Determinants of Inequality in Cameroon: A Regression-Based Decomposition Analysis

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Abstract

This paper applies the regression-based inequality decomposition approach to explore determinants of income inequality in Cameroon using the 2007 Cameroon household consumption survey. The contribution of each source to measured income inequality is the sum of its weighted marginal contributions in all possible configurations of sources as sanctioned by the Shapley value decomposition rule. Regressed-income sources attributable to education, health, urban residency, household size, fraction of active household members, working in the formal sector and farmland ownership are the main determinants of household income inequality in that order. These results have policy vocation that policy-mix that simultaneously combine efforts targeting human capital consolidation with other policy outlets will have an overall higher effectiveness for both total welfare enhancement and human capital development than when implemented alone.

Keywords: Decomposition, Inequality, household Economic well-being and Cameroon.
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Introduction

Conventional decompositions by factor components or population subgroups may provide limited information on the determinants of income inequality (Wan and Zhou, 2005). The regression-based decomposition (RBD) analysis can shed more light to our understanding of factors that determine income inequality (Oyekale et al, 2007; Epo et al., 2011). Difficulties associated to the RBD analysis linked to carrying out an exact decomposition of the estimated sources including the error term, putting aside the functional form or the inequality index adopted have been resolved by Wan (2002; 2004).

This paper decomposes measured household income inequality into the different estimated sources and the error term simultaneously using the Shapley value (Shapley, 1953) procedure. In this regard, the marginal contributions of the estimated-income sources and the error term are computed based on the decomposition framework proposed by Shorrocks (1999). This procedure was implemented with the Distributive Analysis Stata Package (DASP 2.1) (Araar and Duclos, 2009) slotted in STATA 10.

Another value addition of this paper is the construction and use of synthetic variables for education and health that carry multiple aspects subsumed as composite variables. They also translate the key role human capital characteristics (Becker, 1967, Grossman. 1972) play regarding household utility and production functions, and therefore household economic well-being.

Despite a fall in the incidence of poverty between 1996 and 2001, following the increase in the period 1984-1996, inequality has, at best, stagnated in Cameroon (Araar, 2006; INS, 2004; 2005). Overall, between 2001 and 2007 total inequality slightly declined from 0.408 to 0.390, retreating more in cities than rural areas. In terms of inequality decomposition by subgroups, Baye (2008) found under different dimensions and indicators that within group components overwhelmingly accounted for inequality compared to the between group components. However, the main shortcoming of such analyses is that they fail to identify and quantify the fundamental determinants of either of the two components. Thus we appeal to sources that significantly explain household welfare and its redistribution.

The main objective of this paper is to use the regression-based decomposition approach to explore determinants of income inequality in Cameroon using the 2007 Cameroon household survey. Specifically, it (1) estimates factor-endowments that significantly explain household economic well-being and (2) decomposes the relative importance of estimated-income sources vis-à-vis the residual in accounting for measured income inequality. The rest of the paper is organized in five sections. Section 2 gives a review of the literature. Section 3 dwells on the methodology, and the data and variables of interest are explored in Section 4. Section 5 presents the empirical results and Section 6 concludes the paper.

Review of literature

Regression-based inequality decomposition measurement can be traced back to Oaxaca (1973) and Blinder (1973). In the early 1990s, Juhn et al. (1993) applied this approach to allow for the decomposition of between-group differences in the full wage distribution. Bourguignon et al. (2001; 2008) relaxed the requirement of a linear income-generating function of Juhn et al. (1993). DiNardo et al. (1996) and Deaton (1997) respectively proposed semi-parametric and non-parametric techniques that sought to model and compare the whole distribution of income in terms of density functions. Fields and Yoo (2000) and Morduch and Sicular (2002) developed a framework for inequality decomposition, which is an extension of Shorrocks (1999) approach based wholly and directly on conventional regression equations. This was later extended by Wan (2004) to reveal the enormous flexibility and accommodating characteristics of the RBD approach.

A range of different applications of the regression-based income inequality decomposition literature exist (Yuko et al., 2006; and Kimhi, 2007). Wan (2002; 2004), however, noted that most regression-based income inequality decompositions usually ignored or incorrectly treated the constant and the residual terms. Although the error term or its estimated counterpart is a white noise by definition, its presence or absence does result in different income density functions and thus influences income distribution and measured inequality. The value added of including this term in decomposition analysis is that it indicates the proportion of the contribution of sources which are not captured by the income generating function when explaining inequality.

Research on regression-based income inequality decomposition analysis is just beginning to gain prominence in SAA. Among these efforts, one can cite Alayande (2003) and Oyekale et al. (2007) who applied this analysis to Nigerian data. In the case of Cameroon, only the attempt by Tabi (2009) has been made to the best of our knowledge. In spite of these attempts, including synthetic variables, controlling for potential endogeneity, unobserved heterogeneity and using survey-based linear models, as well as computing the share of regressed-income sources simultaneously with the predicted residual to measured income inequality via marginal contributions as sanctioned by the Shapley value decomposition rule are the value additions of this paper.

Methodology

We briefly exposed the econometric model we intend to estimate before exploring the regression-based inequality decomposition framework.

Regression model

To generate reliable parameter estimates needed for the inequality decomposition exercise, we have to assume that both health and education are jointly and simultaneously determined with household welfare, thus we present health and education separately in the household income generating function that follows:

$$Y = w_1\delta_y + \sum_{k=1}^{2}\eta_k HC_k + \varepsilon_1 \qquad (1)$$

where, Y and HC_k, are household economic wellbeing and endogenous determinants of wellbeing such as health and education; w_1 is a vector of exogenous covariates such as individual, household, and community characteristics; δ_y is a vector of parameters including the constant term and those of exogenous explanatory variables that correlate with the income generating function to be estimated; η_k are parameters of the potential endogenous explanatory variables (health and education) in the economic wellbeing function; and ε_1 is the error term.

Since health and education are endogenous, we identify potential instruments. These are justified in the section on Data. We then derive the reduced form equation of household demand for health and education that accommodates such instrumental variables. To account for the potential endogeneity and heterogeneity of responses of unobservable variables, Equation 1 can be augmented to Equation 2, which is the control function model of interest.

$$Y = w_1\delta_y + \sum_{k=1}^{2}\eta_k HC_k + \sum_{k=1}^{2}\alpha_k\hat{\varepsilon}_{2k} + \sum_{k=1}^{2}\lambda_k(\hat{\varepsilon}_{2k} * HC_k) + \varepsilon \tag{2}$$

where, $\hat{\varepsilon}_{2k}$ is fitted residual of an endogenous input, derived from the reduced form model. The predicted residual, $\hat{\varepsilon}_{2k}$, serves as the control for unobservable variables that correlate with HC_k, thus allowing these endogenous inputs to be treated as if they were exogenous covariates during estimation; $\sum_{k=1}\lambda_k(\hat{\varepsilon}_{2k} * HC_k)$ is the interaction of the predicted residuals with the actual values of each of the potential endogenous variables; ε is a composite error term comprising ε_1 and the unpredicted part of ε_2, and δ, η, α and λ are parameters to be estimated.

Regression-based inequality decomposition framework

Given the vector of consistently estimated parameters ($\hat{\beta}$), total income can be expressed as a sum of the estimated-income source flows and the predicted error term ($\hat{\varepsilon}$) as in equation. Since the econometric results yield estimates of the income source flows attributed to household variables, they allow us to make use of decomposition by income sources (or factor endowments). By construction, total income is the sum of these estimated income source flows (plus the predicted regression residual):

$$y_i = \sum_{m=0}^{M+1}\ddot{\hat{y}}_{i,m} \tag{3}$$

where $\ddot{\hat{y}}_{i,m} = \hat{\beta}_m x_{i,m}$ for m=0,1, 2, …, M and $\ddot{\hat{y}}_{i,m} = \hat{\varepsilon}_i$ for m=M+1. We obtain the share of inequality attributable to the income source, $\ddot{\hat{y}}_{i,m}$ as:

$$S_m = \frac{\hat{\beta}_m \sum_i a_i(y)x_{i,m}}{I(y)} \tag{4}$$

$\hat{\beta}_m$ is estimated coefficient associated with income source m, $x_{i,m}$ is the income source m attributable to household *i*, $\sum_i a_i(y)$ is the sum of weights attributable to households and, *I(y)* is the total income inequality index. Using $I(\cdot)$ as an inequality measure, then overall income inequality can be decomposed into the contribution of the constant term $I(y_0)$, the contribution of the estimated income sources and the contribution of the predicted residual.

In general, there are two main approaches for the decomposition of total inequality by income sources: the analytical approach and the Shapley value approach. In terms of inequality indices, we use the Gini coefficient. We also use the Shapley value to generate the expected components of the different income sources $I(\tilde{y})$ that account for inequality in terms of marginal contributions (Shorrocks, 1999).

The Shapley decomposition rule takes its roots in the domain of the cooperative game theory. The aim of this decomposition ties down with the classic question in cooperative game theory, which is how a certain amount of output (or cost) is shared among the set of contributors. Shapley (1953) proposed Shapley decomposition rule, which is a concept in cooperative game theory. The Shapley value for player (factor) k, denoted by, $C_k^{sh}(k, v)$ is defined as the weighted mean of player (source) k's marginal contribution $v(S \cup \{k\}) - v(S)$ over the set of coalitions, $K - \{k\}\, and\, k \notin S$. According to Shorrock (1999) the general decomposition problem turns out to be formally equivalent to the Shapley value, thus referred to as the Shapely decomposition.

Data and Variables of Interest

The data used in this study is the 2007 Cameroon household consumption survey (CHCS III). The targeted sample consisted of 12, 000 households of which 11391 were effectively visited. Data used for this analysis comprises both observed and synthetic variables. Based on the observed data obtained from the CHCS III household survey, the following variables were selected. The dependent variable considered as a proxy for income or production or well-being was household expenditure per capita. This variable is derived by dividing the total household expenditure by the number of individuals living in the household. The assumption with this variable is that there are no economies of scale in the household. The following independent variables were considered. Household size indicated the number of people living in a particular household at a given point in time. Age of household head indicates the age of the household head at the time of the survey. Fraction of active household members was generated as the proportion of active and working adults living in the household. The variable working in the formal sector was constructed to indicate that the household head is employed in the formal sector. The variable owning farmland indicates households in which the household head owns exploitable farmland and most farmland is inherited or owned communally. In terms of geography, urban areas were chosen, excluding rural areas and semi-urban areas to avoid perfect collinearity.

Variables instrumenting for education and health were related to access to information technology and housing quality - ownership of television, radio, and number of sleeping rooms. These values are captured at cluster level and expressed as cluster means. The idea here is that a given household cannot influence a societal variable (community variable), thus considering the cluster means in each primary sampling unit reduces potential endogeneity (Baye and Epo, 2009; Mwabu, 2009). The choice of the first two variables indicate the key role of communication in affecting education (Bailey, 2009; Fedotova, 2008) and health (Jackson et al., 1998; International Institute of Communication and Development (IICD) health sector report, 2008). The number of rooms reflects the role of adequate housing on health (WHO Regional Office for Europe's Health Evidence Network, 2005; Douglas et al., 2003) and educational outcomes (Cheshire and Sheppard, 2002). Concerning the first two variables, one could argue that access to information channeled by radios and televisions owned by households will positively impact on education and health. The last variable shows the important role of housing quality on education and health. The main idea vehicle here is inspired from Becker (1962).

We constructed synthetic variables for education and health by the multiple correspondence analysis (MCA) method that captures the multidimensional notion of health and education. Moreover, as noted by Thomas (2001), it is widely recognized that health is multidimensional - reflecting the combination of an array of factors that include physical, mental and social well-being, genotype and phenotype influences, as well as expectations and information. Education is also multidimensional and includes amount of time spent in school, nature of the curriculum, quality of schooling at each stage, extent of learning in school, post-schooling training and skill acquisition. Modalities used to construct each of these synthetic variables included a wide range of questions that capture their multidimensional character and translate more public policy relevant information. (See, Appendix 1). The ordering of the various scores were generated and normalized to treat for the presence of negative values which may cloud the classification of observations and interpretation of results[2].

[2] See Epo and Baye (2011) for a more complete discussion of the procedure and results of the MCA indexes for education and health.

Variables selected for our empirical work with their sample means and standard deviations are hosted in Table 1.

Empirical results

Descriptive statistics

Weighted descriptive statistics for the CHCS III survey indicated that 17.8 million people lived in Cameroon in 2007 (Table 1). The statistics identify that 55% of the total population live in rural areas and 35% in urban areas. The average age of household head was 44 years. Descriptive statistics indicate that 79 percent of the household interviewed were male. Sixty percent of households interviewed own farmland. In rural areas 20 percent of the households interviewed were headed by women, and 78% of these household owned or exploited farmland. In urban areas, 23% of the total populations interviewed are women. Averagely, households had six members. On average, one-fifth of household members were active and working. Regarding the formal sector, 15% of household heads worked in the formal sector. 52.54% of households own a radio, while about 33% of household own a television in the general population. The cluster means of owning a radio and television were 0.38 and 0.53, respectively. For the number of rooms this value was 2.36.

Table 1: Weighted Descriptive Statistics

Variable	Mean	SD	Min	Max
Log Total Expenditure Per Head	12.427	0.6914	11.1852	16.244
Education *	1.0251	0.3762	0.04123	1.5352
Health*	0.6790	0.3878	0	1.4839
Household Size	6.4763	3.9868	1	43[1]
Age of household head	44.395	14.279	11	99
Gender (1=male and 0=otherwise)	0.7907	0.4067	0	1
Fraction of Active Household Members	0.2090	0.1865	0	1
Formal Sector (1= yes and 0=otherwise)	0.1481	0. 3552	0	1
Own Farmland (1= yes and 0=otherwise)	0.6075	0.4883	0	1
Regions				
Urban	0.3531	0.4779	0	1
Semi-Urban	0.0973	0.2965	0	1
Rural	0.5593	0. 4964	0	1
Instruments for composite variables for education and health				
Household own Television (cluster mean)	0.3896	0.3049	0	1
Household own Radio (cluster mean)	0.5314	0.1983	0	1
Number of rooms (cluster mean)	2.3668	0.9694	1	11.1818
Control for Unobservable variables				
Education residual	$-2.02{*}e^{-11}$	0.2754	-1.1596	0.7809
Health residual	$2.05{*}e^{-10}$	0.3737	-0.8223	0.9447
Education times its residual	0.0758	0.2684	-0.6491	1.1544
Health times its residual	0.1396	0.3160	-0.2791	1.3052

Source: Computed by Authors using CHCS III (2007) and STATA 10. Notes: Variables with stars are synthetic variables obtained from the MCA. Weights used are analytical weights. Sample size for all variables is 17.8 million.

The descriptive statistics of the different modalities used to construct the synthetic variables were also computed. For instance, for the composite variable health, the average time to get to the nearest health district is 35mins. The average distance to the nearest health district is 2.8 kilometers. Over 56% of households chose to consult traditional doctors compared to 8% that visit health districts when they are sick. As for education, average distance to the nearest public school is less than a kilometer. For the nearest private school the distance is between 1 and 2 kilometers. The average time to get to the nearest public school is 25 minutes. To get to the nearest private schools, needs, on average, 35 minutes. 77% of household heads have at least gone to school. 71 % of household heads can read and write (NIS, 2007, 2008).

Regression Results

Table 2 hosts the OLS, the two stage least square (IV 2SLS) and the control function estimates. Findings may suggest that the IV 2SLS and Control function approach produce more robust results than the Ordinary Least Square approach because they account for the potential endogeneity bias. This observation indicates the importance of properly estimating the structural parameters to correctly attribute effects for policy guidance. Furthermore, the fitted residual of the composite variables for education and health in the Control Function Approach estimates significantly reduces expenditure. This entails an endogenous relation that negatively affects expenditure patterns of household members. Controlling for non-linear interactions between education and unobservables, the interaction term was significant for education. However, this interaction term for health was not significant.

Table 2: Determinants of Household Economic Well-being - Dependent variable is log of household expenditure per head

Variable	Ordinary Least Square (1)	Two-Stage Least Squared (2)	Control function excluding interaction term (3)	Control function including interaction term (4)
Endogenous variables				
Education	0.3133***	1.2486***	1.2486***	1.2732***
	(19.98)	(15.07)	(21.60)	(21.83)
Health	0.2000***	1.0817***	1.0817***	1.0665***
	(16.23)	(6.02)	(8.63)	(8.50)
Included Exogenous variables				
Household Size	-0.0267***	-0.0243***	-0.0243***	-0.0241***
	(-18.31)	(-10.12)	(-14.51)	(-14.39)
Age	0.0011***	0.0021**	0.0021***	0.0022***
	(3.24)	(2.21)	(3.17)	(3.28)
Gender (Male=1 and 0=otherwise)	0.0358***	0.1705***	0.1705***	0.1688***
	(3.04)	(6.01)	(8.61)	(8.53)
Fraction of Active Household members	0.9192***	0.9945***	0.9945***	0.9983***
	(30.41)	(23.30)	(33.40)	(33.52)
Formal Sector (1= yes and 0=otherwise)	0.3436***	0.1108***	0.1108***	0.1114***
	(24.65)	(5.09)	(7.29)	(7.33)

Household own farmland (1= yes and 0=otherwise)	-0.1289***	-0.0190	-0.0190	-0.0194*
	(-10.88)	(-1.12)	(-1.61)	(-1.64)
Urban area	0.4432***	0.0663**	0.0663***	0.0651***
	(34.32)	(2.54)	(3.64)	(3.57)
Constant	11.7432***	10.1082***	10.1082***	10.0685***
	(387.07)	(121.5)	(174.13)	(170.11)
Control function variables				
Predicted residual Education			-1.1281***	-1.2687***
			(-18.81)	(-16.96)
Predicted residual for Health			-0.9116***	-0.9660***
			(-7.72)	(-7.33)
Education times its predicted residual				0.1305***
				(3.12)
Health times its predicted residual				0.0838
				(1.51)
R-Squared	0.4929		0.5397	0.5402
Centred/Adjusted R-squared	0.4925	0.9971	0.5392	0.5398
Fisher Test [p-value]	1229.2; [0.000]	705.3; [0.000]	1212; [0.000]	1028; [0.000]
Partial R-Squared for Education		0.1379		
Test of excluded instruments: F-stat[p-value]		606; [0.00]		
Partial R-Squared for Health		0.0181		
Test of excluded instruments: F-stat[p-value]		70.08; [0.00]		
Test of Joint Significance of Identifying Variables/Cragg-Donald weak Identification test				
F-Stat [10 % Relative Bias]		32.93 [13.43]		
Underidentification tests (Aderson canon corr. LR statistics)				
Chi-Sq [p-value]		98.45; [0.00]		
Sargan statistics (Overidentification test of all instruments)				
Chi-Sq (1) [p-value]		0.485; [0.487]		
Endogeneity test of endogenous regressors				
Chi-Sq (2) [p-value]		1050; [0.00]		
Number of Observation	17.8 million million	17.8 million	17.8 million	17.8

Source: Computed by Authors using STATA 10. Notes: ***, ** and * are 1, 5 and 10 percent significance levels, respectively. Variables in parenthesis are t-student values. Sampling weights are used and the standard errors are adjusted for survey design. Weights used are analytical weights.

We also test for the relevance, strength and exogeneity of instruments (Table 2; column 2). According to Shea (1997), the first-stage F statistic and the partial R^2 convey vital information as to the validity and relevance of instruments in the case of a single endogenous variable. The first-stage F statistic on excluded instruments are 606 and 70.8, respectively (p-value=0.000) for the synthetic variables for education and health. The Cragg–Donald statistic is needed to assess the strength of excluded instruments (Stock and Yogo, 2004). This value was 32.9, greater than the Stock-Yogo weak ID test critical values: 10% maximal IV relative bias of 13.34. Tests at the bottom of Table 2 also show the education and health are indeed endogenous (Durbin-Wu-Hausman Chi-square Statistic = 1050, p-value=0.00) which indicates that the OLS estimates are not reliable for inference, implying that the IV estimates are preferred. Lastly, as shown in Column 2 of Table 2, the Sargan Chi-sq test statistic of 0.487 (p-value= 0.485) casts no doubt on the validity of the excluded instruments. This is indication that excluded instruments are justifiably excludable, that is, are appropriately independent of the error process.

Table 2, Column 4 reveals that education and health associate positively with household welfare. Access to better education enhances knowledge and choices made in the face of employment opportunities, production and labour market exigencies, which improve household income. This finding corroborates the result obtained by Awoyemi and Adekanye (2003) for Nigeria; Morduch and Sicular (2002) for China and Maria and Jose (2008) for Cape Verde. In terms of health, the ability to access a district health center, short distances to these centers and quality services imply that these variables are likely to be positively associated with better handling of ill-health that might prevent individuals from undertaking income generating activities. In addition, economies of scale are generated from good health in terms of more labour market participation because health implies fewer sick days per annum.

Table 2 also hosts non-synthetic variables that correlate positively with household economic welfare. These variables are age of the household head, fraction of active household members, working in the formal sector and being a male household head. Working in the formal sector implies having a steady source of income, as well as other advantages like being able to borrow money and to have an adequate insurance policy. These tend to positively impact on household economic well-being.

The fraction of active household members (the ratio of active household members to the household size) contributes positively to household income through the reasoning that an increase in the number of individuals in a given household undertaking income generating activities entails greater income generation with positive effects on household economic welfare. This result is similar to that obtained by Yuko et al. (2006) for farm households in Korea. Age correlates positively with household welfare at the 1% level. This finding is similar to the results obtained by Babatunde et al. (2008) in studying determinants of poverty in South-Western Nigeria. Along gender lines, households headed by men endowed with higher economic welfare because of the likelihood of male heads obtaining jobs more easily than their female counterparts or the discrimination in the job market in favour of men.

Variables that downgrade household welfare are household size and ownership of farmland. Other things being equal, farmland ownership is expected to impact positively on household economic welfare. The negative and significant sign of farmland ownership may be indicating that households might not be operating their farm holdings profitably, but since formal safetynets like insurance, unemployment benefits and old age pension facilities are not accessible to informal sector operators in Cameroon, they might sensibly continue to operate production units even if such units are economically unprofitable. Thus farm ownership might as well impact household economic well-being negatively. Moreover, the mean opportunity cost of rural labour typically approaches zero. We verified this atypical behavior by looking for the correlation between farmland ownership and the dependent variable. This correlation was indeed negative. Moreover, the bulk of the rural population (about 85%) has a household member who has access to farmland, whereas the rest of the rural population operates mainly in the formal sector, which is an important income generating factor. The negative on farmland may be a mechanical outcome of this observation.

The relationship between household size and household income was confirmed to be negative by the correlation matrix. This indicates that a higher number of "dependents" or individuals residing in a particular household will tended to exert a lot of pressure on the meager household income and consequently an overall deterioration in well-being. The findings on farmland and household size corroborate those by Oyakele et al. (2007) in their study of urban and rural poverty in Nigeria.

Urban residency tends to increase household productivity and income generation, while rural residency instead reduces household economic welfare. Generally, households living in urban areas are exposed to many opportunities which are incomes generating than rural dwellers and that may explain why poverty levels appear lower in urban regions. This finding is in tandem with those by Alemayehu et al. (2005) for Nigeria and Mwabu et al. (2000) for Kenya.

Regression-based inequality decomposition Results

To decompose measured income inequality by regressed-income sources, we compute contributions of the various estimated factors using the Shapley value-based approach (Table 3). In Column 1 of Table 3, putting aside the constant term, the estimated income sources for education, health and fraction of active household members had the highest income shares. The income sources: household size and owning farmland registered negative income shares. Column 2 of Table 3 host inequality decomposition of the Gini index based on the Shapley value. Sources that largely explain inequality were education and health. The relative contributions of these factors sum up to 38%. Other sources that contribute in explaining inequality were the fraction of active household members, household size, age of household head, working in the formal sector, owning farmland, the predicted residuals for education and health, and urban residency. The relative contributions of these regressed sources sum up to 27%.

The estimated income source for education reveals the key role education plays over time in enhancing well-being and exacerbating inequality. This result is similar to the findings by Oyakale et al. (2007). Differences in educational achievements imply differences in the ability to earn income and consequently disparities in expenditure. Thus, disparities in access to school infrastructure and knowledge acquisition as indicated by the synthetic variable for education affect household expenditure. This is reflected in the gaps in well-being between those households endowed with this attribute and those that do not have this attribute.

Although health had a positive contribution, its magnitude is smaller compared to education. The smaller contribution of health in measured income inequality is attributable to the modalities used to construct it. These modalities are fixed in nature, comprising durable public investments such as type of health structure constructed and appreciation of health services, which are quasi-accessible to both poor and rich households, and slow to vary overtime. However, the composite health indicator captures inequality relative to the dimensions outlined in Appendix 3.1.

The ratio of active household members to household size registers the second highest contribution in explaining inequality in the distribution of household well-being followed by those working in formal sector employment. This implies that a larger number of active household members will improve household chances of labour market participation, which is an important source of inequality in the distribution of living standards. Formal sector workers fared better in terms of well-being than informal sector employees and consequently contribute positively to measured income inequality.

In terms of location, urban residency contributes about 2% in accounting for measured income inequality. This result indicates that, while poverty is lower because urban dwellers are exposed to more opportunities than rural residents, inequality within the urban dwellers is higher. In contrast, rural areas may tend to host many poor households and disparities among them are low. This result has implications for policies that curb push-factors of rural-urban migration.

Table 3: Decomposition of total inequality by estimated income sources

	Shapley value Approach	
Income Sources	**Income Shares (1)**	**Gini Index (2)**
Composite Variables		
Education*	0.1031	0.0984
		(0.2542)
Health*	0.0596	0.0501
		(0.1298)
Observed Variables		
Household Size	-0.0175	0.0193
		(0.0501)
Age of Household head	0.0079	0.0011
		(0.0029)
Gender(1=male and 0=otherwise)	0.0114	0.0015
		(0.0039)
Fraction of Active Household Members	0.0116	0.0161
		(0.0418)
Formal Sector (1=working in the formal sector and 0=otherwise)	0.0013	0.0071
		(0.0185)
Household own farmland (1=Own farmland and 0=otherwise)	-0.0011	0.0017
		(0.0044)
Urban Area	0.0017	0.0069
		(0.0179)
Complementary Sources for education and health		
Predicted residual for Educational	0.0008	0.0328
		(0.0849)
Predicted residual for Health	0.0009	0.0136
		(0.0352)
Residual	0.0000	0.1378
		(0.3566)
Constant term	0.8197	
Total value	1.000	0.3864
		(1.000)

Source: Computed by authors using STATA 10 and the DASP 2.1 Software developed by Araar and Duclos (2009).
Notes: Income sources with stars are synthetic variables obtained from the MCA approach. Values in brackets are the relative contributions.

Total inequality computed by the Gini index was 0.3864 (Column 2). This value is similar to the Gini index of 0.390 obtained by the National Institute of Statistic using total expenditures per adult equivalent computed from the same survey data (INS, 2008). The contribution of the predicted residual term to income inequality in this case is 35%. As indicated earlier, the residual term informs the political entrepreneurs as to how much regressed-sources can explain the overall measured inequality. In this case, included variables accounted for over 65% of total inequality. This indicates that policy makers may choose to design policies accordingly to deal with inequality based on included variables with some confidence. However, more investigations are needed to increase the margin of confidence in addressing the problem of inequality.

The marginal contributions of the estimated-income sources using the Gini approach are illustrated next. The Gini index is deemed appropriate because it is good for decomposition by sources (Araar, 2006). These marginal contributions are based on the notion of the Shapley value concept developed by Shorrocks (1999), where a regressed-income source joins a league of sources and the marginal contributions are calculated. Thus the Shapley value-based component of each regressed-income source to measured income inequality is the weighted mean of the marginal contributions of the source in all configurations of sources including the residual. These contributions are generated by the DASP 2.1 software package (Araar and Duclos, 2009) slotted into STATA 10. The level of entry indicates the position in which a regressed source is introduced to a set of already existing sources. The introduction of each source into a coalition of sources can be envisaged as a policy-mix.

In Appendix 3, Table A hosts marginal contributions of included and excluded regressed-income sources to measured income inequality along different configurations of sources. For instance, of the weighted mean of marginal contribution of the composite variable for education of about 0.0984 to measured income inequality of 0.3864, about 0.0191 is realised at level 1, that is, in the absence of other regressed-income sources and the predicted residual (see, Table 3 and Table A). As the effect of other regressed-income sources are progressively taken into consideration from level 2 through level 13, the sum of the remaining weighted marginal contributions of education is 0.0793 (Table A). Whereas the source education at all levels of entry registered no negative, the source predicted residual of education subsequently registered an inequality equalizing trend from the ninth level of entry. The implication here is that promoting only education for all would be equity augmenting, but promoting it alongside policies that curb inequality in other income sources would enhance the effectiveness of the education for all policy.

The second estimated income source with the highest marginal contribution is the composite variable for health. Its marginal contribution in explaining inequality at level one is 0.0178. This makes up about 36 percent of the total share of this source (0.0501) in accounting for observed inequality. Progressively including other estimated sources increases the impact of this source in explaining inequality. This finding consolidates the observation made earlier as concerns the source complementary health inputs. What can be drawn is that the combine results of this first two sources show that health also constitutes a key factor in human capital development because it contribute to household utility and productivity. Consequently, targeting modalities used in constructing the synthetic-variable for health for policy formulation will help dissipate inequality. For instance, ameliorating the working conditions of health workers will ameliorate personnel public relations in welcoming and following-up patients. The CHCS

III questioned individuals on their reasons for dissatisfaction with public health facilities. One of the main findings was the poor reception by health personnel. This modality was captured in the composite health variable. This indicates the important role health might play in perpetuating or reducing inequality. This reveals that policies that try to reduce inequality in access to health facilities are important. However, other policies that target other dimensions of well-being should be consolidated as well.

For household size, working in the formal sector, urban residency and owning farmland, we witnessed at certain levels of entry positive and negative values (Table A). The variable household size when considered alone (level 1) has a weighted marginal impact of 0.0047. This amounts to about one-quarter of the total impact of this source in explaining observed inequality. At the seventh level, the weighted marginal contribution of this source becomes constant, the increases very marginal till the 13th level of entry.

A key result that can be identified from this reading is the role of spatial inequality, as made explicit by the estimated-income source - area of residence, in explaining observed inequality is the source urban residency. For urban residency, of the weighted mean of marginal contributions, about 16% is realised at level 1, that is, in the absence of other income sources. As the effect of other income sources is progressively considered from level 2 through level 13, the remaining 84% of the weighted marginal contributions of urban residency is captured. Policies that encourage rural development would be inequality reducing, and would tend to be more effective if additional policy instruments are used to target other sources of measured income inequality. The indication of our analysis is that packaging policy instruments to address the problem of inequality in the distribution of living standards would be more effective than implementing policies in solo.

Conclusions

This paper aimed at investigating regressed-income sources that account for measured income inequality in Cameroon using the 2007 Cameroon household consumption survey. The Shapley value decomposition procedure was applied to compute the contributions of the estimated income sources in explaining measured inequality. It also illustrates the weighted marginal contributions of the estimated-income sources.

The composite variables for education and health -human capital characteristics, were positively and significantly associated with household economic welfare. Non-synthetic variables that also associated positively with household economic well-being were fraction of active household members, working in the formal sector, age of household head, living in urban areas and being a male headed household. Household size and owning farmland related negatively with the income generating function.

Estimated-income sources such as education, health, fraction of active household members and working in the formal sector were prominent in accounting for measured income inequality. Urban residency also contributed to measured income inequality. Assuming that there is no guidance as to the correct framework of inequality decomposition by regressed-income sources to based policy advice, included variables explain 65-88% of total inequality, meaning the residual takes about 22-35%, and policy makers may choose to design policies accordingly to deal with inequality and ignore other factors with some margin of confidence. In this study, we elected to base policy implications on the Gini coefficient because of its popularity and desirable properties, and the Shapley value-based contributions as heralded in the literature. The joint contribution of education and health in accounting for total inequality was 38%, indicating the key role human capital characteristics play in explaining observed inequality in the redistribution of household income.

The component of each regressed-income source to measured income inequality was the sum of the weighted marginal contributions of that source in all configurations of sources as sanctioned by the Shapley value approach. In the case of the synthetic variable – education, of the weighted mean of the marginal contributions of about 25.4% of measured total income inequality, about 5.2% is realised in the absence of other regressed-sources. As its effect in leagues of other regressed-income sources was progressively taken into consideration, the weighted marginal contributions of education reduced progressively, while accounting for the remaining 20.4% of measured income inequality. For the variable health, the weighted mean was about 13% of measured total income inequality. In the absence of other regressed-sources, this value was 4.5%.

The implication was that promoting human capital development through education and health for all would be equity augmenting, but promoting it alongside considerations that target other regressed-income sources of inequality would enhance the effectiveness of the human capital enhancement for all policy. Thus there seems to be more wisdom in packaging policy instruments when addressing problems of inequality than implementing policies unaccompanied.

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Appendix 1: Ingredients of the synthetic variables for education and health

Dimension 1: Education and related basic infrastructures

Knowing how to read and write; Already attended schools; First reason for dissatisfaction regarding the closest public primary school; First reason for dissatisfaction regarding the closest private primary school; Distance to go to the nearest public primary school (0,1,2,3,4,5 or 6km and more.); Distance to go to the nearest private primary school (0,1,2,3,4,5 or 6km and more.); Required Time to go the nearest primary public school (0-5min/6-15min/16-25min/26-35min/36-45min/ 46min or more); Required Time to go the nearest private public school (0-5min/6-15min/16-25min/26-35min/36-45min/ 46min or more)

Dimension 2: ***Health and related basic infrastructures***

Sector of consultation; Type of sanitary centre; Appreciation of health status; First reason for dissatisfaction regarding the closest sanitary centre; Distance to go to the nearest sanitary centre (0,1,2,3,4,5 or 6km and more.); Required Time to go the nearest sanitary centre (0-5min/6-15min/16-25min/26-35min/36-45min/ 46min or more);

Appendix 2: Weighted Reduced Form Estimates for Education and Health

Included Exogenous variables	**Education** (1)	**Health** (2)
Household Size	-0.0051***	0.0048***
	(-6.24)	(4.37)
Age of Household head	-0.0039***	0.0029***
	(-20.59)	(11.08)
Gender (Male=1 and 0 otherwise)	-0.0011	-0.1330***
	(-0.18)	(-14.98)
Fraction of Active Household members	-0.0637***	0.0259

	(-3.76)	(1.13)
Formal Sector (1=working in the formal sector and 0=otherwise)	0.0962***	0.0708***
	(12.26)	(6.65)
Household own farmland (1=Own farmland and 0=otherwise)	-0.0228***	-0.0069
	(-3.36)	(-0.75)
Urban area	0.0578***	-0.0067
	(6.12)	(-0.53)
Constant	1.0360***	0.4808***
	(67.58)	(23.11)
Excluded Exogenous variables		
Household Own Radio (Cluster mean)	0.1388***	0.2305***
	(9.94)	(12.16)
Household Own Television (Cluster mean)	0.5707***	0.0971***
	(36.84)	(4.62)
Number of Room (Cluster means)	-0.0183***	-0.0026
	(-8.31)	(-0.88)
R-Squared	0.4642	0.0712
Adjusted R-Squared	0.4637	0.0704
Fisher Test [p-value]	985.8; [0.00]	87.21; [0.00]
Number of Observation	17.8 million	17.8 million

Source: Computed by Authors using STATA 10.
Notes: ***, ** and * are 1, 5 and 10 percent significance levels, respectively. Variables in parenthesis are t-student values.

Appendix 3: Table A: Marginal contributions of the various estimated income sources based on the Shapley value Approach for 2007

Estimated income Sources	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8	Level 9	Level 10	Level 11	Level 12	Level 13
Education*	0.0191	0.0142	0.0110	0.0089	0.0075	0.0065	0.0057	0.0052	0.0047	0.0043	0.0039	0.0036	0.0033
Health*	0.0178	0.0122	0.0084	0.0058	0.0040	0.0027	0.0017	0.0010	0.0003	-0.0003	-0.0007	-0.0011	-0.0015
Household Size	0.0047	0.0027	0.0018	0.0013	0.0011	0.0010	0.0009	0.0009	0.0010	0.0010	0.0011	0.0011	0.0011
Age Cohorts	0.0012	0.0004	0.0001	0.0000	-0.0000	-0.0000	-0.0000	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
Sex(1=male & 0=otherwise)	0.0017	0.0007	0.0003	0.0001	0.0000	-0.0001	-0.0001	-0.0001	-0.0002	-0.0002	-0.0002	-0.0003	-0.0003
Fraction of Active Household Members	0.0041	0.0023	0.0015	0.0011	0.0010	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008	0.0008
Working in Formal Sector (1=Yes and 0=Otherwise)	0.0011	0.0006	0.0004	0.0004	0.0004	0.0004	0.0004	0.0005	0.0005	0.0006	0.0006	0.0007	0.0007
Household own farmland (1=Yes and 0=otherwise)	0.0003	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0002	0.0002
Urban Area	0.0011	0.0005	0.0004	0.0003	0.0003	0.0004	0.0004	0.0005	0.0005	0.0006	0.0006	0.0007	0.0007
Complementary Educational Input	0.0141	0.0093	0.0062	0.0041	0.0027	0.0017	0.0009	0.0002	-0.0003	-0.0008	-0.0013	-0.0017	-0.0021
Complementary Health Input	0.0137	0.0084	0.0050	0.0027	0.0012	0.0000	-0.0008	-0.0015	-0.0021	-0.0026	-0.0031	-0.0035	-0.0039
Residual	0.0210	0.0162	0.0133	0.0115	0.0102	0.0094	0.0088	0.0084	0.0081	0.0079	0.0077	0.0076	0.0075

Source: Computed by Authors using DASP 2.1 distributive software slotted in STATA 10.
Notes: Levels indicate the point of entry of an estimated source into a coalition of sources. Results are reported in four decimal places.