This paper is a draft submission to

Inequality—Measurement, trends, impacts, and policies

5–6 September 2014 Helsinki, Finland

Presented at the UNU-WIDER Conference on 'Inequality – Measurement, Trends, Impacts, and Policies', Helsinki 5–6 September 2014

Impact of education on inequality along the wage distribution profile in Cameroon: 2005-2010

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Abstract:

This paper sets out to evaluate the impact of education on measured inequality along the wage distribution using pooled records from the 2005 and 2010 Cameroon labour force surveys, sector-selectivity corrected wage equations, and factual and counterfactual experiments to elicit Gini and Generalized Entropy inequality impacts. Returns to education increased monotonically from lower to upper percentiles with a spread of about 7.6 per cent. Yet, incremental returns were registered on average and up to the 25th percentile making the full returns to education for the period 2005-2010 largest for the 5th and 10th percentiles. Inequality decreased from lower to upper percentiles in the counterfactual education-equalizing distributions – thus revealing the inequality increasing effect of education in the actual distribution and a snowballing effect when moving up the wage distribution profile. These findings suggest that education was inclusive between 2005 and 2010 and that leveling the playing field for schooling opportunities would be important when trying to reduce inequality and poverty.

JEL Codes: D31, D60, D63, I24

Keywords: Cameroon, Education, Inequality, Wages, Distribution.

Submitted: August 1, 2014

1. Introduction

A sense of lack of fairness among the citizenry has recently been at the root of regime change in a number of African countries. Such awareness leads to aspirations for more social inclusion, with fair chances for everybody in society as ingrained in the concepts of equity, fairness and social justice (UNDP 2011). Early ideas of equity suggested that individuals should be rewarded according to their contribution to society (Homans 1961; Blau 1964; Adams 1965). Used interchangeably with fairness, equity has come to refer primarily to distributive justice, which draws a distinction between just and unjust inequalities between people (Baye and Epo 2013). There is now an active debate on whether countries should set themselves goals for not only achieving absolute poverty reduction, but also lower inequality in the context of growth and rising inequality in many developing countries (WIDER 2014). In this regard, the discussion would be enriched if we can identify the components/sources of inequality.

Measured inequality is a function of two major components: comprising inequality of circumstances, to which an individual may not be held responsible; and inequality of effort, to which an individual can largely be held responsible. Moreover, popular sentiments would probably support equal pay insofar as wages are different because of the influence of heterogeneous circumstances, but not insofar as they are due to differences in the effort exerted by individuals. Although it may be hard to separate the exact influence of circumstance- or effort-based variables on measured inequality, to address the impact of equalizing selected endowments on measured inequality, proximate classifications into circumstance-base and effort-base variations have been experimented in the literature (Dias 2008; Lefranc et al. 2008; Baye and Epo 2013).

Most empirical studies based on Roemer's (1998) model of measuring inequality of opportunity have embarked on schemes that attempt to equalize circumstance-related variables to generate distributions in which the influence of circumstance-inducing opportunities have been eliminated. Inequality measurements from such schemes are then compared with inequality of outcomes to figure out the unjust components of inequality (Bourguignon et al. 2007; Nunez and Tartakowsky 2007). In such studies, the quality of econometric analysis is central to correctly assign the effect of an explanatory variable on the outcome variable. Most studies that use econometric analysis so far to distinguish between just and unjust inequalities have used regressions at the mean that also failed to correctly address inherent problems such as potential endogeneity and selectivity biases in the income generating process (*see*, Bourguignon et al. 2007; Nunez and Tartakowsky 2007), thus the estimates are typically biased, inconsistent and masking differentials. In the present endeavour, we address some of these gaps by tackling some potential econometric problems, while using quantile regressions that track responsiveness at many points along the income distribution profile before addressing the impact of education on inequality along the wage distribution.

We consider education as essentially an effort-related fundamental determinant of individual wages because it complements with or substitute for exogenous circumstances that enhance or constrain individual livelihood opportunities. Inadequate educational endowments may explain the root of poverty and income disparities in a low income country like Cameroon. It is apparent that an initial highly unequal access to education, as well as associated endowments should make it much harder for the poor to participate in, and gain from, the process of economic growth. This may further compromise other interventions geared at promoting the inclusiveness of growth and reducing poverty. Resolving deficiencies in access and returns to education is, therefore, expected to be instrumental in augmenting the standard of living of the poor more than that of the non-poor. Investment in education and related infrastructures leads to an increase in the labour market participation opportunities opened to economic agents and thus an essential catalyst for the national fight against poverty and inequality. Education increases the skills and productivity of poor households, enhances their employability and earnings, as well as their welfare.

In this context, a key question arises: Is smoothening education more inequality reducing at lower than upper tails of the wage distribution profile? The corresponding objectives are: (1) to evaluate the determinants of employment sector choices; (2) to examine the nature of change in returns to formal education between 2005 and 2010 along the wage distribution; and (3) to evaluate the impact of education on measured inequality along the wage distribution. These objectives are guided by three hypotheses: Other things being equal: (1) education is relatively important in sanctioning wages and allocation of workers to various employment sectors; (2) returns to education were inclusive in the labour market between 2005 and 2010; and (3) smoothening education is more inequality reducing at lower percentiles than at upper percentiles in the distribution of wages.

In the third case, education is thought to be largely effort-related, so fixing it in the counterfactual distribution for all wage earners within percentiles is tantamount to removing the legitimate sources of variation and allowing only the illegitimate (circumstance-based) sources of variation. This counterfactual experiment is based on a structural model estimated correcting for potential employment sector-selectivity bias, and on the pooled 2005 and 2010 Cameroon labor force surveys. Comparing inequality using the standard Gini and the Generalized Entropy measures of inequality generated from the counterfactual distributions with the inequality of outcomes for the selected percentiles would give rise to the inequality impacts under study. Such an analysis would inform public policy of the role of educational expansion on the inclusiveness of the wage distribution process. The rest of the paper is organized as follows: Section 2 deals with literature review. Section 3 dwells on the methodology. Section 4 presents the data. Section 5 focuses on the empirical results, and conclusion and policy implications are sketched in Section 6.

2. Literature Review

The human capital theory associated with Mincer (1958, 1996), Schultz (1960) and Becker (1964) explains wage inequalities as a consequence of differing human capital stocks that determine an individual's productivity. In this regard, investing in education is likely to increase skills and productivity which are rewarded by higher wages. According to Schultz (1960), education can be treated as an investment in the human being and its consequences can be considered a form of capital. Since education becomes an integral part of the recipient, it can be understood as human capital. Among the embodied variables in human capital are education, health and on the job training. Thus, by acquiring formal education and training, workers obtain more knowledge that enables them to analyze and solve problems that might come up at work in a more efficient manner.

Alternatively, screening and signalling (Spencer 1973) are competing theories about the value of education because they assume that formal education rather helps only in sorting out potential productive workers. Meanwhile, the efficiency wage theory relates productivity of the worker to the wages they earn indicating that equilibrium wages are not sufficiently high to cover other factors like health and leisure that affect the productivity of workers. In other words, if a worker is paid more, he/she is likely to work harder and produce more output than if he is paid a wage dictated by the market. Other related theories are embodied in the shirking model (Shapiro and Stiglitz 1984), the gift-exchange model (Arkerlof 1982, 1984) and the adverse selection model (Akerlof 1970).

The role of education in causing or mitigating wage inequalities has been explained theoretically in the human capital theory, the dual labour market theory and discrimination theory. Becker (1964) argues that human capital acquisition determines the productive characteristics of an individual that relate positively to productivity. Differences in the degree of human capital accumulated by the workers, therefore, differentiate their marginal productivities. Since workers are rewarded according to their marginal productivities, this generates wage inequalities. Consequently, the marginal productivity theory may constitute a potential lens in explaining wage inequalities because those at the bottom of the wage profile are perceived to have lower productivity due to their lower human capital attainment compared to those at the top.

Another lens to view inequalities in the distribution of wages is the dual labour market theory that divides the market into the primary labour market (formal sector), which is more organized and the secondary labour market (informal sector), which is rather spontaneous. Wages in the primary market are typically higher than those in the secondary market. Whereas the majority of less educated are generally in the secondary labour market and are perceived as being less skilled (Barron and Norris 1976), the more educated are typically in the primary market and are considered as more skilled, and therefore earn more wages.

Education is arguable the most, or at least one of the most, important factors that can increase individual economic growth, and reduce poverty and inequality. For instance, human capital inputs have been recognized as critical factors in achieving sustained growth in productivity in some African countries (Schultz 2003). Education may enhance technical efficiency directly by improving the quality of labour, augmenting the ability of individuals (farmers) to adjust to idiosyncratic shocks through its effect on input utilization (Moock 1981). Epo and Baye (2011) find that education and health constitute key components of household economic welfare in Cameroon because they directly and indirectly affect household utility and production functions.

In decomposition studies surveyed in Fields (1980), education is viewed as the single most important determinant of income. Yet, exploring literature relating education to inequality reveals mixed results. For example, whereas Chiswick (1971) and Winegarden (1979) find a positive relation between schooling and inequality, Ahluwalia (1976) and Sylwester (2005) find a negative association between school enrolment and income inequality. Castello and Doménech (2012) in a long time series study found that despite the reduction in human capital inequality around the world driven by a decline in the number of illiterates between 1950 and 2010, inequality in the distribution of income has hardly changed. They considered their findings somehow puzzling because one would expect that a large decline in human capital inequality would translate into a decline in income inequality. However, they considered increasing returns to education, external effects on wages of higher literacy rates or the simultaneous concurrence of other exogenous forces as possible factors responsible for the lack of correlation between the evolution of income and education inequality.

For proponents of education inequality correlating positively with income inequality, the main effect of education is through acquisition of skills that affect productivity and therefore earnings. They argue that education provides an outlet for economic and social opportunities for poor individuals (Blanden and Machin 2004) and therefore can be perceived as a means of reducing income inequality. Access to education endows poor individuals with skills and sometimes decreases the gap between skilled and unskilled labourers. Nevertheless, while Chiswick (1968) argues that in the short-run access to education may increase inequality, Schultz (1963) argues that in the long-run this may reduce income inequality through educating unskilled workers, enabling them acquire more skills, become producers and increase their earnings.

Making human capital endowments inclusive is therefore expected to translate into a significant increase in the share of income accruing to the poorest population. However, if it happens that wages in other segments of the population with higher education also increase, such that all of them maintain their income shares, income inequality may not reduce. At country level, whereas some studies point to the positive relation between education and income inequality (see, Jallade (1997) for Brazil and Tsakloglou and Antoninis (1999) for Greece), other studies argue that public expenditure on education by governments as subsidy does not reduce income inequality (Jimenez 1986). The objective in this paper is not to study the relationship between inequality of education and inequality of earnings, but rather to evaluate the impact of education on inequality along the wage distribution profile, using factual and counterfactual experiments.

Since the early works of Mincer (1958, 1996), attempts to model determinants of wage inequalities using different econometric models - ordinary least squares (OLS), IV estimates, panel data regressions, and quantile regressions have been made. Ismail and Jajri (2012) use OLS estimates to identify determinants of wages before furthering their analysis. Neumark (1998) argues that OLS estimates may bias results and suggest the use of IV estimates. On panel data analysis, Polachek and Kim (1994) use the fixed effects technique to identify the sources of changes in the wage inequalities. Other studies like Heitmuller (2004) and Melly (2005) consider issues of endogeneity in a switching model and control for endogeneity related to the choice of sector of employment using an occupational choice model, respectively. Kristjan-Olari (2005) and Melly (2003) use quantile regressions to understand the distribution of the public-private sector wage differentials in Estonia and Germany, respectively. In Cameroon no study appears to have undertaken a quantile regression correcting for sector-selectivity bias to understand the role of education on wage inequalities.

This paper makes a number of empirical contributions by: (1) correcting for potential employment sector-selection bias in the structural wage equation; (2) running quantile wage regressions, (3) designing factual and counterfactual experiments to elicit the impact of education on inequality along the wage distribution, and (4) conducting analyses based on pooled individual records from the 2005 and 2010 Cameroon labour force surveys (CLFSs).

3. Methodology

3.1. Modelling the wage determination process

To study the effects of education on wages, it is useful to exploit the two most recent Cameroon labour force surveys (2005 and 2010) by pooling them together. This enables the testing of how the effect of education on occupational choices and wages changed in the period 2005-2010. Following a Mincer-type tradition of wage determination, a log wage structural equation can take the form:

$$LnW = \alpha_0 + \alpha_1 d2010 + \alpha_2 E + \alpha_3 d2010 * E + \sum_{k=4}^{6} \alpha_k S_k + \sum_{k=7}^{m} \alpha_k C_k + \varepsilon_1 \quad (1)$$

Where LnW is the natural logarithm of wage at the individual level; d2010 is a year dummy variable that takes the value 1 for 2010 records and 0 for 2005 records; E is education measured at individual level as years of schooling; S is a vector incorporating sectors of employment, notably public, private and informal when small-scale agriculture is considered the base-category; C is a vector of other personal, household, location and labour market characteristics that are thought of as exogenous circumstances that are generally beyond the direct control of the individual; the vector α are the parameters to be estimated, and ε_1 is the error term, which may be having a systematic as well as a stochastic component. In particular, α_0 is the intercept for 2005; $\alpha_0+\alpha_1$ is the intercept for 2010; α_2 is the effect of education on log wage in 2005; and α_3 is labour market returns to education between 2005 and 2010. Therefore, α_3 measures how the returns to education have changed over the five-year period. The total effect of education on log wage in the period 2005-2010 (pooled survey) is therefore $\alpha_2+\alpha_3$.

The employment sectors included in the structural log wage equation are potentially endogenous since labour force data are particularly truncated on the basis of the wage variable due to selfselection into various employment sectors. In this context, the process of allocation in the various employment sectors with the resultant earnings is likely not to be entirely random. If the data are censored, OLS estimates of equation 1 would be biased and inconsistent. Thus, to estimate the structural wage equation, it is important to recognize that in terms of main occupations individuals typically face a choice to search for work either in public, private, informal or small-scale agriculture as characterized in the Cameroon labour force surveys. Selection into these sectors of employment are likely not to be a random process. If employment sector choices are not random, then it is important to account for sector choice selectivity when modelling wage determination.

In this paper, we follow Greene (2003) to motivate our employment sector choice model by a random utility function. For the i-th individual facing J choices of employment sectors, the utility of choosing sector j may take the form:

$$U_{ij} = x_{ij}\beta_j + \varepsilon_{ij} \tag{2}$$

where, U_{ij} is the utility derived by individual i from sector j; $x_{ij}\beta_j$ is the deterministic component of the utility function and ε_{ij} the stochastic component of the function. If individual i choses sector j, then it is assumed that U_{ij} is the maximum among the J utilities. This problem can be presented in terms of probability as:

$$P_{ij} = \max((x_{i1}\beta_1, x_{i2}\beta_2, ..., x_{iJ}\beta_J) = x_{ij}\beta_j) \tag{3}$$

Equation 3 is made operational by a particular choice of distribution for the stochastic disturbances in equation 2. In this regard, two models can be considered: logit or probit. Because of the need to evaluate multiple integrals of the normal distribution, the probit model has found rather limited use in the multinomial setting (Greene 2003). However, with the advent of high powered computers programmed to perform multiple intergrals of the normal distribution, this is no longer a binding constraint. Moreover, the risk of violating the assumption of independence of irrelevant alternatives (IIA) associated with the multinomial logit and the attractiveness of the Heckman procedure in deriving inverse Mills ratios from predicted probabilities after estimating probit models, we use the multinomial probit to estimate our employment sector choice model. This is tantamount to assuming that the disturbances in the utility function of the employment sector choice model follow the normal distribution. Equation 3 can be reformulated more explicitly as:

$$\Pr(S = j \mid j = 4; X) = \Phi(\beta_0 + \beta_1 d2010 + \beta_2 E + \beta_3 d2010 * E + \sum_{h=4}^{n} \beta_h Z_h + \sum_{h=n+1}^{n'} \beta_h Z_h) \tag{4}$$

where, S is a multiple employment sector choice indicator, j =1, 2, 3, and 4, representing the public, private, informal and small-scale agricultural sectors of employment, respectively. The reference category is small-scale agriculture, j=4. X is the vector of explanatory variables.

The explanatory variables are:
E is education measured in years of schooling; Z_h is a vector of exogenous variables comprising of n exogenous covariates that also belong to the log wage equation and a vector of $(n'-n)$ instrumental variables that affect employment sector choices but have no direct influence on log wage, except through participation in one of the labour market sectors. β_h is a vector of n' parameters of exogenous explanatory variables in the occupational choice model to be estimated. Analogous to equation 1, β_0 is the intercept for 2005; $\beta_0+\beta_1$ is the intercept for 2010; β_2 is the effect of education on employment sector choice in 2005; and β_3 is effect of education on occupational choice between 2005 and 2010. The total effect of education on choice of sector of employment in the period 2005-2010 (pooled survey) is therefore $\beta_2+\beta_3$. Therefore, β_3 measures how the influence of education on employment sector choice has changed over the five-year period.

After estimating the multinomial probit model in equation 4, we predict a probit index, probit density function and cumulative probit density function for each outcome. Dividing the probability density functions by the respective cumulative density functions generates corresponding inverse Mills ratios *a la* Heckman (1979). Letting the vector λ to represent the inverse Mills ratios for the public, private and informal sectors of employment, we can augment our log wage equation 1 to equation 5 by including the lambdas as additional explanatory variables that render employment sector in the wage equation exogenous.

$$LnW = \alpha_0 + \alpha_1 d2010 + \alpha_2 E + \alpha_3 d2010 * E + \sum_{k=4}^{6} \alpha_k S_k + \sum_{k=7}^{m} \alpha_k C_k + \sum_{k=m+1}^{m'} \alpha_k \lambda_k + v \qquad (5)$$

where the variables are as defined earlier, α the vector of parameters to be estimated, $(m'-m)$ the number of inverse Mills ratios, three in this case; and v the error term. Equation 5 is estimated at the mean, and across selected quantiles of the distribution of wages.

3.2. Quantile regression framework

The standard regression analysis overlooks variations across different parts of the wage distribution, while quantile regression techniques seek to account for the partial effects of individual and job characteristics at different points of the conditional log wage distribution. In this context, quantile regression enables the researcher to take into account the heterogeneity among wage earners along the wage distribution profile, thus more appropriately accounting for the responsiveness of log wage to each of the right hand-side covariates. As noted by Koenker and Bassett (1978), and Koenker and Hallock (2001), quantile regression is a natural extension of the classical least squares estimation of the conditional mean (implemented by minimizing sum of squared errors) to estimations at different conditional quantile functions implemented by minimizing weighted sum of absolute errors. Equation 4 can be written without any loss of generality for a worker *h* as: $W_h = x_h\delta + u_h$. In this context, a general quantile regression model can take the form:

$$W_h = x_h\delta_q + u_{qh} \tag{6}$$

where W_h is log wage of worker h, x_h is a vector of independent explanatory variables; δ_q is a vector of regression parameters associated with the q^{th} quantile; and u_{qh} is the error term of worker h associated with the q^{th} quantile.

The quantile regression method involves letting the partial effects to change at different points in the distribution of wages by estimating $\hat{\delta}_q$ using different values of q, $q \in \left]0,1\right[$. This way, the quantile regression allows for parameter heterogeneity across different points in the distribution of earnings. The estimator, $\hat{\delta}_q$, is obtainable as the solution to the following minimization problem:

$$\hat{\delta}_q = \min_{\delta}\left(\sum_{h:\, W_h \geq x_h\delta_q} q\left|W_h - x_h\delta_q\right| + \sum_{h:\, W_h < x_h\delta_q} (1-q)\left|W_h - x_h\delta_q\right| \right) \tag{7}$$

Equation 7 entails minimizing the weighted sum of absolute errors, where the weights are symmetrical for the median regression case (*q*=0.5) and asymmetrical otherwise. In other words, for those earning a wage above the value of the quantile of interest, the weighting scheme is q and for those who earn below, the weighting scheme is (1-*q*). This way, the observed differences in the estimated coefficients across different quantiles are interpreted as differences in the response of the log wage to changes in the explanatory variables at different points in the conditional distribution of wages. For the purpose of this study we use seven quantiles: $q_{0.05}$, $q_{0.1}$, $q_{0.25}$, $q_{0.5}$, $q_{0.75}$ $q_{0.9}$, and $q_{0.95}$, which are the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles.

3.3. Counterfactual experiments

We set out to evaluate the impact on wage inequality that would obtain if education had no effect on observed labour market wage inequality overall and within percentiles. That is, inequality that would materialize if variations in the distribution of wages within quantiles were independent of educational attainment. To derive a counterfactual benchmark for this exercise, we first write the estimated counterpart–form of equation 5 as equation 8.

$$Ln\hat{W} = \hat{\alpha}_0 + \hat{\alpha}_1 d2010 + \hat{\alpha}_2 E + \hat{\alpha}_3 d2010 * E + \sum_{k=4}^{6}\hat{\alpha}_k S_k + \sum_{k=7}^{m}\hat{\alpha}_k C_k + \sum_{k=m+1}^{m'}\hat{\alpha}_k \lambda_k \tag{8}$$

The factual log wage distribution can be recovered from equation 8 by writing: $LnW = Ln\hat{W} + \hat{v}$, and taking the antilog, to have $W = \exp(Ln\hat{W} + \hat{v})$, which is the factual wage distribution, presented in full in equation 9.

$$W = \exp(\hat{\alpha}_0 + \hat{\alpha}_1 d2010 + \hat{\alpha}_2 E + \hat{\alpha}_3 d2010 * E + \sum_{k=4}^{6} \hat{\alpha}_k S_k + \sum_{k=7}^{m} \hat{\alpha}_k C_k + \sum_{k=m+1}^{m'} \hat{\alpha}_k \lambda_k + \hat{v}) \quad (9)$$

The corresponding counterfactual education-equalizing benchmark is obtainable if workers within each quantile are allocated the mean years of schooling of the quantile ($\overline{E}_q$), while allowing other variables as observed. This gives rise to the counterfactual distribution of wages denoted by $W_{\overline{E}_q}$ and defined as:

$$W_{\overline{E}_q} = \exp(\hat{\alpha}_0 + \hat{\alpha}_1 d2010 + \hat{\alpha}_2 \overline{E}_q + \hat{\alpha}_3 d2010 * \overline{E}_q + \sum_{k=4}^{6} \hat{\alpha}_k S_k + \sum_{k=7}^{m} \hat{\alpha}_k C_k + \sum_{k=m+1}^{m'} \hat{\alpha}_k \lambda_k + \hat{v}) \quad (10)$$

In this set-up, measured wage inequality is attributable to unobservables (the inverse Mills ratios and the predicted structural error term) and other observed variables (sectors of employment, and personal, household and labour market characteristics) since inequality originating from education has been removed.

If we denote the counterfactual distribution by $W_{\overline{E}_q}$, that is, the distribution with policy, the without policy distribution by *W*, and an inequality index represented by *I*, we can define the impact of policy on wage inequality given by Θ_I:

$$\Theta_I = \frac{I(W) - I(W_{\overline{E}_q})}{I(W)} \quad (11$$

If $\Theta > 0$, education is inequality augmenting in the factual distribution.
If $\Theta = 0$, education is inequality neutral in the factual distribution.
If $\Theta < 0$, education is inequality reducing in the factual distribution.

The notation Θ_I indicates that the share of education in wage inequality is predicated on the chosen inequality index. In this paper we used the Gini index and the generalized entropy class of inequality indices.

4. Presentation of data

In this paper, use is made of the first and second Cameroon labour force surveys undertaken in 2005 (CLFS 1) and 2010 (CLFS 2) by the National Institute of Statistics. The first survey was conducted from May 23 to July 10, 2005. This survey was aimed at (1) knowing the activity conditions in the different sectors and their performances; (2) ameliorating national accounting data; (3) measuring the importance of the informal sector in the national economy; (4) identifying the most important activity branches; and (5) proposing ways to ameliorate how activities are conducted in the sector, with a view to monitoring her transition to the formal private sector.

The survey was carried out in two phases. Phase one evaluated the employment situation and phase two household economic activities in the informal sector. In the first phase, the sampling frame of the third general population and housing census was used to define the sampling frames down to primary sampling units. A random sample of 8540 households stratified in to 10 regions and zones of residence was adopted.

The stratification was done in a manner to present representative data at the level of the 10 regions, Yaoundé and Douala, and zones of residence. Each region was sub-divided into three strata: urban, semi-urban and rural. The urban stratum was made up of at least 50,000 inhabitants, semi-urban towns with inhabitants between 10,000 and 4999 and rural stratum with less than 10,000 inhabitants. In total 32 strata were constituted – including the towns of Yaoundé and Douala as separate strata.

The second survey (CLFS 2) was undertaken from May 16 to July 17, 2010. The survey was made up of 8160 households for which 7932 were identified and interviewed. It was aimed at understanding employment, evaluating the economic activities of the non-agricultural informal sector and proposing estimates on employment and the formal sector at the national level, by zone of residence and the 12 regions surveyed. The CLFS 2 sample was stratified by using a two stage sampling frame. Nationally, 17 800 primary sampling units were identified. In the first stage, 756 primary sampling units (PSU) were drawn with a proportion of 700 to 1000 inhabitants form an average of 140 to 220 households per PSU. For the second stage, a fixed number of households were selected in each of the PSU selected in the first stage. The number of households selected per PSU was 14 in Douala, 12 in Yaoundé and 10 in the other strata.

The different strata were obtained by considering the 12 regions with the three strata of residence (urban, semi-urban, and rural). In total, 32 strata were also defined – including Yaoundé and Douala as two separate strata. Three strata were also constructed for each of the 10 regions: urban, semi-urban, and rural.

We extracted variables of primary importance and pooled the 2005 and 2010 Cameroon labour force surveys for the empirical analysis. In particular, as identifying variables of the employment sector choice model, we use presence of children below six years old and other wage earners in the same household as the worker. These two variables are expected to correlate with labour force participation and choice of sector of employment, but not with wages except through labour force participation. Selected variables for the study and their descriptive statistics are presented in Table 1.

5. Empirical results

5.1. Descriptive statistics

Table 1 shows descriptive statistics for the pooled 2005 and 2010 Cameroon labour force surveys. The average wage in the pooled data is about XAF63884 per month.[1] Heterogeneity in

[1] XAF500 is about US$1.

earnings can be perceived by observing earnings along the wage distribution profile. Whereas those at the 10^{th} percentile earn just about XAF7000 per month, the median worker earns about XAF46725 and those at the 90^{th} percentile earned, on average, about XAF185962. Average schooling was 6.73 years overall, ranging from 4.35 years among those at the 10^{th} percentile and 6.39 years for the median wage earner to 9.79 years for those at the 90^{th} percentile in the wage distribution.

Table 1 (About here)

On average, about 40 per cent of workers are engaged in small-scale agriculture and about 40 per cent are engaged in the non-agricultural informal sector and only about 10 per cent are formal sector employees. Formal sector workers are located mainly at upper percentiles. Of those located at the 10^{th} percentile in the income distribution, about 77 per cent are small-scale agriculturalist, whereas for those located at the 90^{th} percentile, only 15 per cent are small-scale agriculturalists. Informal sector workers are more evenly distributed across percentiles than workers in any other employment sector. The overall average time worked per week is about 41.4 hours. Those at the upper percentiles turn to work more hours per week than those at lower percentiles. Average working experience is about 8.9 years overall, meanwhile those at lower percentiles are seemingly having more work experience than their counterparts in upper percentiles. It is only from the 75^{th} percentile that experience is increasing with wages. Overall, about 47 per cent of workers are married. The proportion of those married decreases from the 5^{th} (65 per cent) to the 75^{th} (44 per cent) percentiles of the wage distribution profile before increasing to 58 per cent at the 95^{th} percentile. About 52 per cent of the work force were women, on the average and more are situated in lower than upper percentiles.

Only about 5 per cent of workers in the pooled labour force survey hold secondary jobs or receive fringe benefits, and only about 6 per cent benefited paid leave. About 42 per cent of the pooled work force resides in urban areas. The distribution of urban dwellers across wage percentiles is somewhat skewed – about 13 per cent of those at the 10^{th} percentile and up to about 67 per cent of those at the 90^{th} percentile are urban dwellers. About 60 per cent of individual records overall and at the 25^{th} percentile, and up to 79 per cent of those at the 5^{th} percentile were drawn from the 2010 CLFS. Meanwhile, other percentiles contributed less than 50 per cent of the 2010 observations to the pooled survey.

5.2. Multinomial probit estimates of determinants of employment sector choice

The main employment sectors identifiable from the Cameroon labour force surveys are the public, private, informal and small-scale agricultural sectors. Small-scale agriculture was considered as the reference category in the estimation process. As indicated earlier, individual, household and regional characteristics influence reservation wages and expected earnings, hence determining the allocation of labour market participants into various employment sectors. It is worthwhile to note that the signs of the MNP may be misleading and different from those of the marginal effects. This arises because although the MNP uses the same set of characteristics in modelling determinants of allocation to various sectors of employment, coefficients from J-1 equations enter in the calculation of marginal effects and probabilities.

Table 2 (About here)

Table 2 hosts the multinomial probit coefficients and marginal effects of the determinants of allocation into broad employment sectors. The Wald test statistics reject the hypothesis of the equality of coefficients between any pair of employment sectors at the 1 per cent level of significance. This is indication of the heterogeneity of the various employment sectors in the labour market, thus justifying their inclusion into the wage generating function separately. The presence of other wage earners and children below six year old were used to instrument/identify the probit multiple choice model. The presence of children below six years old in the same household as the worker significantly reduces the probability of employment in both formal and informal sectors of employment by 0.7 per cent, 1.3 per cent and up to 3.4 per cent, respectively, for the public, private and informal sectors of employment, relative to small-scale agriculture,.

Table 2 also shows that education is statistically very important in informing choices related to selecting sectors of employment. In 2005, while an additional year of education increases the probability of working in the public sector by 1.7 and of working in the private sector by 1.2 per cent, it reduces the probability of working in the informal sector by 1.1 per cent relative to small-scale agricultural employment. This underscores the importance of education attainment in allocation to formal sector employment. Between 2005 and 2010, an additional year of schooling significantly increases the likelihood of participating in the informal sector of employment by 1.4 per cent relative to small-scale agriculture. Whereas experience increases the probability of engaging in formal sector work at a decreasing rate, it reduces the probability of informal sector employment by 3 per cent at a decreasing rate relative to participation in small-scale agriculture.

Marriage increases the probability of labour market participation. In particular, marriage increases the probability of public sector employment by about 4 per cent and that of private sector employment by 1.8 per cent relative to their unmarried counterparts. Female workers compared to their male counterparts are less likely to participate in formal sectors of employment. Being a female decreases the probability of public sector employment by 1.3 per cent and of private sector employment by 5.2 per cent. Being an urban resident relative to rural residency increases the probability of participating in the labour market relative to small-scale agriculture. In particular, urban dwelling increases the probability of working in the public sector by 0.9 per cent, of working in the private sector by 4.6 per cent and of working in the informal sector by up to 41.6 per cent relative to small-scale agricultural employment. This is indication that rural-urban migrants are more likely to join the ranks of informal sector worker, perhaps because this is the sector that is still generating work, even though of lower quality.

5.3. Determinants of earnings

Table 4 presents OLS and sector selectivity-corrected estimates of the structural wage equation, overall and across selected quantiles. In particular, Column 1 hosts the OLS estimates and Column 2 the sector selection-corrected estimates of the overall sample, meanwhile selection-corrected quantile regressions are presented in Columns 3-9.

Table 3 (About here)

Education correlates positively and significantly with log wage overall and across percentiles. Returns to education increase progressively from lower to upper percentiles. An average return of about 5.6 per cent for an additional year of schooling masks a return of only 2 per cent in the 5^{th} percentile and up to 9.6 per cent in the 95^{th} percentile. This gives a spread between the top and lower percentiles of 7.6 per cent per additional year of schooling. However, overall and lower percentiles (up to the 25^{th}) register positive and significant incremental returns to an additional year of schooling between 2005 and 2010 as depicted by the interaction of the year dummy and education. This incremental effect is diluted from the 50^{th} percentile upwards. This is an indication that educational expansion could have been pro-poor/inclusive between 2005 and 2010 among labour market participants in Cameroon. Indeed, total returns to education for the entire period 2005-2010 are highest for workers situated at the 5^{th} and 10^{th} percentiles – 10.5 per cent and 12.6 per cent for an additional year of schooling, respectively.

In this context, one may consider educational expansion as a powerful public policy intervention especially if poverty and inequality reduction are high in the policy menu. In this perspective, a more balanced distribution of education may result in a more balanced distribution of earnings between the poor and non-poor, assuming wages are the main source of income.

Table 4 also shows that sectors of employment are important determinants of earnings both overall and across percentiles. In particular, returns to both formal (public and private) and informal sector employment are positive and significantly higher for those at the bottom of the wage distribution than for those at the top. Indeed, returns by sector of employment decrease progressively from the 5^{th} to the 95^{th} percentiles for public, private and informal sectors relative to the small-scale agricultural sector employment.

At the bottom and top percentiles, experience has a non-linear relationship with log wage. Whereas experience has a U-shaped relationship with wages at the bottom percentile, it has an inverted U-shape at top percentiles. This implies that at lower percentiles, returns to experience decrease before eventually increasing, while at upper percentiles it increases before eventually decreasing. This may be reflecting the possibility that those at lower percentiles may be career beginners undergoing a probation period or a period of apprenticeship, while those at the top have reached their potentials.

Labour market related variables such as hours worked, access to fringe benefits and paid leave are positively and significantly related to log wage overall and across percentiles. Returns to hours worked are higher for those at the bottom of the wage distribution than for those at the top. While there is a premium for marriage on the average and for those at higher percentiles in the distribution of income relative to their unmarried counterparts, there is a premium for urban residency overall and among those at lower percentiles relative to their rural counterparts.

Second job holding significantly penalizes wages in the main occupation. This substitution effect implies that second job holding can only increase total earnings if it generates benefits that over compensate for the losses incurred in the main job.

In the overall wage regression, the inverse Mills ratio for public sector relates negatively with log wage, while that for private and informal sectors, relative to the small-scale agricultural sector, correlate positively and significantly with log wage. Significance of the negative selection term for public sector employment implies that earnings of a worker with average characteristics in the population is lower than for any worker who would be drawn randomly into the public sector. By the same token, the significance of the positive selection term for private or informal sector employment implies that earnings of a worker with average characteristics in the population is higher than for any worker who would be drawn randomly into the private or informal sector.

5.4. Impact of education on inequality along the wage distribution

The factual distribution of wages was portrayed in equation (9) and the counterfactual education-equalizing distribution of wages by quantile was derived in equation (10). In the latter case, wage earners are allocated the mean years of education, while allowing other variables as observed to simulate the counterfactual distributions of wages overall and by quantile. Inequality due to years of schooling is therefore eliminated from these counterfactual distributions. This indicates that inequality in the resulting counterfactual distributions of wages is entirely attributable to other observed and unobserved variables in the wage generating function. The variability in the factual distribution of wages depends on years of schooling, and the other observed and unobserved variables, whereas the variations in the counterfactual distributions of wages are attributable entirely to the unobserved and other observed variables excluding education.

Table 4 (About here)

As shown in Table 4, wage inequality as captured by the Gini coefficient is found to be 0.583 for the factual distribution and 0.544 for the overall counterfactual distribution of wages. The indication is that overall wage inequality decreases significantly by 0.039 points when inequality due to years of schooling is eliminated and the overall relative impact of education on wage inequality is 6.7 per cent. This overall finding mimics the relative and absolute impacts on wage inequality of equalizing years of schooling among the median workers. This average/median outcome tends to masks impacts along the wage distribution profile. The absolute (relative) impacts of education on measured wage inequality at the 10^{th}, 25^{th}, 75^{th}, and 90^{th} percentiles are 0.02 points (3.6 per cent), 0.03 points (5.7 per cent), 0.04 points (7.1 per cent) and 0.05 points (7.7 per cent), respectively (Table 4). These results show that observed schooling profiles have inequality increasing tendencies overall and at the various percentiles in the distribution of wages. The general observation is that the snowballing effect of observed years of schooling on inequality doubles as one moves from lower to upper percentiles in the distribution of wages.

Results by the generalized entropy class of inequality measures (for θ=0, θ=1 and θ=2) shown in Table 5 are basically transmitting similar messages overall and across percentiles in the distribution of wages. A general result is that inequality decreases from lower to upper percentiles in the counterfactual distributions – thus translating the inequality increasing effect of education in the factual distribution when moving up the wage distribution profile.

These results indicate that leveling the playing field in terms of schooling opportunities leading to an expansion in education could be an important public policy intervention when trying to reduce wage inequalities and poverty. In this context, a more balanced schooling profile may result in a more balanced distribution of labour market earnings.

Table 5 (About here)

6. Concluding remarks

This paper attempted to empirically enquire whether smoothening education was more inequality reducing at lower than upper tails of the wage distribution profile. The exercise was accomplished using pooled records from the 2005 and 2010 Cameroon labour force surveys collected by the government's statistics office. In particular, the paper investigated the determinants of employment sector choices; examined the nature of change in returns to education between 2005 and 2010 along the wage distribution; and evaluated the impact of education on measured inequality along the wage distribution profile.

By way of methodology, we followed a two-step econometrics estimation procedure and conducted factual and counterfactual experiments for impact assessment. In terms of econometrics, the first step regression involved the estimation of a multinomial probit model of employment sector choice. In the second step, a structural wage equation correcting for employment sector-selectivity bias was estimated at the mean and across selected quantiles of the wage distribution. Using estimates of the selectivity-corrected wage equations, factual and counterfactual experiments were designed. In particular, counterfactual distributions were simulated in which wage inequalities within quantiles were independent of variations in years of schooling. Inequalities computed by the Gini and the Generalized Entropy class of measures using the simulated factual and counterfactual distributions were compared to elicit the impact of education on inequality overall and along the wage distribution profile.

Multinomial probit estimates showed that the presence of other wage earners and children below six years old were relevant identifiers of the employment sector-choice model. The presence of young children in the same household as the worker unambiguously reduced participation in both formal and informal sectors of employment, while the presence of other wage earners significantly reduced participation in private sector employment. Results also indicated that, whereas an additional year of schooling increased the probability of working in the public sector by 1.7 and of working in the private sector by 1.2 per cent, it reduced the probability of working in the informal sector by 1.1 per cent relative to small-scale agricultural employment in 2005. Meanwhile, between 2005 and 2010, an additional year of schooling significantly increased the likelihood of informal sector employment by 1.4 per cent relative to small-scale agriculture. This underscores the importance of education attainment in allocation to various employment sectors. Marriage increased the probability of formal sector employment, while being a female worker reduced the probability of formal sector employment. Urban dwelling increased the probability of working in the public sector by 0.9 per cent, of working in the private sector by 4.6 per cent and of working in the informal sector by up to 41.6 per cent relative to small-scale agricultural employment. This is indication that rural-urban migrants are more likely to find informal sector work than formal sector employment.

Estimates of the sector selectivity-corrected structural wage equation showed that education correlates positively and significantly with log wage overall and across percentiles in 2005. Returns to education increased monotonically from lower to upper percentiles with a spread of about 7.6 per cent for an additional year of schooling between the top and bottom percentiles. Results from the overall regression and those from quantile regressions up to the 25th percentile registered positive and significant incremental returns to an additional year of schooling between 2005 and 2010 as depicted by the interaction of the year dummy and education. These incremental effects were diluted from the 50th percentile onwards. This is an indication that educational expansion was pro-poor or inclusive between 2005 and 2010 among labour market participants in Cameroon. Indeed, total returns to education for the entire period 2005-2010 were highest for workers situated at the 5th and 10th percentiles – 10.5 per cent and 12.6 per cent for an additional year of schooling, respectively. The implication of these findings is that educational expansion may be considered a powerful public policy intervention to galvanize those at the bottom of the wage distribution profile, especially if poverty and inequality reduction are high in the policy menu.

Labour market related variables such as hours worked, access to fringe benefits and paid leave were positively and significantly related to log wage overall and across percentiles. Returns to hours worked were higher for those at the bottom of the wage distribution than for those at the top. While there was a premium for marriage on the average and for those at higher percentiles in the distribution of income relative to their unmarried counterparts, there was a premium for urban residency overall and among those at lower percentiles relative to their rural counterparts.

In terms of the impact of education on inequality along the wage distribution profile, results showed that observed years of schooling had inequality increasing tendencies overall and at various percentiles in the distribution of wages. The general observation was that the snowballing effect of observed years of schooling on inequality doubled as one moves from lower to upper percentiles in the distribution of wages. This implies that inequality generally decreased from lower to upper percentiles in the counterfactual distributions – thus translating the inequality increasing effect of education in the actual distribution and the snowballing effect when moving up the wage distribution profile.

The implication of these findings is that leveling the playing field in terms of schooling opportunities leading to an expansion in education could be an important public policy intervention when trying to reduce inequality and poverty. In this context, a more balanced schooling profile may result in a more balanced distribution of labour market earnings. These findings indorse public policies that favour investments that increase quantity and quality of schooling.

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Table 1: Descriptive Statistics

Variables	Overall	5th Quant	10th Quant	25th Quant	50th Quant	75th Quant	90th Quant	95th Quant
Wages	63884.19	1813.55	6908.89	19278.56	46725.36	98707.76	185962.10	245428.80
	(97090.82)	(1287.22)	(1391.02)	(1209.77)	(2898.60)	(6205.31)	(15665.18)	(17716.49)
Log of wages	10.27	7.19	8.82	9.86	10.75	11.50	12.13	12.41
	(1.43)	(0.84)	(0.21)	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)
Education	6.73	5.47	4.35	6.00	6.39	7.95	9.79	10.74
	(4.23)	(3.34)	(3.68)	(3.62)	(3.84)	(4.07)	(4.19)	(4.67)
Education x Year dummy	4.27	4.71	2.29	4.18	3.75	3.37	3.90	6.52
	(4.79)	(3.76)	(3.60)	(4.27)	(4.47)	(5.09)	(5.99)	(6.83)
Public sector	0.06	0.01	0.01	0.02	0.03	0.10	0.33	0.34
	(0.25)	(0.11)	(0.09)	(0.13)	(0.16)	(0.30)	(0.47)	(0.47)
Private sector	0.04	0.00	0.01	0.00	0.06	0.10	0.11	0.14
	(0.21)	(0.05)	(0.10)	(0.06)	(0.23)	(0.30)	(0.31)	(0.34)
Informal sector	0.40	0.10	0.21	0.53	0.52	0.56	0.38	0.38
	(0.49)	(0.30)	(0.41)	(0.50)	(0.50)	(0.50)	(0.49)	(0.49)
Small-scale agriculture	0.49	0.89	0.77	0.45	0.40	0.24	0.18	0.15
	(0.50)	(0.32)	(0.42)	(0.50)	(0.49)	(0.43)	(0.39)	(0.35)
Hours worked	41.37	36.21	36.09	40.60	44.62	46.08	43.37	43.42
	(19.06)	(16.50)	(17.39)	(20.12)	(19.76)	(20.29)	(18.82)	(18.46)
Experience	8.94	14.19	10.02	9.10	8.50	6.73	8.27	8.71

	(9.58)	(11.75)	(10.03)	(10.07)	(9.09)	(8.20)	(8.43)	(8.53)
Experience squared	171.65	339.43	200.96	184.14	154.672	112.42	139.41	148.45
	(338.15)	(473.25)	(371.25)	(364.48)	(309.883)	(248.57)	(248.93)	(263.90)
marriage	0.47	0.65	0.57	0.47	0.46	0.44	0.48	0.58
	(0.50)	(0.48)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
female	0.52	0.54	0.57	0.53	0.42	0.43	0.43	0.40
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.5)0	(0.50)	(0.49)
Second job holding	0.05	0.04	0.07	0.07	0.07	0.11	0.08	0.05
	(0.22)	(0.20)	(0.26)	(0.26)	(0.26)	(0.31)	(0.27)	(0.23)
Fringe benefits	0.05	0.01	0.00	0.00	0.02	0.08	0.26	0.33
	(0.22)	(0.12)	(0.07)	(0.06)	(0.15)	(0.28)	(0.44)	(0.47)
Paid leave	0.06	0.01	0.00	0.01	0.05	0.11	0.26	0.36
	(0.24)	(0.10)	(0.05)	(0.09)	(0.23)	(0.32)	(0.44)	(0.48)
urban	0.42	0.09	0.13	0.34	0.42	0.56	0.67	0.68
	(0.49)	(0.29)	(0.34)	(0.47)	(0.49)	(0.50)	(0.47)	(0.47)
Year dummy	0.60	0.79	0.41	0.59	0.47	0.32	0.26	0.44
	(0.49)	(0.41)	(0.49)	(0.49)	(0.50)	(0.47)	(0.44)	(0.50)
IMR for public sector	0.60	0.61	0.61	0.61	0.61	0.60	0.59	0.58
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)
IMR for private sector	0.61	0.61	0.61	0.61	0.61	0.61	0.61	0.60
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
IMR for informal sector	0.56	0.58	0.57	0.55	0.55	0.54	0.55	0.56
	(0.05)	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)

Source: Computed by the author using the pooled 2005 and 2010 Cameroon Labour Force Surveys.

Notes: Means and standard deviations in parentheses. Quant is quantile.

Table 2: Determinants of allocations to alternative sectors of employment (Multinomial Probit Model)

VARIABLES	(1) Public		(2) Private		(3) Informal	
	Coefficients	Marginal Effects	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Education	0.299***	0.0172***	0.205***	0.0126***	0.0257***	-0.0113***
	(0.00731)	(0.000539)	(0.00675)	(0.000493)	(0.00454)	(0.00118)
Education x Year dummy	0.0487***	0.000938	0.0331***	-0.000169	0.0575***	0.0140***
	(0.0116)	(0.000635)	(0.0112)	(0.000709)	(0.00769)	(0.00193)
Experience	-0.00140	0.00401***	-0.0542***	0.000441	-0.109***	-0.0300***
	(0.00691)	(0.000409)	(0.00730)	(0.000501)	(0.00442)	(0.00117)
Experience squared	-2.05e-05	-5.81e-05***	0.000633**	-1.54e-05	0.00153***	0.000427***
	(0.000223)	(1.33e-05)	(0.000251)	(1.77e-05)	(0.000135)	(3.69e-05)
marriage	0.700***	0.0405***	0.370***	0.0178***	0.144***	0.000931
	(0.0422)	(0.00292)	(0.0420)	(0.00293)	(0.0278)	(0.00718)
female	-0.336***	-0.0130***	-0.788***	-0.0516***	-0.110***	0.0109
	(0.0409)	(0.00229)	(0.0430)	(0.00278)	(0.0259)	(0.00678)
urban	1.316***	0.00964***	1.801***	0.0462***	1.871***	0.416***
	(0.0423)	(0.00214)	(0.0442)	(0.00263)	(0.0269)	(0.00615)
Year dummy (d2010)	-0.850***	-0.0227***	-0.974***	-0.0362***	-0.738***	-0.151***
	(0.123)	(0.00684)	(0.113)	(0.00717)	(0.0621)	(0.0163)
Other wage earners	0.00510	0.000357	-0.0208***	-0.00170***	0.00259	0.00145
	(0.00701)	(0.000411)	(0.00682)	(0.000464)	(0.00421)	(0.00110)
Children < 6 years	-0.227***	-0.00651*	-0.282***	-0.0128***	-0.188***	-0.0343***

	(0.0593)	(0.00365)	(0.0607)	(0.00457)	(0.0400)	(0.0101)
Constant	-3.993***		-2.580***		0.156***	
	(0.109)		(0.100)		(0.0607)	
Wald Chi2 [df; p-val]	10877.04					
	[30; 0.00]					
Log likelihood	-19330.01					
Pr(predict)		0.03671584		0.04474397		0.59213254
Observations	24.383		24.383		24.383	

Source: Computed by the author using the pooled 2005 and 2010 Cameroon Labour Force Surveys.

Notes: Small-scale agriculture is the based sector of employment. Standard errors in parentheses.
*** p<0.01. ** p<0.05. * p<0.1 .
Pr(Small-scale agriculture employment(Base group)) = 0.32640764.

Table 3: Determinants of Wages Overall and along Selected Quantiles

VARIABLES	OLS (1)	Corrected for Sector Selection Bias: Overall (2)	Qreg(0.05) (3)	Qreg(0.1) (4)	Qreg(0.25) (5)	Qreg(0.5) (6)	Qreg(0.75) (7)	Qreg(0.9) (8)	Qreg(0.95) (9)
Education	0.0521***	0.0566***	0.0203*	0.0347***	0.0417***	0.0626***	0.0714***	0.0885***	0.0961***
	(0.00273)	(0.00329)	(0.0107)	(0.0112)	(0.00657)	(0.00436)	(0.00712)	(0.00801)	(0.00823)
Education x d2010	0.0233***	0.0152***	0.0846***	0.0915***	0.0240***	-0.00442	-0.00748	-0.00684	-0.0116
	(0.00374)	(0.00384)	(0.0100)	(0.0115)	(0.00691)	(0.00468)	(0.00791)	(0.00937)	(0.00975)
Public sector	1.001***	0.979***	1.916***	1.640***	1.125***	0.984***	0.647***	0.389***	0.239***
	(0.0403)	(0.0405)	(0.119)	(0.156)	(0.0806)	(0.0487)	(0.0763)	(0.0840)	(0.0928)
Private sector	0.981***	0.993***	1.597***	1.531***	1.128***	0.949***	0.687***	0.529***	0.528***
	(0.0400)	(0.0400)	(0.134)	(0.119)	(0.0649)	(0.0423)	(0.0675)	(0.0798)	(0.0799)
Informal sector	0.722***	0.724***	1.358***	1.263***	0.804***	0.634***	0.423***	0.376***	0.421***
	(0.0204)	(0.0205)	(0.0758)	(0.0726)	(0.0423)	(0.0282)	(0.0482)	(0.0575)	(0.0716)
Hours worked	0.00670***	0.00678***	0.00855***	0.00937***	0.00773***	0.00583***	0.00485***	0.00497***	0.00307***
	(0.000413)	(0.000412)	(0.00143)	(0.00137)	(0.000793)	(0.000490)	(0.000778)	(0.000928)	(0.00110)
Experience	0.0149***	-0.00754**	-0.0316**	-0.00748	-0.0211***	-0.00712	-5.20e-05	0.0292***	0.0287**
	(0.00246)	(0.00371)	(0.0126)	(0.0125)	(0.00723)	(0.00498)	(0.00831)	(0.00986)	(0.0114)
Experience squared	-0.000288***	0.000117	0.000644**	0.000185	0.000332*	0.000172	-6.50e-05	-0.000586***	-0.000627**
	(6.85e-05)	(8.43e-05)	(0.000283)	(0.000280)	(0.000173)	(0.000120)	(0.000188)	(0.000216)	(0.000246)
marriage	0.0672***	0.0528***	-0.000189	0.0851	0.0833***	0.0789***	0.0579*	0.117***	0.137***
	(0.0158)	(0.0163)	(0.0503)	(0.0522)	(0.0306)	(0.0201)	(0.0334)	(0.0392)	(0.0466)
female	-0.140***	-0.191***	-0.248***	-0.237***	-0.259***	-0.150***	-0.150***	-0.141***	-0.201***
	(0.0156)	(0.0167)	(0.0536)	(0.0543)	(0.0328)	(0.0219)	(0.0355)	(0.0414)	(0.0464)
Second job holding	-0.176***	-0.174***	-0.156**	-0.127*	-0.153***	-0.142***	-0.151***	-0.147**	-0.0999
	(0.0281)	(0.0280)	(0.0759)	(0.0744)	(0.0510)	(0.0341)	(0.0551)	(0.0674)	(0.0877)
Fringe benefits	0.346***	0.321***	0.121	0.410***	0.463***	0.341***	0.299***	0.330***	0.332***
	(0.0417)	(0.0420)	(0.135)	(0.124)	(0.0672)	(0.0436)	(0.0722)	(0.0823)	(0.0944)
Paid leave	0.349***	0.325***	0.700***	0.585***	0.369***	0.281***	0.159**	0.0287	0.0134
	(0.0386)	(0.0386)	(0.133)	(0.119)	(0.0625)	(0.0402)	(0.0618)	(0.0642)	(0.0719)
urban	0.295***	0.728***	1.457***	0.946***	0.914***	0.628***	0.531***	0.194	0.259
	(0.0194)	(0.0577)	(0.207)	(0.189)	(0.0988)	(0.0669)	(0.116)	(0.141)	(0.157)
Year dummy	-0.865***	-0.877***	-1.906***	-1.756***	-0.838***	-0.518***	-0.516***	-0.556***	-0.525***
	(0.0307)	(0.0320)	(0.0907)	(0.104)	(0.0614)	(0.0412)	(0.0682)	(0.0762)	(0.0854)
IMR for public sector		-1.768**	7.874**	1.420	-3.626***	-2.974***	-3.203**	-3.237*	-1.516
		(0.729)	(3.085)	(2.728)	(1.393)	(0.850)	(1.391)	(1.654)	(1.684)
IMR for private sector		39.06***	41.60***	37.53***	44.47***	39.38***	31.97***	20.91**	29.29***
		(4.165)	(10.43)	(10.98)	(6.196)	(4.197)	(7.114)	(8.412)	(8.780)
IMR for informal sector		4.429***	9.163***	4.326**	5.967***	4.219***	3.382***	-0.522	0.973
		(0.610)	(2.147)	(1.976)	(1.045)	(0.704)	(1.194)	(1.385)	(1.546)
Constant	9.422***	-15.70***	-27.80***	-18.37**	-19.35***	-15.02***	-9.133*	0.223	-6.357
	(0.0316)	(2.910)	(8.454)	(8.182)	(4.521)	(3.032)	(5.093)	(5.986)	(6.217)
Observations	22.801	22.801	22.801	22.801	22.801	22.801	22.801	22.801	22.801
R2/Pseudo R2	0.325	0.328	0.2916	0.2461	0.1945	0.1900	0.1919	0.1757	0.1446

Source: Computed by the author using the pooled 2005 and 2010 Cameroon Labour Force Surveys.

Notes: IMR is inverse Mills ratio. Standard errors in parentheses. *** p<0.01. ** p<0.05. * p<0.1. Qreg(.)= the Q-th Quantile regression.

Table 4: Gini Inequality Impacts of Equalizing years of Education within selected Quantiles

Group Variable	Gini Index		Inequality Impact:
	Factual	Counterfactual	$\Delta I\ [\Theta_I\,\%]$
Quantile (0.05)	0.5833	0.5624	0.0209*** (0.0019)
	(0.0039)	(0.0042)	[3.58]
Quantile (0.10)	0.5833	0.5623	0.0209*** (0.0022)
	(0.0039)	(0.0042)	[3.58]
Quantile (0.25)	0.5833	0.5502	0.0331*** (0.0016)
	(0.0039)	(0.0043)	[5.67]
Quantile (0.50)	0.5833	0.5442	0.0390*** (0.0018)
	(0.0039)	(0.0044)	[6.69]
Quantile (0.75)	0.5833	0.5420	0.0413*** (0.0020)
	(0.0039)	(0.0044)	[7.08]
Quantile (0.90)	0.5833	0.5387	0.0446*** (0.0025)
	(0.0039)	(0.005)	[7.65]
Quantile (0.95)	0.5833	0.5390	0.0443*** (0.0027)
	(0.0039)	(0.005)	[7.59]
Cameroon	0.5833	0.5444	0.0389*** (0.0019)
	(0.0039)	(0.0044)	[6.67]

Source: Computed by the author using the pooled 2005 and 2010 Cameroon Labour Force Surveys, the overall and quantile regression results correcting for sector choice selection bias, descriptive statistics in Table 1 and DASP 2.1 in Stata 10.1.
Note: (.) denote standard error and [.] denote relative contribution/impact. The counterfactual distribution is the wage distribution in which years of schooling are equalized at the mean values within the selected quantiles. ΔI is absolute change in inequality.

Table 5: Generalized entropy inequality impacts of equalizing years of Education within selected Quantiles

Inequality index/ Wage Quantiles	Generalized Entropy Indices		Inequality Impact: $\Delta I\ [\Theta_I\ \%]$
	Factual	Counterfactual	
Generalized Entropy ($\theta=0$)			
Quantile (0.05)	0.7434 (0.0114)	0.6852 (0.0114)	0.0581*** (0.0043) [7.82]
Quantile (0.10)	0.7434 (0.0114)	0.6859 (0.0114)	0.0574*** (0.0052) [7.72]
Quantile (0.25)	0.7434 (0.0114)	0 .6603 (0.0112)	0.0830*** (0.0034) [11.16]
Quantile (0.50)	0.7434 (0.0114)	0.6479 (0.0112)	0.0954*** (0.0037) [12.83]
Quantile (0.75)	0.7434 (0.0114)	0.6430 (0.0112)	0.1003*** (0.0020) [13.49]
Quantile (0.90)	0.7434 (0.0114)	0.6354 (0.0114)	0.1079*** (0.0025) [14.51]
Quantile (0.95)	0.7434 (0.0114)	0.6366 (0.0114)	0.1067*** (0.0056) [14.35]
Cameroon	0.7434 (0.0114)	0.6472 (0.0113)	0.0961*** (0.0040) [12.93]
Generalized Entropy ($\theta=1$)			
Quantile (0.05)	0.6354 (0.0116)	0.5943 (0.0130)	0.0410*** (0.0059) [6.45]
Quantile (0.10)	0.6354 (0.0116)	0.5938 (0.0128)	0.0415*** (0.0066) [6.53]
Quantile (0.25)	0.6354 (0.0116)	0.5573 (0.0127)	0.0780*** (0.0051) [12.28]
Quantile (0.50)	0.6354 (0.0116)	0.5423 (0.0127)	0.0931*** (0.0057) [14.65]
Quantile (0.75)	0.6354 (0.0116)	0.5380 (0.0129)	0.0973*** (0.0063) [15.31]
Quantile (0.90)	0.6354 (0.0116)	0.5337 (0.0134)	0.1016*** (0.0078) [15.99]
Quantile (0.95)	0.6354 (0.0116)	0.5353 (0.0134)	0.1000*** (0.0083) [15.74]
Cameroon	0.6354 (0.0116)	0.5442 (0.0044)	0.0911*** (0.0061) [14.34]
Generalized Entropy ($\theta=2$)			
Quantile (0.05)	1.0929 (0.0405)	1.0439 (0.0486)	0.0489*** (0.0226) [4.47]
Quantile (0.10)	1.0929 (0.0405)	1.0373 (0.0474)	0.0556*** (0.0247) [5.09]
Quantile (0.25)	1.0929 (0.0405)	0.9150 (0.0456)	0.1778*** (0.0217) [16.27]
Quantile (0.50)	1.0929	0.8726	0.2203*** (0.0245)

	(0.0405)	(0.0451)	[20.16]
Quantile (0.75)	1.0929	0.8666	0.2263*** (0.0266)
	(0.0405)	(0.0455)	[20.71]
Quantile (0.90)	1.0929	0.8700	0.2229*** (0.0322)
	(0.0405)	(0.0481)	[20.40]
Quantile (0.95)	1.0929	0.8779	0.2150*** (0.0339)
	(0.0405)	(0.0480)	[19.67]
Cameroon	1.0929	0.8850	0.2079*** (0.0257)
	(0.0405)	(0 .0470)	[19.02]

Source: Computed by the author using the pooled 2005 and 2010 Cameroon Labour Force Surveys, the overall and quantile regression results correcting for sector choice selection bias, descriptive statistics in Table 1 and DASP 2.1 in Stata 10.1.
Note: (.) denote standard error and [.] denote relative contribution/impact. The counterfactual distribution is the wage distribution in which years of schooling are equalized at the mean values within the selected quantiles. ΔI is absolute change in inequality.