuals work both in a family business and in the formal sector. However, the data does not have information on multiple job holding. Each person reports one current employment status.

where S_{ji} is a function of observed variables and ϵ_{ji} is a function of unobserved variables. The probability that individual i will select the j^{th} participation status is given by

$$\text{Pji} = \Pr[\text{Vji} > V\text{ki}] \text{ for k} \neq \text{j}, \text{k} = pu, pr, s, u], \qquad (3.2)$$

or, substituting in from (1),

$$\text{Pji} = \Pr[\text{Sji} - \text{Ski} > \epsilon\text{k}i - \epsilon ji \text{ for k} \neq \text{j}, \text{k} = pu, pr, s, u] \qquad (3.3)$$

If the stochastic components have independent and identical Weibull distributions, the the difference between the errors (ϵ_{ki} - ϵ_{ji}) has a logistic distribution and the choice model is multinomial logit (McFadden, 1974).[6] This is a direct extension of a binary logit model to a dependent variable with several unordered categories since the decision to work in a particular sector is not sequential or ordered; rather this depends on the sector in which an individual finds a job.[7]

In order to estimate this model, a functional form of the non-stochastic component of the indirect utility function S_{ji} must be specified. When approximated in a linear form (S_{ji} = βjXi), yielding an empirical specification of the form

$$P_{ji} = \frac{exp(\beta_j X_i)}{exp(\beta'_{pu} X_i) + exp(\beta'_{pr} X_i) + \exp(\beta'_s X_i) + exp(\beta'_u X_i)} \qquad (3.4)$$

where Xi is a vector of independent variables that explain labour force participation and β_j is the parameter vector.

Coefficients obtained in the logistic estimation serve to provide a sense of the direction of the effects of the covariates on participation and sector choice in the labour market but cannot be used for magnitude of impact analysis. To examine the magnitude of impact, we calculate the average partial effects of

6 Weibull distribution has a unimodal bell shape roughly similar to the normal distribution.

7 Some individuals decide to join the informal sector while awaiting modern wage employment job, others also leave modern sector jobs to become self-employed in the informal sector and vice versa. The choices made, do not follow any particular order and this serves as a justification for the MNL model.

the covariates on the probability of participation in the different labour market state.

The criticism of the multinomial logit model is the independence of irrelevant alternatives (IIA). Bourguignon, Fournier and Gurgand, 2007 in Monte Carlo experiments, show that the selection bias correction based on the multinomial logit model can provide fairly good correction for the outcome equation even when IIA assumption is violated.

Following Heckman (1979) and Lee (1983), the earnings equation can be corrected for selectivity by including the inverse of Mills ratio[8] (selection correction term) as an additional explanatory variable in the earnings equation.

$$lnw_{ij} = \propto_{ij} + \beta_{ij}X_{ij} + \rho_{ij}\lambda_{ij} + u_{ij};\ u_{ij} \sim N(0, \sigma^2) \qquad (4.1)$$

where w_{ij} is the is monthly earnings of individual i in sector j, X_{ij} represent explanatory variables, β_{ij} are estimated parameters, λ_{ij} is the selectivity correction term and ρ_{ij} measures the effect and direction of non-random selection into employment sectors, if this is statistically significant, the null hypothesis of 'no bias' is rejected.

Quantile Regression

It is possible that earnings determinants, particularly education may be different for individuals at different points in the earnings distribution. Standard OLS techniques concentrate on estimating the mean of the dependent variable subject to values of the independent variables where variables are included as uncentred regressors. As an alternative to OLS, quantile regression is based on the entire sample available and allows us to estimate the return to education within different quantiles of the earnings distribution (Buchinsky, 1994). In particular, while OLS captures the effect of education and other covariates of an individual on the mean earnings, quantile regression look at the determinants at some other points of the earnings distribution for example

8 The inverse Mill's ratio is defined as $\lambda_{ji} = \frac{\emptyset(H_{ij})}{\Phi(H_{ij})}$, where $H_{ij} = \Phi^{-1}(P_{ij}), \emptyset(.)$ is the standard normal density function, $\Phi(.)$ the normal distribution function, and P_{ij} is the estimated probability that the i^{th} worker chooses the j^{th} occupation.

bottom or top quartile. In essence, we focus on quantile treatment effects of education and other covariates on earnings rather than on the average treatment effect and this add value to estimation results.

The estimation of the model at different quantiles enables us to trace the entire conditional distribution of earnings given a set of regressors. Afterwards, comparing the estimated returns (premiums) across the whole earnings distribution, we can infer the extent to which education exacerbates or reduces underlying inequalities. Particularly, how schooling, individual characteristic, sector of employment and firm size affect earnings differently at different points of the conditional distribution of earnings. An additional advantage of employing this estimation method is that the regression coefficient vector is not sensitive to outlying values of the dependent variable, as the quantile regression objective function is a weighted sum of absolute deviations. Provided error terms are homoscedastic, according to Koenker and Bassett (1982) and Rogers (1992), this method would be adequate to calculate the variance –covariance matrix. Rogers (1992), shows in the presence of heteroscedastic errors, this method understates the standard errors. We consequently use bootstrapped estimator of standard errors as suggested by Roger to cater for any such under estimated standard errors. This method however requires that, there is adequate dispersion of the independent variables over the earnings distribution to enable identification of coefficients for each quartile. The Tanzania and Ghana urban household worker surveys appear satisfactory in this regard.

According to Koenker and Bassett (1978), quantile regression estimation is by minimising the following equation;

$$\min_{\beta \epsilon R^k} \sum_{t \epsilon (t: y_t \geq x_t \beta)} \theta |y_t - x_t \beta| + \sum_{t \in (t: y_t < x_t \beta)} (1-\theta) |y_t - x_t \beta| \qquad (5.0)$$

Where y_t is the dependent variable, x_t is the k by 1 vector of explanatory variables, β is the coefficient vector and 1 is the quantile to be estimated.

Following Bushnisky (1994, 1998), the quantile regression model of the earnings function can be specified as follows;

$$\ln w_i = x'_i \beta + u_{\theta_i} \qquad (5.1)$$

$$Quant_\theta(lnw_i|x_i) = x'_i\beta_\theta; Quant_\theta\left(u_{\theta_i}|x_i\right) = 0 \qquad (5.2)$$

where w denotes monthly earnings, x is a vector of explanatory variables and u_θ is a random error term. The $i=1,.........,n,$ is the index for individual worker and n is the number of workers in the sample. The parameter vector 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 minimise the absolute sum of the errors from a particular quantile of the log earnings across individuals, the problem is to obtain the θ^{th} quantile regression parameter to

$$Min\left\{\sum_{i:lnw_i \geq x'_i\beta_\theta} \theta|lnw_i - x'_i\beta_\theta| + \sum_{i:lnw_i < x'_i\beta_\theta} (1-\theta)|lnw_i - x'_i\beta_\theta\right\} \qquad (5.3)$$

The median regression or least absolute deviation (LAD) is when $\theta = 0.50$. Other quantile regressions are estimated through the weighting of the absolute sum of the errors. In essence, if $lnw_i \geq x'_i\beta_\theta$, then the deviation is positive and θ is the weight used. On the other hand, when $lnw_i < x'_i\beta_\theta$, the deviation is negative and the weight used is $1-\theta$. By estimating earnings functions at different quantiles simultaneously, we are able to conduct a hypothesis testing of cross quantiles restrictions.

Studies that have utilised quantile regression method within the Mincerian framework include Buchinsky (1994), Fitzenberger and Kurz (1998), Machado and Mata (2000). In Sub Saharan Africa, we know of a study Mwabu and Schultz (1996) on South Africa, Wambugu (2002) on Kenya and Geeta et al. (2007) on Ghana. Particularly on Tanzania, there is no known study on earnings that applies quantile regression method. We add to the literature by using quantile regression in a comparative study on Tanzania and Ghana.

3. Data and Empirical Strategy

The study uses all three waves of the Tanzania and Ghana Urban Household Worker Surveys (UHWS), conducted in urban areas (regions) of both countries[9]. The samples are based on a stratified random sample of urban households from the 2000/01 Household Budget Survey (HBS) for Tanzania whiles that of Ghana is from the 2000 census in Ghana. The surveys have been conducted in 2004, 2005 and 2006. Survey questions include: levels of education and other training and qualifications in addition to individual and household characteristics. Information on jobs include: type and length of each episode of employment; remuneration; and other sources of income. The unit of analysis in the data is the individual. The UHWS data has a feature which is important in answering the questions posed in this paper, as it provides comparable information including income data on both formal and informal (self-employment) sector workers. The study uses all three waves of the data for the respective countries in pooled samples with year dummies to control for time trend.

The three rounds of the UHWS for Tanzania and Ghana after cleaning consist of the following for the respective years: 2004 (1818 in Ghana and 653 in Tanzania), 2005 (895 in Ghana and 443 in Tanzania) and 2006 (309 in Ghana and 572 in Tanzania). There is a small panel dimension and recall aspect of the data that is not used in this study.

The sample for Tanzania is summarised in tables 1, 2 and 3 in terms of employment status by gender, years of education and tenure on the job, average earnings by employment sector, gender and level of education. As shown in table 1, individuals active in the labour market are categorised into formal public sector employment, formal private sector employment, informal sector (self-employment) and not-working (this includes unpaid family workers and the unemployed). Overall, the informal sector (self-employment) category is the largest sector in terms of employment (42.4%), followed by not-working (33.9%), private (16.5%) and public (7.3%) respectively. Average years of schooling and tenure on the job for public sector workers are more than all other sectors. Individuals not-working for income are the least educated in the sample followed by the self-employed with the private sector worker being more educated than the self-employed. This suggest the

9 Surveys are conducted by the Centre for the Study of African Economies at the University of Oxford.

existence of a hierarchy in occupations in terms of education with public sector employment at the top consisting of the most well paid and better educated, private sector as the next and self-employment as the last. Average years of tenure on the job are higher in self-employment than in private sector. Generally, the long years of tenure on average depicted in the table across all sectors may suggest labour turnover is low in the Tanzania labour market. Important differences also emerge between males and females when we decompose employment status by gender. Though females constitute 54% (percent) of the sample, their proportion is less than males in all employment types, as 41% of females are not-working compared to 25.6% males.

Average monthly earnings by employment sector and gender presented in table 2 shows huge differences in earnings between public sector employed people and those in either private or self-employment. Average earnings in public sector are about 133% and 264% more than private sector and self-employment earnings respectively. However, since earnings distribution is mostly skewed, the mean can be a misleading measure of central tendency, but figure 1 shows the distribution of the log of earnings and confirms the hierarchy in earnings between sectors. Disaggregation of earnings by gender shows men on average earn more in all sectors than women. A further disaggregation of earnings by level of education (table 3) indicates incremental returns by level of education since average earnings to individuals with high levels of education are more than those with low or no education (table 3). 52% of individuals in the sample have primary education followed by secondary education of 31%, 13% with no education and 3% with tertiary education.

Table 1: ***Labour Market Status Distribution by Gender with Education and Tenure for Tanzania***

Employment Status	*All (%)*	*Female (%)*	*Male (%)*	*Education (yrs)*	*Tenure (yrs)*
Public	7.30	7.19	7.39	11.91	17.44
Private	16.45	10.84	23.23	8.25	8.91
Self- employment	42.39	40.98	43.74	7.27	10.77
Unemployment	33.86	40.98	25.64	6.33	-
Total	1,465	793	663	7.40	11.04

Source: Calculations from Tanzania UHWS 2004, 2005 and 2006

Table 2: ***Average Monthly Earnings by Employment Sector and Gender; Tanzania***

Employment Sector	All ($)		Female ($)		*Male ($)*	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Public	134.66	137.96	131.56	146.49	140.54	129.38
Private	57.71	60.69	48.36	46.73	62.95	66.99
Self-employment	36.89	65.56	27.72	33.47	46.99	87.40
Total	52.90	81.63	44.14	69.77	61.33	90.91

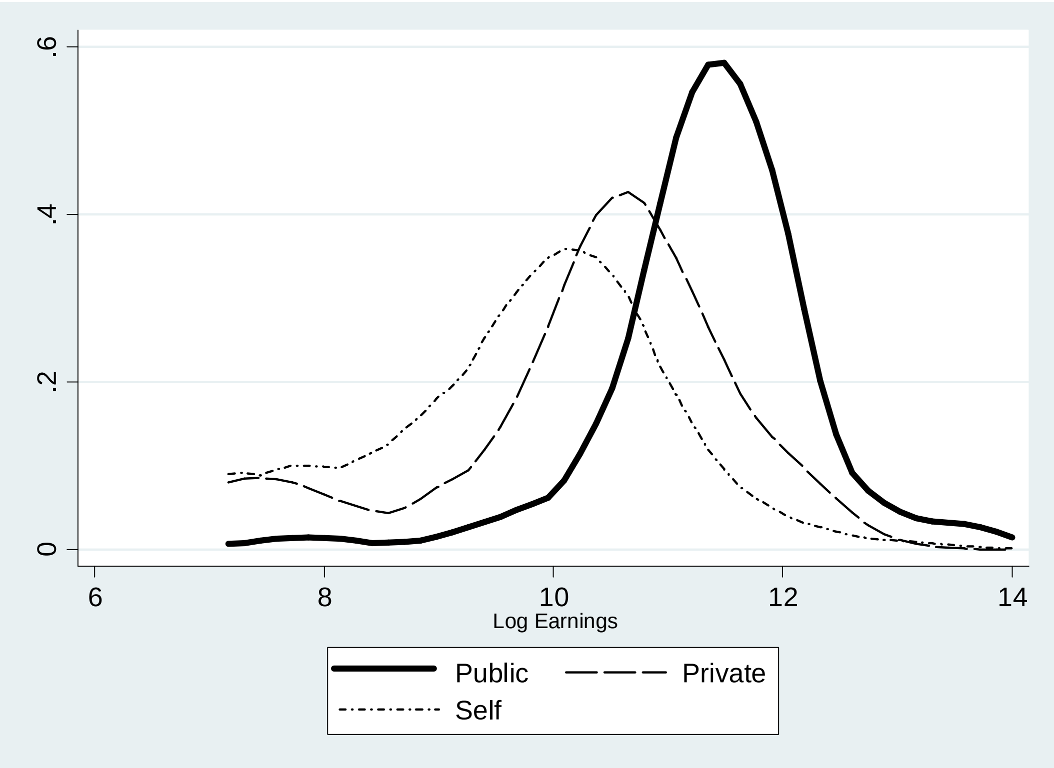
Source: Calculations from Tanzania UHWS 2004, 2005 and 2006

Table 3: ***Monthly Earnings by Employment Sector and Educational level; Tanzania***

	All		Public		Private		Self-employment	
	Mean	Std.dev	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
No Education	25.08	35.39	64.49	53.47	28.42	31.01	22.46	34.80
Primary	34.92	42.92	69.28	35.40	38.56	33.87	31.66	45.30
Secondary	71.92	82.63	134.24	97.11	81.75	66.89	45.92	70.73
Tertiary	162.76	213.36	208.45	243.54	119.07	114.11	142.71	253.21

Source: Calculations from Tanzania UHWS 2004, 2005 and 2006

Figure1: Sample Distribution of Earnings by Sector: Tanzania



Comparable summary of the Ghana sample are provided in tables 4, 5 and 6. The sample distribution by sector and gender in table 4 shows unlike Tanzania, the private sector is the largest sector in terms of employment (47%) followed by not-working for income (29.8), self-employment (22.6%) and public sector (6.3%) respectively. Decomposition of the sample by sex indicates this pattern is consistent with the male distribution. Among females, almost the same proportions of the sample are not-working and in self-employment with the remaining in private and public sectors respectively. Average years of schooling are high for the two formal sectors (public and private) with self-employment as the least in terms of education. Again we find a hierarchy in occupations with respect to education with public sector at the top, followed by the private sector, not-working and self-employment. Unlike in Tanzania, the not-working (unemployed) in Ghana possess mean education that are close to those in formal sector (private sector), this gives an indication that in Ghana the unemployed seem to queue for suitable job opportunities in the formal sector. Average number of years of tenure on the job indicates self-employment is the highest followed by public sector and the least is in the private sector. Compared to Tanzania, the low overall tenure on the job suggests labour turnover is high in Ghana.

Average monthly earnings by employment sector and gender in table 5 shows earnings differences between sectors exist, though not as huge as in Tanzania. Persons employed in the public sector earn on average about 26% and 49% more than private sector and self-employed persons respectively as depicted in figure 2. A disaggregation of earnings by gender shows with the exception of public sector, average earnings to males are more than females in all sectors. Earnings by level of education (table 6) indicate incremental returns by level of education as in Tanzania. Within the Ghana sample, 53.2% have primary education, 19% have secondary education, followed 20% with no education and 7.8% with tertiary education. Summary statistics of all variables used in estimations are presented by country in Tables A1 and A2.

Table 4: ***Labour Market Status Distribution by Gender with Education and Tenure for Ghana***

Employment Status	*All (%)*	*Female (%)*	*Male (%)*	*Education (yrs)*	*Tenure (yrs)*
Public	6.3	3.9	8.7	10.62	6.73
Private	41.3	25.5	56.2	9.09	2.64
Self- employment	22.6	35.0	10.9	6.60	8.79
Not-working	29.8	35.6	24.2	8.21	-
Total	2,396	1,185	1,211	8.16	5.70

Source: Calculations from Ghana UHWS 2004, 2005 and 2006

Table 5: ***Average Monthly Earnings by Employment Sector and Gender; Ghana***

Employment Sector	All ($)		Female ($)		*Male ($)*	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Public	111.18	100.18	120.85	122.86	107.16	89.56
Private	87.63	124.44	61.42	63.25	97.79	139.96
Self-employment	74.19	180.20	55.87	55.49	131.38	346.60
Total	84.60	145.10	60.71	64.83	104.43	184.84

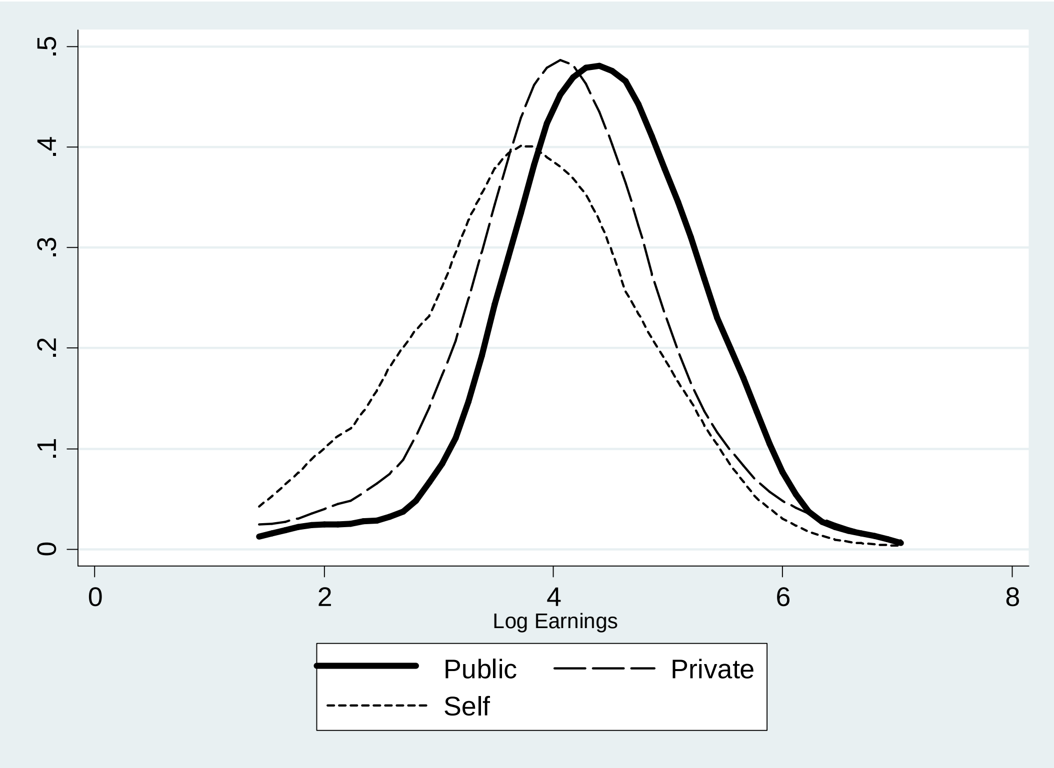
Source: Calculations from Ghana UHWS 2004, 2005 and 2006

Table 6: ***Monthly Earnings by Employment Sector and Educational level; Ghana***

	All		Public		Private		Self-employment	
	Mean	Std.dev	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
No Education	55.08	101.65	72.40	63.57	46.10	37.58	60.84	126.10
Primary	65.08	72.55	74.40	47.29	61.41	61.61	69.89	90.04
Secondary	93.88	109.93	112.70	90.86	95.18	121.03	75.83	77.95
Tertiary	210.60	334.17	160.28	133.50	210.11	234.71	424.25	402.68

Source: Calculations from Ghana UHWS 2004, 2005 and 2006

Figure 2: Sample Distribution of Earnings by Sector: Ghana



Empirical strategy

We begin our empirical strategy by estimating the earnings function for the three occupations and a pooled sample using the simple Ordinary Least Squares (OLS) as the baseline model for Tanzania and Ghana. Here, we focus on two specifications: a standard linear model with years of education and a model with dummy variables for highest level of education completed. The first specification give results that are straightforward to interpret whiles the second specification enables us to analyse how returns to education differ across different levels of education. Additionally attempt is made to address the problem of endogeneity in specification (1) by the use of parental education as instruments for education. We further investigate if there is significant sample selection bias due to estimating the earnings function separately for the occupational groups on the premise that individuals in these occupations may not be a random draw from the population. Finally, earnings functions are estimated by quantile regression (QR) method. If schooling affects the conditional distribution of the dependent variable differently at different points in the earnings distribution, then quantile regression is of use as it allows the contribution of schooling and other covariates to vary along the distribution of the dependent variable. Unlike OLS which models the mean of the conditional distribution of the dependent variable the estimation of earnings equation by quantile regressions is more informative. The use of quantile regressions enables us to investigate how earnings vary with education and other occupational characteristics at the 25^{th} (low), 50^{th} (median) and 75^{th} (upper) percentiles of the earnings distribution. If observations close to the 75^{th} percentile are indicative of higher ability than at the lower percentile (25^{th}) on the presumption that such individuals typically have high earnings given their characteristics, then quantile regression is informative of the effect of education and other covariates on earnings across individuals with different ability[10].

The earnings equations in this study are estimated for both formal (wage employment) and informal (self employment) sector workers. Formal sector employment are further categorised into public and private. Years of schooling is derived from information on the highest completed educational or vocational degree by attaching an average number of years to standardised educational levels based on the educational systems of Tanzania and Ghana respectively.

10 If education is assumed to be exogenous, then quantile regression gives us the return to education for people with different levels of ability. Arias, Hallock and Sosa-Escudero (2001), give similar caution by sitting quantile regression studies of returns to education as by Buchinsky 1994; Machado and Meta 2000; Schultz and Mwabu 1999) to be interpreted with caution since they do not control for problems of endogeneity bias.

4. Empirical Results and Discussion

OLS results of the earnings equation are presented in Table 7 and 8 for Tanzania and Ghana respectively, similar results with years of schooling are presented in Tables A3 and A4 in appendix. Earnings function is specified for the total sample without occupational variables (pooled 1) and with occupational controls (pooled 2). Control variables include tenure and tenure square, educational level variables (years of education in appendix) and gender[11] dummy. To evaluate the impact of enterprise characteristics on earnings, firm size (number of workers) and dummies[12] for sector of employment are introduced in the pooled (2) model. Location dummy is also used to control for differences in earning opportunities by location. The term returns to education is commonly used in the Mincerian earnings literature but the coefficients are not returns in its strictest sense but the gross earnings premium from an extra year or level of education and not 'return' to education since it does not take into consideration the cost of education. We consequently interpret our results with this caveat in mind.

Tables A3 and A4 show the average marginal returns (premium) to education in Tanzania is 11.3% and 7.9% in Ghana. These drop to 7.7% and 6.2% respectively once we introduce occupational level variables. This highlights the general tendency to underestimate returns to education in earnings function that includes occupational level variables. Knight and Sabot (1990) confirm this by noting education can influence wages by influencing the choice of occupation, sector or firm size a worker enters. Appleton and Balihuta (1996) also note this in a study on education and agricultural productivity on Uganda where inclusion of variable inputs whose usage depends on education in farm production functions that also include education resulted in the decline of returns to education estimates. Results from specification (2) with levels of education in tables 7 and 8 reiterate this fact as coefficient of all schooling levels relative to no education which captures the premium to education at that

11 Sex dummy equal 1 if respondent is a male and zero otherwise

12 Private and self dummies are in reference to the public sector

particular level are higher in pooled (1) than those in pooled (2) in Tanzania and Ghana respectively.

The average premium to an additional year of schooling in both Tanzania and Ghana (Tables A3 and A4) are highest in the private sector at 12.1% and 8.7% respectively. This is followed by the public sector of 6.9% and 8.4% and lastly in self-employment of 5.7% and 2.3% for Tanzania and Ghana respectively. The overall greater premium on education in Tanzania is most likely a reflection of the relative scarcity educated people in Tanzania compared to Ghana. The low returns to education in self-employment particularly in Ghana are worrying as self-employment is the fastest growing occupation in both countries. The implication here is that education may not be an effective means by which incomes can be increased and poverty levels reduced among the working population that is growing the fastest.

Results in table 7 indicate, the premiums associated with the different levels of education are positive and significant in the pooled model for Tanzania, and particularly so in self-employment and private sector employment. This is an indication that on average, attainment of an additional level of education, relative to no education leads to higher earnings in urban Tanzania. A confirmation of the convex relationship between education and earnings as individuals with high levels of education earn more compared to those with low education similar to Quinn and Teal (2008). In Ghana, we find a fairly similar pattern with the strong convex earnings education relation found predominantly in the private sector since no earnings premiums are found to be associated with primary education in the pooled model.

Within the private sector, individuals who work in large firms enjoy earnings premium of 71.3% in Tanzania and 60.7% in Ghana. Overall, workers in private and self-employment earn less relative to their counterparts in the public sector in Tanzania but no such evidence is found in Ghana. In general, living in Dares Salaam is associated with earnings premium in Tanzania but this is not the case for living in Accra for Ghana.

Table 7: Earnings function estimates; Tanzania

	Self	Private	Public	Pooled (1)	Pooled (2)
Log of hours	0.579***	0.193	0.828**	0.469***	0.457***
	(0.140)	(0.152)	(0.398)	(0.104)	(0.105)
Tenure	0.006	0.085***	0.058***	0.049***	0.035***
	(0.016)	(0.024)	(0.019)	(0.013)	(0.013)
Tenure^2	0.000	-0.001**	-0.001***	-0.001*	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Primary	0.444***	0.915**	0.059	0.651***	0.535***
	(0.169)	(0.365)	(0.230)	(0.150)	(0.147)
Secondary	0.669***	1.549***	0.631***	1.292***	0.953***
	(0.184)	(0.369)	(0.157)	(0.155)	(0.154)
Tertiary	1.113**	1.914***	0.676***	1.986***	1.218***
	(0.464)	(0.437)	(0.236)	(0.228)	(0.233)
Sex	0.124	-0.195	0.047	0.021	0.030
	(0.111)	(0.170)	(0.172)	(0.087)	(0.084)
Firm size		0.713***			0.511***
		(0.164)			(0.122)
Private					-0.759***
					(0.121)
Self					-1.102***
					(0.128)
Dares Salaam	0.465***	0.074	0.505***	0.402***	0.434***
	(0.122)	(0.190)	(0.169)	(0.100)	(0.095)
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	5.855***	7.271***	5.864**	6.050***	7.270***
	(0.789)	(0.942)	(2.252)	(0.596)	(0.602)
R^2	0.123	0.305	0.312	0.189	0.278
Sample size	610	238	105	953	953

Notes: Dependent variable is the logarithm of monthly earnings. Robust standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1

Table 8: Earnings function estimates; Ghana

	Self	Private	Public	Pooled(1)	Pooled(2)
Log of hours	0.027	0.135	0.243	0.023	0.082
	(0.191)	(0.091)	(0.222)	(0.083)	(0.082)
Tenure	0.109***	0.048*	-0.004	0.063***	0.071***
	(0.033)	(0.025)	(0.017)	(0.020)	(0.021)
Tenure^2	-0.004***	-0.000	0.001	-0.002**	-0.002**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Primary	-0.015	0.325**	-0.000	0.234**	0.158
	(0.132)	(0.156)	(0.345)	(0.095)	(0.098)
Secondary	0.406**	0.733***	0.498	0.742***	0.568***
	(0.186)	(0.154)	(0.354)	(0.097)	(0.104)
Tertiary	1.244	1.302***	0.664*	1.356***	1.071***
	(1.090)	(0.171)	(0.379)	(0.120)	(0.126)
Sex	0.354	0.215***	0.109	0.367***	0.255***
	(0.245)	(0.079)	(0.121)	(0.072)	(0.082)
Firm size		0.607***			0.644***
		(0.073)			(0.071)
Private					-0.042
					(0.077)
Self					0.062
					(0.130)
Accra	-0.206	0.004	0.122	0.020	-0.010
	(0.232)	(0.071)	(0.124)	(0.062)	(0.062)
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	2.872***	2.231***	2.524**	3.058***	2.600***
	(0.997)	(0.505)	(1.211)	(0.439)	(0.436)
R^2	0.107	0.295	0.307	0.191	0.237
Sample size	386	737	130	1,253	1,253

Notes: Dependent variable is the logarithm of monthly earnings. Robust standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1

OLS estimates of the mincerian equation potentially suffer from sample selection bias and endogeneity bias. First, we address endogenous education problem by estimating the earnings function in a two stage least squares estimation technique using instrumental variables. Parents education (mother and father's education) is used as instruments for education due to the high positive correlation between individual's education and that of his/her parents. To check the validity of our instruments, we conduct weak exogeneity test, test of over-identifying restrictions and Hausman test to confirm endogeneity of education in our sample. Test results reported in Tables A6 and A7 confirm the endogeneity of education and the validity of our instruments.

Results in Tables A6 and A8 for Tanzania and Ghana show correcting endogeneity bias changes returns to education estimates as IV estimates are appreciably higher. The average premium to an additional year of education in both Tanzania and Ghana increases to 12.5% and 10.9% respectively. Similarly, it increases to 11% and 15.9% in self-employment and private sector in Tanzania, but no evidence is found in the public sector. In Ghana, returns to education in private sector increases to 11.7% but no evidence is found in self-employment and the public sector. Similar to Rankin, Sandefur and Teal (2010), within the public sector in both countries we do not find evidence of returns to an additional year of education. All other variables in the IV estimation for the two countries drop marginally.

Estimations based on OLS in the subsamples that ignore sample selection bias is known to lead to biased estimates if for example high ability types (individuals who are highly motivated and more ambitious) systematically select into a particular occupation like the private sector. In such a situation, individuals in the private sector are more motivated and ambitious than the rest of the population and as such not a random draw from the whole population. Consequently, we follow Heckman (1979) and Lee (1983) to correct for sample selection bias in our sub-samples. This is done by first of all modelling selection into employment state in a multinomial logit model in which not-working is taken as the base for normalization. Labour market participation in specific sectors is identified by the use of individual and household characteristics expected to have direct impact on participation and choice of employment sector. Variables used include age, educational levels, marital status and whether an individual has dependent children, household headship which connotes the level of economic responsibility on the individual, access to non-labour income and dummy variables for location to control for differential opportunities in access to jobs based on location. Results of multinomial logit model are presented Tables A9 and A10. To ascertain whether the sectoral decomposition of the labour market is justified in the multinomial model, Wald test is used to test the equality of slope coefficient vectors associated with each sector choice in both models. The null hypothesis of equality of coefficients is rejected at 1% level of significance for both countries. This is an indication that the labour markets are heterogeneous and the decompositions into public, private, self-employment and not-working is suitable. Average partial effects from multinomial logit model for the two countries are presented in tables 9 and 10.

In Tanzania, age is found increases the probability of participation in all three employment sectors and decreases the probability of not-working. Having a primary or secondary education relative to no education reduces the probability of not-working by about 7% in Tanzania. Secondary and tertiary education levels reduce the probability of participation in self-employment by 10% and 29% respectively, whereas these levels of education increase the probability of formal sector employment particularly in the public sector by 14% and 19% accordingly. This is an indication of the existence of preference for formal sector employment in the Tanzania labour market and the important role education plays in sector choice. In addition, being a male increase the probability of employment in all sectors and at reduces not-working probability. While access to non-labour income increases not-working probability since such individuals can afford to remain in unemployment due the availability of resources other than income earned by working. This lends credence to Appleton et al. (1990) who found asset incomes to have a negative impact on work decision and participation rates in Cote d'Ivoire. Father's education is also found to reduce not-working probability and increase the probability of self-employment in Tanzania.

In Ghana, average partial effects presented in table 10 highlights a stricter preference by education for formal sector employment. All levels of education reduce the likelihood of self-employment in Ghana and increase the probability of formal sector employment particularly in public sector. Men in Ghana have increases probability of employment in all sectors and a reduced probability of not-working. Marriage reduces the probability of not-working and increases the probability of self-employment whereas access to non-labour income increases the likelihood of self-employment. This is a reflection of the phenomenon particularly among low educated women in Ghana who otherwise would have remained unemployed, are set up in trading by their husbands after marriage. Having children increases not-working probability by about 8% and reduces the probability of private sector employment by about 9%. In a similar manner, household headship reduces the tendency of not-working by about 9% due mainly to the economic burden on such individuals in Ghana. Also, the probability of not-working is largely reduced (about 35%) by residing in Accra relative to other urban areas. In both countries, we find that young people are more prone to unemployment than the old and education is particularly important in job attainment in the public sector.

Table 9: Average partial effects for Tanzania

	Not-working	Self-employment	Private	Public
Age	-0.011***	0.005***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Primary	-0.068**	0.010	0.010	0.048
	(0.029)	(0.042)	(0.037)	(0.035)
Secondary	-0.067**	-0.096**	0.022	0.141***
	(0.033)	(0.043)	(0.038)	(0.034)
Tertiary	-0.034	-0.289***	0.131*	0.193***
	(0.115)	(0.087)	(0.067)	(0.037)
Sex	-0.135***	0.056**	0.116***	0.038**
	(0.017)	(0.026)	(0.022)	(0.016)
Married	-0.041	0.022	-0.001	0.020
	(0.041)	(0.036)	(0.036)	(0.019)
Children	-0.010	0.070*	-0.025	-0.035
	(0.040)	(0.043)	(0.041)	(0.028)
Household head	-0.002	-0.042	0.029	0.015
	(0.063)	(0.045)	(0.040)	(0.019)
Non-Labour income	0.147**	-0.132***	-0.017	0.003
	(0.064)	(0.044)	(0.040)	(0.017)
Father's education	-0.010***	0.007**	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.002)
Mother's education	-0.001	0.000	0.003	-0.002
	(0.003)	(0.004)	(0.003)	(0.002)
Dares Salaam	-0.053*	0.046*	0.032	0.025*
	(0.029)	(0.027)	(0.027)	(0.014)
Observation	1,408	1,408	1,408	1,408

Note: These results are based on multinomial logit estimates reported in appendix A9. Levels of significance are; * p<0.1; ** p<0.05; *** p<0.01

Table 10: Average partial effects for Ghana

	Not-working	Self-Employment	Private Sector	Public Sector
Age	-0.012***	0.005***	0.004***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Primary	-0.029	-0.071***	0.052*	0.047**
	(0.023)	(0.019)	(0.028)	(0.022)
Secondary	0.057**	-0.164***	0.042	0.065***
	(0.027)	(0.026)	(0.033)	(0.023)
Tertiary	0.013	-0.271***	0.130***	0.128***
	(0.039)	(0.046)	(0.044)	(0.024)
Sex	-0.019	-0.181***	0.175***	0.025**
	(0.017)	(0.017)	(0.019)	(0.012)
Marriage	-0.092***	0.074***	0.018	-0.001
	(0.023)	(0.020)	(0.027)	(0.015)
Children	0.077***	-0.001	-0.094***	0.018
	(0.026)	(0.024)	(0.031)	(0.018)
Household head	-0.089***	0.039*	0.056**	-0.005
	(0.023)	(0.020)	(0.024)	(0.012)
Non-Labour income	0.003	0.040**	-0.034	-0.008
	(0.021)	(0.019)	(0.022)	(0.011)
Father’s education	0.008***	-0.002	-0.010**	0.004
	(0.003)	(0.003)	(0.004)	(0.002)
Mother’s education	-0.003	-0.004	0.009**	-0.002
	(0.003)	(0.004)	(0.004)	(0.002)
Accra	-0.352***	0.051***	0.273***	0.027***
	(0.023)	(0.017)	(0.019)	(0.010)
N	2,301	2,301	2,301	2,301

Note: results are based on multinomial logit estimates reported in appendix A9. Levels of significance are; * p<0.1; ** p<0.05; *** p<0.01

Results with selectivity correction based on the multinomial logit model are reported in tables 11 and 12. Weighted least squares are applied in the second stage regression to account for heteroskedasticity present in the model due to selectivity and standard errors are bootstrap to account for the two stage nature of the procedure. The results indicate overall, selection bias is not an issue in the Tanzania sample given that the selection correction term is not significant in all the three sectors. Similar to Rankin, Sandefur and Teal (2010), no evidence is found for educational premiums in the public sector. The pattern of results in the selection corrected model is fairly consistent with the ordinary least squares results of a positive and convex relationship between education and earnings particularly in the private sector. In the Tanzania labour market, being a man in self employment is associated with earnings premium whereas working in a large firm increases earnings in the private sector.

In Ghana, results with sample selection correction are fairly similar to OLS estimates with a convex earning education relation in private sector. The selection correction term is however positive and significant in the public sector but insignificant in the private sector and self-employment. This means earnings of a worker with average characteristics are higher in this sector than that of any worker who would be drawn randomly into the public sector. Conversely, earnings of a worker with average characteristics in either the private sector or self-employment do not differ significantly from those of a worker who would be randomly drawn into the sector.

In both countries, we find that education plays an important role in job attainment particularly in the public sector but within the sector, no evidence of earnings premium associated with educational levels are found.

Table 11: Selectivity Corrected Earnings Equation Estimates: Tanzania

	Self	**Private**	**Public**
Log of hours	1.017***	-0.269	0.171
	(0.145)	(0.603)	(0.486)
Tenure	0.025	0.022	0.038
	(0.017)	(0.058)	(0.042)
Tenure^2	0.000	0.000	-0.001
	(0.001)	(0.002)	(0.001)
Primary	0.660***	2.633**	0.032
	(0.147)	(1.188)	(0.363)
Secondary	1.172***	3.511***	0.462
	(0.169)	(1.273)	(0.503)
Tertiary	0.630***	4.461***	0.341
	(0.228)	(1.199)	(0.497)
Sex	0.447***	-0.018	0.105
	(0.092)	(0.347)	(0.318)
Firm size	-	0.848***	-
		(0.288)	
Dare Salaam	0.138	0.316	0.750***
	(0.088)	(0.328)	(0.266)
Selection correction term	0.014	-0.385	0.035
	0.225	(0.582)	(0.544)
Year dummies	Yes	Yes	Yes
Constant	-4.013***	-0.850	2.760
	0.817	(3.335)	(3.578)

Notes: Dependent variable is the log of monthly earnings. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Regressions include two year dummies to control for any time specific effects but not included for brevity. Result obtained via Stata Selmlog command.

Table 12: Selectivity Corrected Earnings Equation Estimates: Ghana

	Self	Private	Public
Log of hours	0.053	0.091	0.295
	(0.204)	(0.098)	(0.478)
Tenure	0.103***	0.045	-0.026
	(0.038)	(0.035)	(0.025)
Tenure^2	-0.004**	0.000	0.001
	(0.001)	(0.001)	(0.001)
Primary	-0.008	0.416**	-0.534
	(0.147)	(0.173)	(0.418)
Secondary	0.472**	0.900***	0.000
	(0.227)	(0.181)	(0.379)
Tertiary	1.413	1.487***	-0.211
	(1.125)	(0.208)	(0.450)
Sex	0.488	0.307**	-0.029
	(0.319)	(0.152)	(0.231)
Firm size		0.004*	
		(0.002)	
Accra	-0.224	0.042	-0.050
	(0.230)	(0.162)	(0.223)
Selection correction term	0.182	-0.072	0.890*
	(0.210)	(0.385)	(0.536)
Year dummies	Yes	Yes	Yes
Constant	2.918***	2.451***	4.545*
	(1.042)	(0.899)	(2.530)

Notes: Dependent variable is the log of monthly earnings. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Regressions include two year dummies to control for any time specific effects but not included for brevity. Result obtained via Stata Selmlog command.

Heterogeneity in earnings determination

The simple Mincerian earnings equation is based on a restrictive assumption that the marginal return to education and other earnings determinants are the same for all individuals. This may not be true in practice since earnings determinants can vary among individuals due to unobserved factors such as motivation, ability and initiative. To this end, we examine heterogeneity in earnings determinants particularly on earnings premiums with educational levels to determine whether some works benefit more from education than others and its implications for educational policies and on inequality.

Tables 13 and 14 report regression estimates respectively for the full samples at three different quantiles, namely, 25th, 50th (median) and 75th of the earnings distribution for Tanzania and Ghana, OLS results are also reported for comparison. The results show a consistent pattern with earnings determinants being different at different points in the conditional distribution of earnings. A test of the null hypothesis of equal covariates effects across quantiles in both specifications are rejected at 1%; this means all coefficients in the model differ across quantiles of the earnings distribution, hence the justification for quantile estimation technique.

Results in table 13 for Tanzania indicate hours of work, tenure, sex and residence in Dar es Salaam are associated with earnings premium at all quantiles though not always significant (for tenure and sex at bottom quantile). Penalties associated with working in the private sector or in self-employment relative to the public sector are found to be low among the top quantile (75%) compared to the bottom and median quantiles of conditional earnings distribution. Similarly, premiums with working in large firms reduce along the earnings distribution. All educational levels relative to no education as in OLS estimates, increase earnings along the conditional earnings distribution and evidence of convex relationship between earnings and education levels are found at the median and upper quantile of the earnings distribution. The highest premium to both primary and secondary education in Tanzania is at the bottom quartile (25^{th} percentile) while that of tertiary level education is largest at the top quartile (75%) of the conditional earnings distribution. In essence, we find earnings premium with primary and secondary education to decrease from the bottom of the earnings distribution to the top whiles the reverse is the case for tertiary education. We obtain additional support from the *F*-tests statistics; the null hypothesis of equality of education level coefficients across quantiles is rejected for higher against lower quantiles. This is an indication that among the workers in Tanzania, those with low ability have higher premiums with primary and secondary education and further suggest these levels of education are inequality reducing as it lowers the earnings differences between low and high ability individuals rather than increase it.

In Ghana, hours of work, tenure, sex and residence in Accra increase earnings along the earnings distribution though not always significantly so at all quantiles of the conditional earnings distribution (hours of work is significant at the median and Accra is at the 25^{th} percentile). Firm size premium is highest at the bottom quantile and decline along the conditional earnings distribution.

Table 13: Quantile Regression Estimates for Tanzania

	OLS	25%	50%	75%
Log of hours	0.457***	0.571***	0.357**	0.248***
	(0.105)	(0.202)	(0.144)	(0.075)
Tenure	0.035***	0.040	0.035*	0.030**
	(0.013)	(0.027)	(0.019)	(0.012)
$Tenure^2$	-0.000	-0.001	-0.001	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Primary	0.535***	0.679**	0.397**	0.252**
	(0.147)	(0.296)	(0.200)	(0.100)
Secondary	0.953***	1.024***	0.693***	0.669***
	(0.154)	(0.321)	(0.179)	(0.131)
Tertiary	1.218***	0.794**	0.894**	1.275***
	(0.233)	(0.351)	(0.363)	(0.234)
Sex	0.030	-0.019	0.179*	0.147***
	(0.084)	(0.163)	(0.092)	(0.057)
Firm size	0.511***	0.513***	0.463***	0.295**
	(0.122)	(0.173)	(0.103)	(0.138)
Private	-0.759***	-0.838***	-0.677***	-0.458***
	(0.121)	(0.178)	(0.112)	(0.115)
Self	-1.102***	-1.540***	-0.967***	-0.747***
	(0.128)	(0.242)	(0.132)	(0.153)
Dares Salaam	0.434***	0.442***	0.417***	0.300***
	(0.095)	(0.151)	(0.088)	(0.096)
Constant	6.924***	6.691***	8.126***	9.249***
	(0.600)	(1.000)	(0.779)	(0.433)
R^2/Pseudo R^2	0.278	0.176	0.169	0.202
Observations	953	953	953	953
Testing equality of education coefficients: F-Stat (Prob>F)				
Primary 25% (1, 953)			3.27 (0.0741)	8.27 (0.042)
Primary 50%				0.90 (0.342)
Secondary 25%			3.82 (0.051)	2.35 (0.126)
Secondary 50%				0.02 (0.884)
Tertiary 25%			0.11 (0.737)	1.40 (0.238)
Tertiary 50%				2.61 (0.107)

Notes: Dependent variable is the logarithm of monthly earnings. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. The F-stat tests the null hypothesis of equal coefficients (probability of rejecting the null in parenthesis). Regressions include two year dummies to control for time specific effects but not included for brevity.

Table 14: Quantile Regression Estimates for Ghana

	OLS	25%	50%	75%
Log of hours	0.082	0.110	0.117**	0.038
	(0.082)	(0.108)	(0.055)	(0.101)
Tenure	0.071***	0.027	0.038**	0.026*
	(0.021)	(0.018)	(0.017)	(0.013)
Tenure^2	-0.002**	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Primary	0.158	0.143	0.096	0.182**
	(0.098)	(0.130)	(0.074)	(0.078)
Secondary	0.568***	0.483***	0.456***	0.587***
	(0.104)	(0.141)	(0.071)	(0.088)
Tertiary	1.071***	0.730***	0.975***	1.205***
	(0.126)	(0.145)	(0.114)	(0.079)
Sex	0.255***	0.257***	0.374***	0.399***
	(0.082)	(0.088)	(0.050)	(0.077)
Firm size	0.644***	0.660***	0.488***	0.478***
	(0.071)	(0.096)	(0.073)	(0.082)
Private	-0.042	-0.066	-0.033	0.069
	(0.077)	(0.104)	(0.090)	(0.059)
Self	0.062	-0.099	0.039	0.277*
	(0.130)	(0.178)	(0.113)	(0.157)
Accra	-0.010	0.115*	0.045	0.025
	(0.062)	(0.068)	(0.049)	(0.050)
Constant	2.725***	2.357***	2.767***	3.418***
	(0.438)	(0.653)	(0.249)	(0.515)
R^2/Pseudo R^2	0.237	0.151	0.160	0.184
Observations	1,253	1,253	1,253	1,253
Testing equality of education coefficients: F-Stat (Prob>F)				
Primary 25% (1, 1248)			0.24 (0.621)	0.16 (0.685)
Primary 50%				1.03 (0.312)
Secondary 25%			0.06 (0.800)	0.73 (0.392)
Secondary 50%				2.44 (0.118)
Tertiary 25%			4.58 (0.033)	12.01 (0.071)
Tertiary 50%				6.68 (0.010)

Notes: Dependent variable is the logarithm of monthly earnings. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. The F-stat tests the null hypothesis of equal coefficients (probability of rejecting the null in parenthesis). Regressions include two year dummies to control for time specific effects but not included for brevity

All educational levels compared to no education, are associated with earnings premiums across quantiles in the Ghanaian labour market (though not always significantly) with larger premiums to high levels of education evident of a convex relationship between earnings and education. Results from the *F*-tests statistics confirm the differential earnings premiums across quantiles. The null hypothesis of equality of educational level coefficients across quantiles is rejected for higher against lower quantiles. What emerges from these results is that, in the Ghanaian labour market, high ability individuals (in the top quartile of the earnings distribution) have more premiums with all levels of education (primary, secondary and tertiary) compare to low ability earners. Results from quantile regressions for the different employment sectors are presented in Tables A11-A16.

5. Conclusion

Identification of the factors that determine earnings in the different labour market sectors with particular emphasis on the role of education in the various sectors of employment in urban Tanzania and Ghana was undertaken in this study with three main objectives; (1) examine the role of education and other earnings determinants in the labour market by sector of employment; (2) evaluate the role of education, individual and household characteristics in selection into the different employment states; and (3) assess the effect of education and other earnings determinants at different points in the conditional earnings distribution to determine whether earnings determinants are homogeneous among workers within countries. Ordinary least squares and quantile regression techniques were applied, in addition, we attempted to resolve two main endogeneity issues in the earnings equations which are omitted variable bias and sample selection bias by the use of instrumental variables and sample selection correction terms as by Heckman (1979) and Lee (1983) to achieve the stated objectives.

In both Tanzania and Ghana, we find that education plays an important role in promoting access to lucrative jobs particularly in the public sector but has no direct impact on earnings in the public sector. Our results show, a strong convex education earning relationship is evident in both countries consistent with Quinn et al, (2008) and Rankin et al, (2010) and particularly so in the private sector as individuals with high levels of education earn more than those with low levels of education. We find evidence of sample selection bias within the public sector in Ghana where individuals positively select themselves into the sector but no such evidence is found in Tanzania.

Estimated earnings determinants along the earnings distribution indicates primary and secondary education are inequality-reducing among workers in

Tanzania, low ability earners have higher premiums with primary and secondary education than high ability ones. The situation in the Ghana is, on the contrary, that high ability earners have higher premiums with primary and secondary education than low ability ones. In terms of tertiary education, we find a consistent pattern in both Tanzania and Ghana that it widens earnings inequality.

The significant sectoral earnings differentials found with OLS are confirmed by quantile regression estimates on Tanzania. Conditional earnings are lower in the private sector and in self employment relative to the public sector, although the gap in earnings is highest at the lower quartile of the earnings distribution and begins to decrease along the upper tail of the earnings distribution. However, no such evidence is found for Ghana.

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Appendix

Table A1: Sample means by labour market state for Tanzania; (sample standard deviation of variables other than dummies in parenthesis)

	Unemployment	**Self Employment**	**Private Sector**	**Public Sector**
Education (yrs)	6.33 (3.42)	7.27 (4.32)	8.25 (4.22)	11.91 (4.41)
Education level:				
None	0.19	0.12	0.09	0.03
Primary	0.73	0.77	0.63	0.36
Secondary	0.06	0.02	0.12	0.08
Tertiary	0.02	0.09	0.16	0.53
Married	0.16	0.60	0.35	0.70
Children	0.24	0.77	0.42	0.81
Age (in years)	29.79 (17.31)	38.08 (13.03)	35.07 (12.36)	43.60 (10.10)
Non-labour income	0.03	0.17	0.12	0.17
Household head	0.15	0.46	0.43	0.55
Dares Salaam	0.28	0.40	0.36	0.31
Number of Observations	496	621	241	107

Table A2: Sample means by labour market state for Ghana; (sample standard deviation of variables other than dummies in parenthesis)

	Unemployment	Self Employment	Private Sector	Public Sector
Education (yrs)	8.61 (4.39)	6.60 (4.78)	9.09 (4.10)	10.62 (3.68)
Education level:				
None	0.17	0.32	0.13	0.06
Primary	0.50	0.56	0.54	0.42
Secondary	0.26	0.10	0.22	0.23
Tertiary	0.07	0.02	0.11	0.29
Married	0.23	0.70	0.54	0.66
Children	0.34	0.78	0.56	0.72
Age (in years)	26.75 (9.78)	36.17 (9.52)	34.43 (11.55)	38.58 (11.40)
Non-labour income	0.27	0.30	0.37	0.36
Household head	0.16	0.31	0.42	0.48
Accra	0.02	0.26	0.49	0.44
Number of Observations	424	542	989	152

A3: Earnings Equation with years of schooling; Tanzania

	Self	Private	Public	Pooled (1)	Pooled (2)
Education (yrs)	0.057***	0.121***	0.069***	0.113***	0.077***
	(0.013)	(0.019)	(0.016)	(0.010)	(0.010)
Log of hours	0.599***	0.169	0.860**	0.480***	0.470***
	(0.140)	(0.157)	(0.369)	(0.105)	(0.105)
Tenure	0.007	0.081***	0.049**	0.046***	0.033***
	(0.016)	(0.024)	(0.019)	(0.013)	(0.012)
Tenure^2	0.000	-0.001**	-0.001**	-0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Sex	0.106	-0.222	0.033	0.015	0.021
	(0.112)	(0.162)	(0.156)	(0.087)	(0.084)
Firm size		0.721***			0.506***
		(0.161)			(0.120)
Private					-0.702***
					(0.121)
Self					-1.047***
					(0.128)
Dares Salaam	0.461***	0.051	0.491***	0.398***	0.427***
	(0.122)	(0.189)	(0.152)	(0.099)	(0.094)
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	5.782***	7.510***	5.391***	5.926***	7.167***
	(0.787)	(0.913)	(2.034)	(0.593)	(0.598)
R^2	0.127	0.318	0.334	0.199	0.284
Observations	610	238	105	953	953

Notes: Dependent variable is the log of monthly earnings. Robust standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

A4: Earnings Equation with years of schooling; Ghana

	Self	Private	Public	Pooled (1)	Pooled (2)
Education (yrs)	0.023*	0.087***	0.084***	0.079***	0.062***
	(0.013)	(0.011)	(0.022)	(0.008)	(0.008)
Log of hours	-0.006	0.142	0.248	-0.009	0.064
	(0.199)	(0.089)	(0.205)	(0.085)	(0.083)
Tenure	0.106***	0.042*	0.003	0.060***	0.070***
	(0.033)	(0.025)	(0.017)	(0.020)	(0.021)
$Tenure^2$	-0.004***	-0.000	0.000	-0.002*	-0.002**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Sex	0.361	0.201***	0.058	0.319***	0.198**
	(0.249)	(0.078)	(0.110)	(0.073)	(0.081)
Firm size		0.608***			0.679***
		(0.072)			(0.070)
Private					-0.108
					(0.076)
Self					-0.023
					(0.127)
Accra	-0.250	0.021	0.139	0.041	-0.001
	(0.231)	(0.069)	(0.125)	(0.062)	(0.062)
Constant	2.988***	1.906***	1.924*	3.007***	2.566***
	(1.043)	(0.481)	(1.087)	(0.446)	(0.438)
R-squared	0.095	0.278	0.294	0.159	0.216
Observations	387	736	130	1,253	1,253

Notes: Dependent variable is the log of monthly earnings. Robust standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1. OLS estimation method

A5: Earnings equation controlling for endogenous schooling (yrs.); Tanzania

	Self	Private	Public	Pooled (1)	Pooled (2)
Education (yrs)	0.110***	0.159***	-0.058	0.152***	0.125***
	(0.041)	(0.052)	(0.089)	(0.029)	(0.030)
Log of hours	0.581***	0.169	0.580	0.476***	0.462***
	(0.142)	(0.149)	(0.408)	(0.106)	(0.105)
Tenure	0.007	0.091***	0.062**	0.043***	0.034***
	(0.017)	(0.024)	(0.026)	(0.013)	(0.013)
$Tenure^2$	0.000	-0.002***	-0.001**	-0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Sex	-0.008	-0.239	-0.038	-0.039	-0.053
	(0.133)	(0.159)	(0.212)	(0.094)	(0.090)
Firm size		0.700***			0.480***
		(0.176)			(0.128)
Private					-0.520***
					(0.166)
Self					-0.824***
					(0.174)
Dares Salaam	0.404***	0.028	0.619***	0.344***	0.370***
	(0.128)	(0.199)	(0.200)	(0.105)	(0.101)
Constant	5.524***	7.155***	8.513***	5.679***	6.650***
	(0.858)	(0.910)	(2.795)	(0.650)	(0.689)
R^2	0.098	0.309	0.026	0.178	0.261
Observations	571	236	99	906	906

Notes: Dependent variable is the log of monthly earnings. Robust standard errors in parenthesis
*** p<0.01, ** p<0.05, * p<0.1. Instrumental variable estimations.

A6: Instrumental variable test results for Tanzania

Weak exogeneity test
First-stage regression summary statistics

Variable	Adjusted R-sq.	Partial R-sq.	Robust R-sq.	F (2,893)	Prob > F
Education	0.2664	0.2565	0.1049	59.1444	0.0000

Test of exogeneity of instruments (overidentifying restrictions)

Score chi2(1) = .722326 (p = 0.3954)

Hausman test of endogeneity of education
Test: Ho: difference in coefficients not systematic
chi2 (10) = 13.17
Prob>chi2 = 0.2144

A7: Instrumental variable test results for Ghana

Weak exogeneity test

First-stage regression summary statistics

Variable	Adjusted R-sq.	Partial R-sq.	Robust R-sq.	F (2,1236)	Prob > F
Education	0.2193	0.2117	0.0654	46.5277	0.0000

Test of exogeneity of instruments (overidentifying restrictions)

Score chi2 (1) = .073593 (p = 0.7862)

Hausman test of endogeneity of education
Test: Ho: difference in coefficients not systematic
chi2 (10) = 19.79
Prob>chi2 = 0.0313

A8: Earnings equation controlling for endogenous schooling (yrs.); Ghana

	Self	Private	Public	Pooled (1)	Pooled (2)
Education	0.091	0.117***	0.097	0.119***	0.106***
	(0.062)	(0.030)	(0.085)	(0.021)	(0.025)
Log of hours	-0.042	0.174*	0.234	0.034	0.091
	(0.218)	(0.096)	(0.183)	(0.088)	(0.084)
Tenure	0.095***	0.041*	0.001	0.062***	0.067***
	(0.033)	(0.025)	(0.020)	(0.020)	(0.022)
Tenure^2	-0.003**	-0.000	0.000	-0.002*	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sex	0.164	0.201**	0.083	0.250***	0.174**
	(0.311)	(0.079)	(0.179)	(0.078)	(0.080)
Firm size		0.547***			0.591***
		(0.094)			(0.085)
Private					-0.061
					(0.083)
Self					0.103
					(0.146)
Accra	-0.357	0.019	0.141	0.014	-0.010
	(0.252)	(0.071)	(0.123)	(0.066)	(0.063)
Constant	2.861***	1.501**	1.833	2.472***	2.039***
	(1.098)	(0.623)	(1.313)	(0.518)	(0.519)
R^2	0.024	0.265	0.291	0.134	0.188
Observations	385	725	130	1,240	1,240

Notes: Dependent variable is the log of monthly earnings. Robust standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Instrumental variable estimations.

A9: Multinomial logit estimates for Tanzania (Omitted category: Not-working)

	Self-Employment	Private Sector	Public Sector
Age	0.337***	0.326***	0.697***
	(0.036)	(0.039)	(0.095)
Age^2	-0.004***	-0.004***	-0.007***
	(0.000)	(0.000)	(0.001)
Primary	0.643**	0.589*	1.481**
	(0.313)	(0.344)	(0.699)
Secondary	0.387	0.706*	3.111***
	(0.351)	(0.377)	(0.697)
Tertiary	-0.538	1.077	3.567***
	(1.159)	(1.132)	(1.307)
Sex	1.159***	1.597***	0.451
	(0.207)	(0.216)	(0.356)
Married	0.433	0.314	0.743
	(0.400)	(0.451)	(0.525)
Children	0.292	-0.082	-0.487
	(0.391)	(0.450)	(0.637)
Household head	-0.122	0.183	0.254
	(0.618)	(0.640)	(0.695)
Non Labour income	-1.629***	-1.187*	-1.320*
	(0.626)	(0.648)	(0.693)
Father's education	0.109***	0.089***	0.133***
	(0.032)	(0.033)	(0.044)
Mother's education	0.004	0.019	-0.030
	(0.034)	(0.036)	(0.050)
Dares Salaam	0.537*	0.551*	0.013
	(0.288)	(0.321)	(0.382)
Constant	-3.769***	-4.759***	-15.183***
	(0.933)	(1.008)	(2.137)
Wald χ^2 (D.F)	1187.97 (45)		
Log-likelihood	-1125.82		
Pseudo-R2	0.35		
Observations	1,408		

Standard errors in parenthesis *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level: Reference categories are; no education, female for sex and Iringa, Arusha, Morogoro, Tanga and Mwanza for region of residence

A10: Multinomial logit estimates for Ghana (Omitted category: Not-working)

	Self-employment	Private Sector	Public Sector
Age	0.497***	0.211***	0.254***
	(0.049)	(0.039)	(0.070)
Age^2	-0.006***	-0.002***	-0.003***
	(0.001)	(0.001)	(0.001)
Primary	-0.264	0.372**	1.038**
	(0.180)	(0.180)	(0.410)
Secondary	-1.239***	-0.075	0.911**
	(0.243)	(0.213)	(0.442)
Tertiary	-1.641***	0.511*	2.346***
	(0.414)	(0.286)	(0.476)
Sex	-0.951***	0.717***	0.735***
	(0.168)	(0.132)	(0.236)
Married	0.894***	0.525***	0.475
	(0.191)	(0.185)	(0.300)
Children	-0.398*	-0.690***	-0.180
	(0.225)	(0.207)	(0.359)
Household head	0.676***	0.636***	0.419
	(0.195)	(0.175)	(0.258)
Non-Labour income	0.219	-0.139	-0.197
	(0.184)	(0.156)	(0.241)
Father’s education	-0.049*	-0.069***	0.013
	(0.029)	(0.024)	(0.045)
Mother’s education	-0.011	0.043*	-0.015
	(0.030)	(0.024)	(0.046)
Accra	2.081***	2.738***	2.556***
	(0.212)	(0.191)	(0.258)
Constant	-8.985***	-4.256***	-8.608***
	(0.829)	(0.657)	(1.293)
Wald χ^2 (D.F)	1449.98 (45)		
Log-likelihood	-2124.22		
Pseudo-R2	0.26		
Observations	2,301		

Robust standard errors in parenthesis *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level: Reference categories are; no education, female for sex and Kumasi, Cape Coast, Tema and Takoradi for location of residence

A11: Quantile regression estimates with years of schooling for Tanzania

	OLS	25%	50%	75%
Log of hours	0.470***	0.468**	0.350***	0.268***
	(0.105)	(0.199)	(0.123)	(0.061)
Tenure	0.033***	0.042**	0.034**	0.033***
	(0.012)	(0.020)	(0.014)	(0.011)
$Tenure^2$	-0.000	-0.001	-0.001	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.077***	0.082***	0.064***	0.067***
	(0.010)	(0.017)	(0.013)	(0.009)
Sex	0.021	0.000	0.160	0.157**
	(0.084)	(0.159)	(0.117)	(0.061)
Firm size	0.506***	0.537***	0.418***	0.314**
	(0.120)	(0.172)	(0.127)	(0.150)
Private	-0.702***	-0.602***	-0.591***	-0.406***
	(0.121)	(0.165)	(0.085)	(0.106)
Self	-1.047***	-1.336***	-0.940***	-0.679***
	(0.128)	(0.231)	(0.125)	(0.122)
Dares Salaam	0.427***	0.403***	0.410***	0.276***
	(0.094)	(0.116)	(0.098)	(0.075)
Year dummies	Yes	Yes	Yes	Yes
Constant	6.915***	7.125***	8.137***	8.980***
	(0.593)	(1.028)	(0.768)	(0.319)
R^2/Pseudo R^2	0.284	0.176	0.172	0.204
Observations	953	953	953	953

Notes: Dependent variable is the logarithm of monthly earning. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1.

A12: Quantile regression estimates with years of schooling for Ghana

	OLS	25%	50%	75%
Log of hours	0.064	0.145	0.165*	0.085
	(0.083)	(0.102)	(0.090)	(0.143)
Tenure	0.070***	0.035***	0.038***	0.027*
	(0.021)	(0.010)	(0.014)	(0.015)
$Tenure^2$	-0.002**	-0.000	-0.001	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Education	0.062***	0.058***	0.050***	0.060***
	(0.008)	(0.012)	(0.009)	(0.006)
Sex	0.198**	0.186***	0.258***	0.377***
	(0.081)	(0.070)	(0.054)	(0.073)
Firm size	0.679***	0.626***	0.500***	0.555***
	(0.070)	(0.092)	(0.057)	(0.081)
Private	-0.108	-0.044	-0.085	-0.024
	(0.076)	(0.093)	(0.092)	(0.072)
Self	-0.023	-0.176	-0.023	0.220**
	(0.127)	(0.159)	(0.120)	(0.108)
Accra	-0.001	0.092	0.032	0.024
	(0.062)	(0.059)	(0.047)	(0.042)
	(0.121)	(0.182)	(0.115)	(0.121)
Year dummies	Yes	Yes	Yes	Yes
Constant	2.698***	1.868***	2.447***	3.088***
	(0.436)	(0.618)	(0.469)	(0.754)
R^2/Pseudo R^2	0.216	0.143	0.135	0.143
Observations	1,262	1,262	1,262	1,262

Notes: Dependent variable is the logarithm of monthly earning. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1.

A11: Quantile Regression Estimates for Private Sector, Tanzania

	OLS	0.25	0.5	0.75
Log of hours	0.193	0.125	0.253	-0.060
	(0.152)	(0.285)	(0.194)	(0.175)
Tenure	0.085***	0.083**	0.056	0.036
	(0.024)	(0.033)	(0.035)	(0.026)
Tenure^2	-0.001**	-0.002*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Primary	0.915**	2.366***	0.984***	0.417
	(0.365)	(0.760)	(0.339)	(0.284)
Secondary	1.549***	2.971***	1.400***	1.091***
	(0.369)	(0.752)	(0.408)	(0.326)
Tertiary	1.914***	3.370***	1.601***	1.481***
	(0.437)	(0.714)	(0.418)	(0.351)
Sex	-0.195	-0.365	0.173	0.165
	(0.170)	(0.331)	(0.175)	(0.124)
Firm size	0.713***	0.642***	0.512***	0.505***
	(0.164)	(0.236)	(0.165)	(0.118)
Dares Salaam	0.074	0.034	0.186	-0.026
	(0.190)	(0.318)	(0.142)	(0.097)
Constant	7.477***	6.123***	7.476***	10.250***
	(0.899)	(1.399)	(1.097)	(1.069)
R-squared	0.305	0.217	0.169	0.209
Observations	238	238	238	238

Notes: Dependent variable is the logarithm of monthly earning. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Regressions include year dummies to control for any time specific effects but not reported for brevity.

A12: Quantile Regression Estimates for Private Sector; Ghana

	OLS	0.25	0.5	0.75
Log of hours	0.135	0.177***	0.208*	0.021
	(0.091)	(0.061)	(0.114)	(0.110)
Tenure	0.048*	-0.003	0.039**	0.049
	(0.025)	(0.019)	(0.017)	(0.032)
Tenure^2	-0.000	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Primary	0.325**	0.295***	0.166**	0.112
	(0.156)	(0.111)	(0.067)	(0.087)
Secondary	0.733***	0.646***	0.487***	0.494***
	(0.154)	(0.109)	(0.093)	(0.086)
Tertiary	1.302***	0.915***	1.099***	1.326***
	(0.171)	(0.148)	(0.113)	(0.107)
Sex	0.215***	0.237***	0.305***	0.373***
	(0.079)	(0.064)	(0.061)	(0.049)
Firm size	0.607***	0.620***	0.456***	0.483***
	(0.073)	(0.089)	(0.065)	(0.053)
Accra	0.004	0.115**	0.089	-0.020
	(0.071)	(0.046)	(0.057)	(0.067)
Constant	2.423***	2.036***	2.312***	3.546***
	(0.511)	(0.362)	(0.642)	(0.550)
R^2/Pseudo R^2	0.295	0.172	0.173	0.215
Observations	737	737	737	737

Notes: Dependent variable is the logarithm of monthly earnings. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Regressions include year dummies to control for time specific effects but not included for brevity.

A13: Quantile Regression Estimates for Public Sector, Tanzania

	OLS	0.25	0.5	0.75
Log of hours	0.828**	0.509	0.447	0.505
	(0.398)	(0.377)	(0.371)	(0.319)
Tenure	0.058***	0.068***	0.047*	0.049
	(0.019)	(0.018)	(0.024)	(0.031)
Tenure^2	-0.001***	-0.002***	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)
Primary	0.059	-0.306	-0.064	0.137
	(0.230)	(0.232)	(0.276)	(0.246)
Secondary	0.631***	0.328	0.719**	0.755***
	(0.157)	(0.216)	(0.282)	(0.178)
Tertiary	0.676***	0.224	0.578*	0.914**
	(0.236)	(0.210)	(0.313)	(0.416)
Sex	0.047	0.167	0.051	0.122
	(0.172)	(0.210)	(0.167)	(0.128)
Dares Salaam	0.505***	0.318***	0.202	0.393
	(0.169)	(0.115)	(0.197)	(0.284)
Constant	5.870**	7.812***	8.215***	7.910***
	(2.346)	(2.464)	(2.260)	(1.810)
R-squared	0.312	0.240	0.168	0.153
Observations	105	105	105	105

Notes: Dependent variable is the logarithm of monthly earning. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Regressions include year dummies to control for any time specific effects but not reported for brevity.

A14: Quantile Regression Estimates for Public Sector, Ghana

	OLS	0.25	0.5	0.75
Log of hours	0.243	0.410	0.391	0.316
	(0.222)	(0.248)	(0.348)	(0.222)
Tenure	-0.004	-0.011	-0.019	-0.017
	(0.017)	(0.026)	(0.022)	(0.026)
Tenure^2	0.001	0.001	0.001	0.001
	(0.000)	(0.001)	(0.001)	(0.001)
Primary	-0.000	0.157	0.401	0.327
	(0.345)	(0.227)	(0.525)	(0.717)
Secondary	0.498	0.535*	0.940	0.859
	(0.354)	(0.308)	(0.583)	(0.708)
Tertiary	0.664*	0.955***	1.197**	1.133
	(0.379)	(0.317)	(0.550)	(0.725)
Sex	0.109	-0.005	0.147	0.396***
	(0.121)	(0.127)	(0.128)	(0.117)
Accra	0.122	0.072	0.139	0.227**
	(0.124)	(0.173)	(0.114)	(0.111)
Constant	3.300***	2.267*	2.080	2.579***
	(1.219)	(1.191)	(1.764)	(0.961)
R-squared	0.307	0.193	0.251	0.314
Observations	130	130	130	130

Notes: Dependent variable is the logarithm of monthly earning. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Regressions include year dummies to control for any time specific effects but not reported for brevity

A15: Quantile Regression Estimates for Self-employment, Tanzania

	OLS	0.25	0.5	0.75
Log of hours	0.579***	0.849***	0.413*	0.309***
	(0.140)	(0.317)	(0.227)	(0.083)
Tenure	0.006	0.001	0.016	0.026*
	(0.016)	(0.017)	(0.020)	(0.016)
Tenure^2	0.000	0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)
Primary	0.444***	0.532	0.334**	0.188
	(0.169)	(0.358)	(0.157)	(0.154)
Secondary	0.669***	0.675**	0.374*	0.445***
	(0.184)	(0.313)	(0.192)	(0.160)
Tertiary	1.113**	0.543	0.672	1.349*
	(0.464)	(0.826)	(0.905)	(0.704)
Sex	0.124	0.065	0.180**	0.206**
	(0.111)	(0.120)	(0.085)	(0.097)
Dares Salaam	0.465***	0.605***	0.551***	0.364***
	(0.122)	(0.219)	(0.170)	(0.089)
Constant	6.103***	4.219**	6.851***	7.933***
	(0.750)	(1.745)	(1.148)	(0.457)
R-squared	0.123	0.107	0.064	0.081
Observations	610	610	610	610

Notes: Dependent variable is the logarithm of monthly earning. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Regressions include year dummies to control for any time specific effects but not reported for brevity.

A16: Quantile Regression Estimates for Self-employment, Ghana

	OLS	0.25	0.5	0.75
Log of hours	0.027	0.191	-0.039	-0.271
	(0.191)	(0.302)	(0.122)	(0.364)
Tenure	0.109***	0.067**	0.079***	0.054*
	(0.033)	(0.031)	(0.010)	(0.031)
Tenure^2	-0.004***	-0.002*	-0.002***	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Primary	-0.015	-0.174	-0.033	0.214
	(0.132)	(0.149)	(0.098)	(0.140)
Secondary	0.406**	0.233	0.246	0.578***
	(0.186)	(0.215)	(0.170)	(0.186)
Tertiary	1.244	0.098	1.079	0.715
	(1.090)	(1.146)	(1.601)	(1.961)
Sex	0.354	0.801***	0.529***	0.618***
	(0.245)	(0.194)	(0.094)	(0.208)
Accra	-0.206	-0.409	0.013	0.025
	(0.232)	(0.398)	(0.280)	(0.297)
Constant	2.982***	1.778	3.378***	4.943**
	(0.962)	(1.464)	(0.613)	(1.982)
R-squared	0.107	0.057	0.067	0.070
Observations	386	386	386	386

Notes: Dependent variable is the logarithm of monthly earning. Bootstrap standard errors in parenthesis *** p<0.01, ** p<0.05, * p<0.1. Regressions include year dummies to control for any time specific effects but not reported for brevity.