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The Nexus between Poverty, Inequality and Growth: A Case Study of Cameroon and Kenya

Boniface Ngah Epo[a,*], Francis Menjo Baye[a], Germano Mwabu[b], Martin N. Etyang[c] and Paul M. Gachanja[c]

[a]Faculty of Economics and Management, University of Yaoundé II, P.O. Box 1365, Yaoundé, Cameroon
[b]Department of Economics, University of Nairobi, P.O. Box 30197-00100, Nairobi, Kenya
[c]School of Economics, Kenyatta University, P.O. Box 43844-00100, Nairobi, Kenya

*Corresponding author: Boniface Ngah Epo. E-mail: epongahb@yahoo.fr

Abstract

We conduct an in-depth analysis of the nexus between inequality of opportunity and inclusive growth in Cameroon and Kenya employing cross-sectional data collected over two time periods in each country. Empirical results show that changes in education, health and labour market endowments have large effects on household economic well-being, as proxied by total expenditures per adult equivalent. Employing the regression-based decomposition, we find that effort-based variables are associated with greater Gini inequality compared with circumstance-based variables—more so for Cameroon than Kenya. Among the effort-based variables, education in Cameroon and health in Kenya, are the main correlates of income inequality. The factual and counterfactual distribution analyses undertaken demonstrate that equalisation of human capital endowments is strongly inequality-reducing and further promotes pro-poor growth. Meanwhile, elimination of circumstance disparities in Cameroon reduces Gini inequality, enhances pro-poorness of the growth process, promotes shared-prosperity in urban areas and reduces inequality between the tails of the distribution of well-being. In Kenya, elimination of circumstance-based disparities is pro-poor improving, shared prosperity enhancing, but Gini inequality augmenting. In contrast to the Cameroonian case, equalisation of circumstances increases inequality between the tails of the distribution of well-being. The mechanisms behind these findings are probably the country-specific redistributive policies.

Keywords: Kenya, Cameroon, factual-counterfactual distributions, efforts, circumstances, equality of opportunity, inclusive growth, inequality, poverty

JEL classification: I10, I20, I30, J10, I38

1. Introduction

While economic growth is generally accepted as a condition for poverty reduction, a good understanding of the nature, sources and quality of growth required to reduce poverty is lacking. Thus, exploring the determinants of household well-being, as well as the impacts of regression-based well-being sources[1] on social inequalities, and growth inclusiveness, would be a useful input into the ongoing policy debates on pathways to poverty reduction in African countries. These issues are often dealt with in isolation, but our present endeavor is arguably a new attempt at addressing poverty and inequality comprehensively.

We contextualize and concretize these issues with a case study of Cameroon and Kenya, the leading economies in the Central African Economic and Monetary Union[2] and the East African Community (African Development Bank, 2020a, 2020b), respectively. In SSA countries, the downsizing of social spending that started in the early 1990s and continued into the 2000s to attenuate macroeconomic imbalances might have led to the current social disparities in Cameroon and Kenya. Economic and social policies in these countries are now directed at reducing disparities in opportunities, while focusing on inclusive growth. Evidence on impacts of household endowments on well-being, inequalities and inclusive growth is needed to sustain debate and implementation of these policies.

In terms of welfare indicators, the poverty headcount ratio at national poverty lines in Kenya fell by 10.7 percentage points from 46.8% in 2005 to 36.1% in 2015. The Gini inequality fell by 5.7 percentage points from 46.5% to 40.8% between 2005 and 2015 (Kenya National Bureau of Statistics, 2005, 2015). In the case of Cameroon, the poverty rate fell by 2.4 percentage points from 39.9% in 2007 to 37.5% in 2014, meanwhile, the Gini inequality increased by 5 percentage points from 39% in 2007 to 44% in 2014 (National Institute of Statistics, 2014). These differential trends make the assessment of the poverty–inequality–growth nexus in these two countries an interesting and informative case study.

Without tackling inequality, the economic growth rates required to eradicate poverty among African countries may not be achievable. However, inequality, *per se*, may not be a 'bad thing' because some effort-based inequality is essential for freedom of choice, which itself is a source of well-being (Sen, 1993, 1999). Therefore, it is useful to understand the nature, sources and consequences of inequality in order to design and implement effective and socially acceptable growth and anti-poverty policies. The phenomenon of jobless growth reported in African countries has deepened income inequalities, a situation that calls for growth inclusiveness. Identification of a household economic well-being generating function for each country and accounting for inequality of this well-being that is driven by circumstance-based and effort-based variables, is the first contribution made in this paper.

The other contribution is the conceptualisation of inequality of household well-being, as being generated by inequality of exogenous circumstances for which an individual household may not entirely be held responsible, in contrast to that stemming from inequality of efforts. While the conceptualisation itself is not new as such, we make it concrete using African evidence. We analyse the levels and inequalities of well-being outcomes among Cameroonian and Kenyan households, generated by differences in circumstances and efforts. We examine circumstances and efforts, as an integral pair in a well-being function, in an endeavor to provide a better understanding of the sources of a household's economic prosperity and its disparity over time and space. We argue that inequality of opportunity emanating arguably from inheritance and other exogenous conditions (Arneson, 1989 and Cohen, 1989), leads to inequality of outcomes. Equalisation of circumstance-based opportunities, as a response to inequality in the well-being outcome, has a long and veritable

[1] Regression-based wellbeing sources are obtainable after regressing total expenditures per adult equivalent—the proxy for household economic wellbeing, on individual, household, community and regional characteristics and then predicting the expenditure flows using the estimated coefficients.

[2] CAEMU is a subregional organization with six member states: Cameroon, Central African Republic, Chad, Congo, Gabon and Equatorial Guinea. The EAC is a subregional body with six partner states: Burundi, Kenya, Rwanda, South Sudan, Tanzania, and Uganda.

literature (Roemer, 1998, 2002; Bourguignon and Morrison, 2002 and Lefranc *et al*., 2008). However, to our knowledge, no published works exist in Africa that link inequality of household well-being to inequality of opportunity and inequality of effort. This linkage is rigorously demonstrated in this paper.

We argue that evidence on the nature and quality of growth is key to the design of desirable redistributive policies. We estimate the relative measure of pro-poor growth (Kakwani *et al*., 2006)[3] using comparable survey data sets from Cameroon and Kenya and show that pro-poor growth strategies reduce extreme poverty in study countries. We conclude the analysis of inclusive growth by comparing income growth among the 40% least well-off households, with that of the overall population, and find sizeable shared prosperity gains for both countries, driven by human capital accumulation.

This study differs from past research on poverty and inequality in several important respects. First, while previous studies on distributive analysis largely ignore potential econometric problems associated with the estimation of the contributions of effort-based and circumstance-based variables to the well-being of a household, we fully address these issues using the control function modelling strategy explained in Wooldridge (2015). In particular, we use the approach to specify an income generating function that corrects for potential sample selection bias due to non-random participation of households in labor markets, and controls for the endogeneity of human capital regressors in the household well-being function. We also net out any unobserved heterogeneity from the parameter estimates of regressors of policy interest, particularly those associated with health and education inputs into the well-being function. Second, while previous works using SSA data are generally saddled on the growth incidence curve or on the poverty growth curve, we adopt a non-parametric relative measure of growth inclusiveness (Kakwani *et al*., 2006, 2010) to gauge the extent of income improvements over time and to assess success of any redistributive policies in reducing inequality. Since inclusive growth implies both participation in the growth process and fair redistribution of the fruits of growth, we extend our analysis to measure the extent of shared prosperity.

In addition to applying control functions to measure household welfare levels, we employ regression-based decompositions and simulated factual and counterfactual distributions to elicit impacts of human capital on social inequalities as measured by the Gini index. We further measure pro-poorness of growth and isolate the extent of shared prosperity by locality. In each case, we use cross-sectional household surveys for 2007 and 2014 (Cameroon) and 2005 and 2015 (Kenya).

The counterfactual distribution of total expenditures per adult equivalent (our proxy for well-being) is simulated in two steps. First, we equalize well-being/income sources of interest (e.g., effort) in the predicted factual distribution, which corresponds to the distribution of income as measured in the survey. Second, we estimate the well-being–generating function when income sources of interest are equalised for everyone, and then similarly predict a new income distribution. The simulated new income is the counterfactual distribution, in the sense that it does not exist in survey data. It is a distribution of economic well-being generated by a notional policy scenario that removes disparities from well-being sources of interest, e.g., differences due to exogenous circumstances. We compute well-being impacts of the hypothetical policy measure by comparing the Gini indices, relative pro-poor growth indices, shared prosperity indices and the Palma ratios, in the factual and counterfactual distributions.

[3] Growth is said to be pro-poor in the absolute sense when it leads to an increase in the incomes of poor people, whereas, it is pro-poor in the relative sense, only if the incomes of the poor grow faster than the incomes of the overall population.

2. Literature and knowledge gaps

An overview of the literature indicates that considerable research has been done using parametric and non-parametric methods to characterize and measure inequality (Heshmati, 2004). However, until around 2000s, economists had not seriously attempted to develop a regression-based approach to decomposing measured inequality (Fields and Yoo, 2000; Morduch and Sicular, 2002; Wan, 2004 and Bourguignon *et al*., 2008), as the classical papers (Blinder, 1973; Oaxaca, 1973; Juhn *et al*., 1993) served the purpose of the day. Despite the rapidly growing research on inequality, regression-based decomposition analysis of income inequality in Africa is sparse (Alayande, 2003; Epo and Baye, 2013; Gutema, 2019).

In Roemer's (1998) theory of equality of opportunity, the type of income source is an important construct in characterisation of the well-being distribution. The novelty of the equal-opportunity approach is the art of partitioning income differentials into two categories, the first is due to circumstances beyond the control of individuals, and the second arises from voluntary effort. Inequality studies over the past decades have been less challenging to conduct than what is accomplished here because the older investigations concentrated on observed drivers of inequalities of outcomes, neglecting influences of unmeasured or unmeasurable variables, such as innate ability or motivation of workers.

As indicated in Lefranc *et al*. (2008), previous studies did not give sufficient attention to identification of the kind of inequalities that are attributable to circumstances and to efforts. Most empirical works measuring inequality of opportunity have relied on the ordinary least squares (OLS) estimates to simulate benchmark distributions that equalize observed circumstance-related variables, to generate well-being distributions in which the influence of exogenous factors have been eliminated. The simulated inequalities are then compared with inequalities of observed outcomes to isolate the effect of opportunity equalisation on inequality of outcomes (Bourguignon *et al*., 2007; Nunez and Tartakowsky, 2007). However, the earlier studies fail to use methods that adequately address commonly encountered estimation problems, such as endogeneity, sample selectivity and unobserved heterogeneity (Wooldridge, 2002; Schultz and Strauss, 2008; Mwabu, 2009; Baye and Epo, 2015; Wooldridge, 2015).

Pro-poor growth has broadly been defined by a number of international organisations as growth that leads to significant reduction in poverty. In the literature, absolute (Ravallion and Chen, 2003) and relative (Kakwani and Son, 2003; Son, 2004) pro-poor growth have been the main strands of distributive analysis. The construct of pro-poor growth is embedded in the concept of income elasticity of poverty (Essama-Nssah and Lambert, 2006). It is evident from a review of the literature on pro-poor growth that there has been a vigorous search for measures that can indicate whether growth has been pro-poor or not (Son, 2007). Other studies in this vein include Mohamd Shoukry *et al*. (2018); Grosse *et al*. (2008); Kraay (2006); Duclos and Wodon (2004); and Kakwani *et al*., (2004).

In Africa, few studies on pro-poor growth are available (Harmáček *et al*., 2017; Epo and Baye, 2012, 2016; Mpenya *et al*., 2017; Essama-Nssah and Bassolé, 2010). However, aggregate analysis of pro-poor growth, as undertaken in most studies, masks the heterogeneity in growth patterns with sources of pro-poor growth (Ravallion, 2001), complicating rather than simplifying the policy issue as to what can be done to reduce poverty.

3. Methodology

3.1. Overall framework

We assume that the household economic well-being is generated by two sets of inputs: a vector of exogenous variables that an individual cannot influence directly and a vector of endogenous variables, essentially under the control of an individual/household. Following Roemer (1998, 2002), these inputs into the well-being generating function can loosely be labelled circumstance-related and effort-related factors, respectively.

Equation 1a is an implicit form of such a welfare generating function that exploits notions of circumstances and efforts.

$$W = W\ \left(E\left(C, \varepsilon_2\right), C_1, \varepsilon_1\right) \tag{1a}$$

where, *W* is the welfare generating function; *E* is a vector of effort-based variables; C_1 is a vector of included circumstance-based variables; *C* is an expanded vector of circumstance-based variables.

Since C_1 is a subset of *C,* and *C* minus $C_1 = C_2$, it follows that C_2 is a vector of the excluded variables, that is, the instrumental variables for *E* that help identify the effect of *E* on the welfare function. As suggested earlier, effort-related variables are largely attributable to individual responsibility and those related to circumstances are generally exogenous to an individual/household; ε_1 is the error term of the structural equation and ε_2 is the error term of the reduced-form equation (the first stage regression) that projects each endogenous effort-based variable onto exogenous instruments and other circumstance-based variables. Thus, effort-based variables (*E*) depend on circumstances, but circumstances do not depend on idiosyncratic efforts. The effort-based variables are largely endogenous due to unobserved innate ability, measurement error or simultaneous occurrence of income and effort; ε_1 is a proxy for unobserved variables in ε_2 that co-vary with effort-based variables.

The key effort-based variables of interest are the human capital related, i.e., education, health and wage employment. Meanwhile, circumstance-based variables are captured at the individual or societal levels. At the individual level, the circumstances include age, gender, location, disability, ethnicity, family socioeconomic background and inherited genetic endowments. At the societal level, they encompass public provision of healthcare and educational services, customs and conventions, climatic conditions and government regulations, as long as the unit of analysis is the individual. Most of these factors belong in vector *C*. Since many of these factors are not captured in our survey data, the reduced-form error term (ε_2) also absorbs the unmeasured circumstance-based variables. In this context, ε_2 becomes a critical unobservable variable to measure and predict because it fundamentally affects the well-being generating function. It is the capturing of the predicted reduced-form error term of the effort-based variables that distinguishes the present endeavor from most of the previous studies in this literature. It is worth stressing that without using the predicted reduced-form error term of the effort function (the predicted value of unobserved effort) to specify the well-being generating function, the impacts of unobserved effort on both the level and distribution of household well-being cannot be identified.

To derive the reduced-form equation, we project the human capital endogenous variables on a vector of exogenous circumstance-based variables as follows:

$$E = E\left(C, \varepsilon_2\right) = E\left(C_1, C_2, \varepsilon_2\right) \tag{1b}$$

where C_1 is the vector of included variables and C_2 is a vector of variables excluded from the structural equation—the instrumental variables. In this paper, we use the non-self-cluster means/proportions of the endogenous variables for C_2, which can be considered universal instrumental variables. A non-self-cluster mean is the neighborhood average of the potential endogenous variable. It is this average that is assigned to a household which is excluded from its calculation. Neighborhood average characteristics are typically exogenous to the referenced household because by design, these characteristics cannot be influenced by the excluded entity. The idea of non-self-cluster means or proportions can be understood in the context of social interactions and emulations. In particular, the average neighborhood characteristics can influence the actions of the excluded household but not the other way round. That is the cluster average influences the excluded household's actions and decisions, but the household does not influence the value of the neighborhood cluster-mean. Non-self-cluster mean years of schooling is in the vector C_2 for Cameroon, but this specification does not apply for Kenya, as sickness reporting is the endogenous variable. After estimating the reduced form equation, the reduced form residual is predicted and included as an additional variable in the structural equation to control for endogeneity.

In the case of Kenya, it is the household total land holding that is in C_2. To identify the effect of sickness reporting in the survey on household well-being, we instrumented sickness with total household landholding. The underlying idea is that the size of total landholding was fixed during the reporting (survey) period. Thus, total land is exogenous to the income generating decisions of households. Since land is a good proxy for wealth, especially in agriculture, it is assumed to correlate strongly with sickness reporting, in accordance with related literatures in Asia and Africa (Akin *et al.*, 1986; Mwabu, 1986).

Inclusion of sector of employment in our income generating function implies the need to account for sample selectivity bias (Heckman, 1976; Wooldridge, 2015). Formal sector work is contingent on labor market participation and being employed. The selection issues considered are therefore the decision to participate in the labor market and being in employment. These are binary outcomes that we represent implicitly in equations (1c) and (1d):

$$LMP = LMP\,(1\,(C_1, C_3, \varepsilon_3) > 0) \tag{1c}$$

$$LME = LME\,(1\,(C_1, C_4, \varepsilon_4) > 0) \tag{1d}$$

where LMP, is the labor market participation indicator, which takes the value 1 when the market wage is greater than the reservation wage and 0 otherwise. C_1 is as defined before and C_3 or C_4 is a vector of instrumental variables for selection into the labor market or employment. LME is an indicator for labor market employment, which takes the value 1 when the household head is employed and a value of zero otherwise. We use the non–self-cluster identification strategy. Specifically, we use the non–self-cluster proportion of labor market participation in the case of Cameroon and the non–self-cluster of labor market employment in the case of Kenya.

In the case of Cameroon, since ε_3 and ε_4 are likely to be dependent, we use the bivariate probit model to jointly estimate equations (1c) and (1d). Subject to the usual test, we generated the inverse Mills ratio (IMR) upon estimating the joint decision of participating in the labor market and finding wage employment. In the case of Kenya, we used the simple probit estimates to generate the IMR for labor market employment. In both countries, the computed IMRs are used as additional regressors in the well-being equations.

3.2. The household well-being generating function

The final well-being generating function is shown in Equation 2 and expressed in semi-logarithmic form as:

$$LnY = \alpha_0 + \sum_{k=1}^{m} \alpha_k C_{1k} + \sum_{j=1}^{3} \eta_j E_j + \sum_{j=1}^{2} \theta_j \hat{\varepsilon}_{2j} + \sum_{j=1}^{2} \lambda_j \left(\hat{\varepsilon}^*_{2j} E_j\right) + \omega IMR + u \tag{2}$$

Table 1. A Typology of Circumstance and Effort Variables in the Outcome Equation

Sources of variation in Ln*Y*	Circumstance-based variables	Effort-based variables	Ln*Y* (outcome)
Observed	C	E	C, E
Unobserved		$\hat{\varepsilon}_{2j}$, IMR	$\hat{\varepsilon}_{2j}$, IMR
Residual of outcome		$\hat{u}$	$\hat{u}$

Source: Classified by Authors

where, Y is household total expenditures per adult equivalent, C_{1k} is a vector of m exogenous covariates, such as individual, household, community and regional characteristics; E_j are endogenous effort-related human capital (j = 1,2) and labor market (j = 3) endowments; $\hat{\varepsilon}_{2j}$ are residuals of the endogenous inputs (education and education times year dummy, or sickness and sickness times year dummy) derived after estimation of the reduced form equations, and *IMR* is the inverse Mills Ratio. In the case of Cameroon, the year dummy variable takes the value 1 for 2014 observations and 0 for 2007 observations and for Kenya it takes the value 1 for 2015 observations and 0 for 2005 observations. The residuals, $\hat{\varepsilon}_{2j}$, serve as the controls for unobservable variables that correlate with E_j (j = 1, 2), thus allowing these endogenous inputs to be treated as if they were exogenous during estimation while $\left(\hat{\varepsilon}^{*}_{2j}E_j\right)$ is the interaction of the residuals with the actual values of each of the potential endogenous explanatory variables. The interaction term is designed to capture indirect effects of the endogenous variables, say, in parental unobserved heterogeneities—innate ability or resistance inherited by household heads from their parents or unobserved heterogeneities in regions of upbringing and schooling—school quality. The error term, u, is a well-behaved structural error term—with the white noise property, while α, η, θ, λ and ω are vectors of parameters to be estimated. The determinants of household economic well-being provide the inputs into the simulation of the factual and counterfactual distributions that are required for inequality and inclusive growth analyses.

Concerns about unobservable variables (the potential control function variables) in the well-being generating function in terms of the circumstance versus the effort dichotomy, is an important one in some instances. For simplicity, Table 1 shows that the control function variables are entirely attributable to the effort-based component of the welfare generating function as reflected in Equations 7 and 8.

3.3. Regression-based decomposition of inequality of outcomes

Given the vector of consistently estimated parameters ($\hat{\beta}$), well-being (Equation 3) can be expressed as the sum of estimated well-being source flows and the predicted error term. Since the econometric results yield estimates of the well-being source flows attributed to household variables, they allow us to make use of decomposition by factor endowments. By construction, total well-being is the sum of these estimated well-being source flows (plus the predicted regression residuals) as shown in Equation 3.

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

where $\hat{\ddot{y}}_{i,m} = \hat{\beta}_m x_{i,m}$ for m = 0,1, 2, ..., M and $\hat{\ddot{y}}_{i,m} = \hat{\varepsilon}_i$ for m = M + 1.

We then obtain the share of inequality attributable to the well-being source, $\ddot{\hat{y}}_{i,m}$ as[4]:

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

$\hat{\beta}_m$ is estimated coefficient associated with well-being source m; $x_{i,m}$ is the well-being source m attributable to household i; $\sum_i a_i(y)$ is the sum of inequality weights attributable to households and, $I(y)$ is the inequality of outcomes. Using $I(\cdot)$ as an inequality measure, the overall income inequality can be decomposed into the contribution of the constant term$I\left(y_0\right)$, the contribution of the estimated well-being sources $I\left(\tilde{y}\right)$ (without the constant term), and the contribution of the predicted residual $I\left(\hat{\varepsilon}\right)$ as follows:

$$I(y) = I\left(y_0\right) + I\left(\tilde{y}\right) + I\left(\hat{\varepsilon}\right) \tag{5}$$

3.4. Factual and counterfactual analyses to capture inequality impacts of welfare sources

Following Roemer (1998) and Bourguignon *et al.* (2007), we associate exogenous-opportunity with circumstance-related variables: determinants of well-being over which individual households are thought to have little or no control. We also follow Roemer (1998) and Bourguignon *et al.* (2007) in classifying the other determinants of well-being that can be influenced by households' decisions as endogenous effort-related variables.

After estimating equation (2), we generate the predicted well-being distribution, i.e., the factual distribution of household well-being as follows:

$$Y = Exp\left[\hat{\alpha}_0 + \sum_{k=1}^{m} \hat{\alpha}_k C_{1k} + \sum_{j=1}^{3} \hat{\eta}_j E_j + \sum_{j=1}^{2} \hat{\alpha}_j \hat{\varepsilon}_{2j} + \sum_{j=1}^{2} \hat{\lambda}_j \left(\hat{\varepsilon}^*_{2j} E_j\right) + \hat{\omega} IMR + \hat{u}\right] \tag{6}$$

The counterfactual benchmark distribution that equalizes human capital endowments captured in Equation (6) is expressed as follows:

$$Y_{\overline{E}} = Exp\left[\hat{\alpha}_0 + \sum_{k=1}^{m} \hat{\alpha}_k C_{1k} + \sum_{j=1}^{3} \hat{\eta}_j \overline{E}_j + \sum_{j=1}^{2} \hat{\alpha}_j \hat{\varepsilon}_{2j} + \sum_{j=1}^{2} \hat{\lambda}_j \left(\hat{\varepsilon}^*_{2j} \overline{E}_j\right) + \hat{\omega} IMR + \hat{u}\right] \tag{7}$$

[4] Following the lead by Shorrocks (1982), Morduch and Sicular (2002) introduced a new integrated regression-based approach to inequality decomposition. By letting $I(y)$ be the weighted sum of a household welfare indicator, say income/wellbeing, corresponding to a measure of inequality; $a_i(y)$ be the proportional share of the household welfare measure, y; and y_i be the wellbeing of household i, Shorrocks (1982) developed an inequality measure, where I(y) in Equation 4 is expressed as a weighted sum of the household welfare indicator: $I(y) = \sum_i a_i(y) y_i$. Notice that the denominator of Equation 4, i.e., I(y), is the mean income of all households from all sources, while its numerator is the mean income of all households from source ***m***. Furthermore, the numerator has two parts: (1) the weighted sum of the welfare determinant x_i of type m for household i, say, education, where x is years of schooling, the mean of which can be denoted as x_m; and (2) return ($\hat{\beta}_m$) per unit of input x. Thus, the numerator in Equation 5 is the mean income from source ***m***, and can be expressed as $y_m = \hat{\beta}_m * x_m$. Thus, S_m in Equation 4 is the weighted sum of incomes of all households (i = 1 . . . n) from source ***m*** divided by the weighted sum of household incomes from ***all*** sources. This ratio (the share) of income from source ***m*** in total income is unit free, in sharp contrast to I($\boldsymbol{y}$) which is monetized, and, the distribution of which is determined by a_i(y). If $a_i(\boldsymbol{y})$, for example, is uniform, inequality of $\boldsymbol{y}$ is zero, verifying that I(y) is indeed an inequality measure. Moreover, if $S_m = 1$, the contribution of ***m*** to I($\boldsymbol{y}$) is 100%, a confirmation that Equation 4 can be used to decompose inequality by income source.

In this setup, measured inequality is attributable to observed circumstance-related variables and unobserved effort-based variables since the observed effort-based variables are equalized.

The second simulated well-being distribution equalizes opportunity-induced circumstances ($Y_{\overline{O}}$). In the setup in equation (8), measured inequality is entirely attributable to effort-based variables (observed and unobserved).

$$Y_{\overline{O}} = Exp\left[\hat{\alpha}_0 + \sum_{k=1}^{m} \hat{\alpha}_k \overline{C}_{1k} + \sum_{j=1}^{3} \hat{\eta}_j E_j + \sum_{j=1}^{2} \hat{\alpha}_j \hat{\varepsilon}_{2j} + \sum_{j=1}^{2} \hat{\lambda}_j \left(\hat{\varepsilon}^*_{2j} E_j\right) + \hat{\omega} IMR + \hat{u}\right] \quad (8)$$

If each of the counterfactual distributions is denoted by $Y_{\overline{A}}$, that is, the distribution with policy, the without policy distribution by Y and an inequality index represented by I, we can define the impact of policy on measured inequality denoted by $\Theta_I$as:

$$\Theta_I = \frac{I\left(Y_{\overline{A}}\right) - I(Y)}{I(Y)} = \frac{\Delta I}{I(Y)} \quad (9)$$

If $\Theta_I > 0$, the equalised source is inequality reducing in the factual distribution. If $\Theta_I = 0$, the equalised source is inequality-neutral in the factual distribution. If $\Theta_I < 0$, the equalised source is inequality augmenting in the factual distribution. $I\left(Y_{\overline{A}}\right)$ is an inequality index with implemented policy. The notation Θ_I indicates that the explained share of inequality is conditional on the chosen inequality index. By the same token, the unexplained share of inequality is given by the complement of Θ_I. To address these issues empirically, we appeal to the Gini index.

3.5. Analysing growth inclusiveness

3.5.1. Pro-poor growth (Kakwani et al., 2006)

Let x be the well-being captured by an endowment, with its density function f(x). The actual mean of the population is expressed as:

$$\mu = \int_0^{\infty} x f(x) dx \quad (10)$$

Let the growth rate of the endowment be $\gamma = \Delta In(\mu)$. Letting $u(x)$be the utility function which is increasing in x and concave, then we can generate a general money-metric class of social welfare function, w. Let the logarithmic utility function for $u(x)$be expressed as$Ln(x)$. Invoking the idea of equally distributed equivalent level of well-being (Atkinson, 1970), we can obtain a money-metric social welfare function. Kakwani *et al.* (2006) develop a weighting scheme to capture relative deprivation, which is an individual's deprivation that depends on the number of persons who are better off than him or her in society:

$$w(x) = 2\left[1 - F(x)\right] \quad (11)$$

where $F(x)$represents the distribution function.

Substituting $u(x) = Ln(x)$ and $w(x)$ gives the social welfare function which can be manipulated to obtain the form:

$$Ln\left(x^*\right) = Ln(\mu) - Ln(I) \quad (12)$$

where $Ln(I) = 2\int_0^{\infty} [1 - F(x)] [Ln(\mu) - Ln(x)] f(x)dx$ and I is a new measure of inequality proposed by Kakwani *et al.* (2006). Taking the first difference of (12) gives:

$$\gamma^* = \gamma - \delta \tag{13}$$

where $\gamma^* = \Delta Ln(x^*)$ is the growth rate of the money-metric social welfare, $\gamma = \Delta Ln(\mu)$ is the growth rate of mean income/well-being and $\delta = \Delta Ln(I)$ is the growth rate of inequality as measured by I. Kakwani *et al.* (2006) identify γ^*as the pro-poor growth rate. If δ is positive, then growth is accompanied by an increase in inequality, in which case $\gamma^* < \gamma$, since there is a loss in growth rate of poor people's incomes because of an increase in inequality. If δ is negative, then growth is accompanied by a decrease in inequality and $\gamma^* > \gamma$, since there is a gain in growth rate of the incomes of the poor because of a fall in inequality. Growth is defined as pro-poor (anti-poor) if there is a gain (loss) in growth rate of the incomes of the poor because of a fall (increase) in inequality.

3.6. Shared prosperity analysis

In a partial sense, inclusive growth relates to pro-poor growth, which concerns the extent to which the fruits of growth benefit the poor in absolute or in relative terms. In a complete sense, it refers to the extent to which the least well-off participate in the growth process, as well as benefit from the fruits of that growth. Although to the best of our knowledge, no index has been constructed in the literature that captures the dual aspects of inclusive growth, it has been argued by the World Bank, and perhaps others—that the shared prosperity index mimics the dual aspects. The World Bank (2013) considers the least well-off to be households at the bottom 40% of the distribution of a well-being indicator. In this context, shared prosperity is the change in average well-being at the bottom 40% of the distribution of well-being between two periods. This is typically operationalised as the annualised growth rate in average well-being at the bottom 40% of the well-being distribution. In this case, there is shared prosperity premium when the annualised growth rate in average well-being in the bottom 40% of the well-being distribution is greater than the annualised overall average growth rate in well-being.

3.6.1. Measuring shared prosperity

Let $Y = (y_1, y_2, \ldots, y_n)$ be nonnegative values of economic well-being of households with probability density function $P(Y = y_h)$ and where the element y_h of vector Y represents the well-being of household h. Ordering the elements of vector Y from the least endowed to the most endowed: $y_1 \le y_2 \le \cdots \le y_n$ and denoting z, the largest integer such that $P(Y \le z) = 0.4$, then, the weighted average well-being per adult equivalent at the bottom 40% is defined as:

$$\overline{Y}_{B40} = \frac{\sum_{h=1}^{z} y_h P(Y = y_h)}{P(Y \le z)} \tag{14}$$

where B40 is the bottom 40% representing the poorest 40% of the population or least well-off household and $\overline{Y}_{B40}$ the weighted average well-being per adult equivalent of the least well-off households.

As in the World Bank (2015), we measure shared prosperity by growth in average expenditure at the bottom 40% of the well-being distribution between two periods. Considering $\overline{Y}_{t0,B40}$ and $\overline{Y}_{t1,B40}$ the mean well-being per adult equivalent at the bottom 40% at two time periods (years) t_0 and t_1 where $t_1 > t_0$, then the measure of shared prosperity is given as:

$$\theta_{B40} = \left(\frac{\overline{Y}_{t1,B40}}{\overline{Y}_{t0,B40}}\right)^{(t1-t0)} - 1 \qquad (15)$$

where θ_{B40} is the World Bank's Shared Prosperity Index. When observations are recorded over years, the shared prosperity index presents the annualised growth in average expenditure at the bottom 40% of the well-being distribution. The corresponding annualised growth rate in population mean well-being is defined as:

$$\theta = \left(\frac{\overline{Y}_{t1}}{\overline{Y}_{t0}}\right)^{(t1-t0)} - 1 \qquad (16)$$

where $\overline{Y}_{t0}$ and $\overline{Y}_{t1}$ are the population mean well-being in time t_0 and t_1, respectively, θ, the annualised growth in population mean well-being, which represents average prosperity. Shared prosperity premium (SPP) is given by: SPP $= (\theta_{B40} - \theta) > 0$ and $(\theta_{B40} - \theta) < 0$ is shared prosperity deficit.

3.6.2. Measuring the Palma ratio

Notwithstanding the attractiveness of the Gini coefficient as a measure of inequality, it is typically insensitive to the tails of a distribution. For this reason, the Palma ratio, which measures inequality between those at the top and bottom of the well-being distribution, turns out to be preferred to the Gini coefficient in the context of prosperity sharing. The World Bank measures the Palma ratio as the well-being share of the richest 10% divided by that of the poorest 40% of the distribution. The downside of the Palma ratio is that it may satisfy the transfer sensitivity principle only weakly[5], if at all.

3.7. The data

We perform the case study analyses with survey data from Cameroon and Kenya. The third (CHCS III) and fourth (CHCS IV) Cameroonian Household Consumption Surveys data were collected by the Cameroon National Institute of Statistics in 2007 and 2014 using a similar sampling frame (National Institute of Statistics, 2007, 2008, 2014). We recognize that prices can vary across regions and over time. There is, therefore, need to harmonize the third and fourth data sets both spatially and inter-temporally. This harmonisation is carried out by using a spatial index to reflate household expenditures of the different regions to render them comparable with a referenced locality, Yaoundé. After spatially harmonising expenditure, the poverty lines for the initial and final periods are used to rendered comparable expenditures in the two surveys.

The Kenya Integrated Household Budget Surveys for 2005 and 2015 were produced by the Kenya National Bureau of Statistics [KNBS] (Kenya National Bureau of Statistics, 2005, 2015). The Kenyan household surveys were conducted using the same approaches as those used in Cameroon, as both sets of data follow the principles used in the Living Standards Measured Surveys (LSMS), pioneered by the World Bank in the 1980s (Deaton, 1989). The Kenya surveys were subjected to a similar spatial and intertemporal harmonisation as Cameroon's, *mutatis mutandis*. Tables 1A and 1B provide descriptive statistics for Cameroon and Kenya, respectively.

5 The transfer sensitivity condition holds if an income transfer from a wealthier to a poorer person brings about a decrease in the measure of inequality without reversing the direction of welfare.

4. Findings and discussions

We present empirical results for Cameroon in Tables 2 to 13 and Kenya (Tables 14 to 25), respectively.

4.1. Results for Cameroon

Table 2 hosts estimates of reduced-form OLS and of the control function approach for the structural equation of the well-being generating function. The sample selection estimates resulting from biprobit estimates of the labor market participation and employment models are hosted in Table 2A in the Appendix. The sample statistics are in Appendix Table 1A.

4.1.1. Determinants of the well-being generating function

Reduced form parameter estimates for the education equation

Table 2, columns 1 and 2 show reduced-form estimates of years of schooling and years of schooling times year dummy. The instrumental variable for education is the non–self-cluster mean years of schooling, whereas a unit increase in neighborhood average years of schooling increases the excluded household head's educational attainment by 0.54 years, a unit increase in the proportion of neighborhood labor market participation is associated negatively with the educational attainment of the excluded household head. Being a female head or residing in rural areas correlates negatively whereas marriage and community ownership of land are associated positively with years of schooling. Household heads drawn from the 2014 survey are more schooled compared to those from the 2007 survey.

The effects of effort-based variables on household well-being

Table 2, column 3 shows OLS estimates for the well-being function that are likely to suffer from endogeneity, sample selection and unobserved heterogeneity biases. Column 4 of Table 2 presents unbiased and consistent control function estimates. The results in columns 3 and 4 of Table 2 show that education is positively and significantly correlated with household economic well-being. Since the control function variables—the residual of years of schooling, the IMR and the interaction of education with its residual are statistically different from zero; we prefer the control function estimates.

The control function estimates in column 4 of Table 2 indicate that an additional year of schooling produced a 3.4% increase in household economic well-being in 2007. Between 2007 and 2014, an additional year of schooling increased household economic well-being by 2.1%. The implication is that gains in household economic well-being emanating from a year of schooling is about 5.5% over the study period. The indirect effect of education as indicated by the interaction of education with its reduced-form residual has a positive coefficient. This shows that the reduced-form unobservable variables are complementary to education in explaining household economic well-being. Improving education would increase household well-being via better employment opportunities and rational spending strategies as articulated by Becker (1964, 1975).

Other effort-based variables included in Table 2 are formal sector employment and marriage. Column 4 of Table 2 also show that correcting for sample selectivity bias, securing formal sector employment is associated with a 15.9% increase in household economic well-being relative to that of informal sector operators. Meanwhile, household heads who are married were less endowed in terms of well-being compared with their unmarried counterparts.

Effects of circumstance-based variables

The circumstance-based variables in the income generating function are age, age squared, gender, location and regions. Column 4 of Table 2 shows that below 43 years of age any additional year associates negatively with household economic well-being, while above

Table 2. Determinants of Household Expenditure per Adult Equivalent—Cameroon

Variables	Reduced form equations		Well-being equation	
	Schooling equation (column 1)	Schooling times year-dummy (column 2)	OLS estimates (column 3)	Control function estimates (column 4)
Years of schooling			0.0284***	0.0335***
			(0.0013)	(0.0046)
Years of schooling times year-dummy			0.0120***	0.0212***
			(0.0014)	(0.0027)
Formal sector (1 = yes and 0 = otherwise)			0.2055***	0.1587***
			(0.0124)	(0.0126)
Married (1 = yes and 0 = otherwise)	0.1490*	−0.0238	−0.0499***	−0.0586***
	(0.0823)	(0.0627)	(0.0103)	(0.0103)
Age	−0.0343***	−0.0145*	−0.0099***	−0.0171***
	(0.0115)	(0.0088)	(0.0014)	(0.0026)
Age squared	−0.0004***	−0.0001	0.0001***	0.0002***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Female (1 = yes and 0 = otherwise)	−1.2657***	−0.4173***	0.0524***	0.0899***
	(0.0875)	(0.0666)	(0.0108)	(0.0140)
Rural area (1 = yes and 0 = otherwise)	−1.5949***	−0.8923***	−0.2698***	−0.2456***
	(0.0838)	(0.0638)	(0.0105)	(0.0143)
Own land at cluster level	0.2931	1.6869***	−0.0794***	−0.1107***
	(0.1849)	(0.1408)	(0.0209)	(0.0236)
Adamaoua	−3.0595***	−1.6316***	−0.2482***	−0.1872***
	(0.1765)	(0.1344)	(0.0207)	(0.0292)
Centre	−0.0269	−0.1831	−0.2705***	−0.2527***
	(0.1615)	(0.1229)	(0.0193)	(0.0200)
East	−1.4911***	−1.0795***	−0.2550***	−0.2291***
	(0.1779)	(0.1355)	(0.0229)	(0.0253)
Extreme North	−3.8683***	−2.6858***	−0.5134***	−0.4696***
	(0.1510)	(0.1149)	(0.0156)	(0.0278)
Littoral	−1.1356***	−1.2588***	−0.2719***	−0.2547***
	(0.1690)	(0.1287)	(0.0245)	(0.0257)
North	−4.0303***	−3.0992***	−0.4401***	−0.4038***
	(0.1585)	(0.1207)	(0.0172)	(0.0289)
North West	−0.3191**	−1.1735***	−0.4828***	−0.4658***
	(0.1466)	(0.1116)	(0.0169)	(0.0181)
West	−0.7819***	−1.0289***	−0.2151***	−0.2157***
	(0.1461)	(0.1113)	(0.0163)	(0.0182)
South	0.3610**	−0.7442***	−0.2086***	−0.2005***
	(0.1783)	(0.1358)	(0.0247)	(0.0247)
South West	0.0300	−0.8671***	−0.1725***	−0.1611***
	(0.1491)	(0.1135)	(0.0181)	(0.0183)
Year dummy (1 = 2014 and 0 = 2007)	1.9035***	1.7223***	−0.0480***	−0.0982***
	(0.1751)	(0.1333)	(0.0117)	(0.0204)
Residual of years of schooling				−0.0222***
				(0.0048)

(Continued)

Table 2. Continued

Variables	Reduced form equations		Well-being equation	
	Schooling equation (column 1)	Schooling times year-dummy (column 2)	OLS estimates (column 3)	Control function estimates (column 4)
Years of schooling times its residual				0.0026***
				(0.0001)
Residual of years of schooling times year-dummy				−0.0145***
				(0.0032)
IMR				−0.4017***
				(0.1195)
Non–self-cluster years of schooling	0.5392***	−0.2301***		
	(0.0223)	(0.0169)		
Non–self-cluster market participation	−0.6051	0.0015		
	(0.4416)	(0.3362)		
Non–self-cluster years of schooling times year-dummy	−0.2176***	0.7715***		
	(0.0257)	(0.0196)		
Constant	7.4000***	3.3174***	13.5420***	13.6234***
	(0.5197)	(0.3957)	(0.0360)	(0.0844)
Fisher [24, 20957]	411.45	973.33	695.51	604.37
Prob > F	0.0000	0.0000	0.0000	0.0000
R-squared/Adjusted R-squared	0.2819/0.2812	0.4815/0.4810	0.3989/0.3983	0.4090/0.4084
Observations	20,982	20,982	20982	20,982

Source: Computed by authors. Notes: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ are 1%, 5% and 10% levels of significance, respectively. Yaoundé and Douala are omitted regional dummies.

43 years any additional year improves household welfare. Lack of education, precarious jobs, underemployment or outright unemployment characterize the early life course of most household heads. Contrary to the general expectation as to gender bias, the income endowment of female household heads is 9% higher than households headed by men.

In addition, rural household heads are less endowed compared with their urban counterparts. Similarly, land ownership at the community level associates negatively with household economic well-being. This finding is attributable to the observation that financiers seldom accept community land as individual collateral security to attract a credit facility due to farmer-grazer conflict risks. Relative to dwellers in the two metropolitan regions of Yaoundé—the political capital city and Douala—the economic capital city, households in the other 10 regions register household economic well-being deficits ranging from 47% in the Extreme North and Northwest regions to 16% in the Southwest region. In the case of the year dummy variable, households in the 2014 sample incurred well-being deficits in the order of 10% compared to those in the 2007 sample.

Regression-based inequality decomposition analysis

In this section, we compute the weighted contribution of the income sources for the effort component and the circumstance component in explaining total inequality using

Table 3. Regression-based Decomposition for Cameroon

Income sources	Analytical approach		Shapley value approach
	Income shares (1)	Gini index (2)	Gini index (3)
Effort component			
Years of schooling	0.5221	0.3137 (0.7628)	0.2337 (0.5684)
Formal sector (1 = yes and 0 = otherwise)	0.0361	0.0265 (0.0645)	0.0162 (0.0396)
Married (1 = yes and 0 = otherwise)	0.0282	0.0005 (0.0012)	0.0138 (0.0335)
Circumstance component			
Combined circumstance variables	0.3178	−0.0136 (−0.0332)	0.0457 (0.1113)
Residual		0.0841 (0.2045)	0.1016 (0.2470)
Total value		0.4113 (1.0000)	0.4113 (1.0000)

Source: Computed by authors using the DASP software by Araar and Duclos (2009). Values in brackets are the relative contributions.

the analytical and Shapley value decomposition approaches[6] (Table 3). We comment on the results using the Shapley value decomposition. The Shapley decomposition of the Gini shows that the effort component (0.2637 [relatively by 63%]) contributed more than the circumstance component (0.0457 [relatively by 11%]) in accounting for observed total inequality in both absolute and relative terms (Table 3, column 3). These suggest that policy orientations that target effort-based sources would have a significant impact in reducing total inequality. Decomposing the effort component into the different estimated sources indicates that education overwhelmingly contributes to explaining total inequality (0.2337 [relatively by 56%]). Labor force participation and marriage are other important determinants of inequality (Table 3, column 3). The contribution of the predicted residual term to income inequality for Cameroon was 25%. Informing political leaders on how regressed-sources can explain overall measured inequality, included variables accounted for over 75% of total inequality suggesting some level of confidence in terms of policy value of the results presented.

Table 4 shows marginal contributions of the income sources to measured overall inequality when we consider two scenarios, i.e., when we include and when we exclude a given source. For education, the 0.1980 of the overall contribution of 0.2337 to total inequality (0.4113) is realised at level 1, that is, when we exclude all the regressed-income sources. As we gradually consider level 2 to level 5, the sum of the outstanding marginal contributions of education is 0.0357 with the entries of levels 4 and 5 registering negative values. The implication here is that promoting education together with policies that curb inequality associated with circumstances and other unobserved income sources as revealed by the predicted residual would enhance the effectiveness of education in mitigating income inequality.

6 The difference between the analytical approach and the Shapley value approach is that, while the former computes inequality by the Gini index as the product of the income shares and the coefficients of the concentration curve; the latter is based on a set of axioms (Shorrocks, 1999), which permit computation of the weighted marginal contributions associated with factors determining the household wellbeing, as if the factors are a coalition of players in a cooperative game.

Table 4. Marginal Contributions of the Income Sources Based on the Shapley Value Approach

Estimated sources	Level 1	Level 2	Level 3	Level 4	Level 5
Years of schooling	0.1980	0.0943	0.0247	−0.0238	−0.0594
Formal sector (1 = yes and 0 = otherwise)	0.0108	0.0017	−0.0001	0.0003	0.0034
Married (1 = yes and 0 = otherwise)	0.0343	0.0084	−0.0017	−0.0085	−0.0187
Combined circumstance variables	0.1577	0.0572	−0.0109	−0.0601	−0.0980
Residual	0.1987	0.0833	0.0002	−0.0638	−0.1168

Source: Computed by authors.

For the income source—formal employment, its marginal contribution in explaining inequality at level one was 66% of its share in explaining observed inequality. The remaining levels accounted for 33%. Considering marriage, the overwhelming share of level 1 in worsening total inequality withers off from levels three to five when we consider policies associated with other estimated sources.

Looking at the circumstance component, the first level of entry posts a marginal contribution of 0.1577. As we incorporate other regressed sources, it is observed that combining circumstances related with effort related sources and the predicted residuals considered in this study reduces inequality from the third to the fifth entries.

Analysis of Inequality in well-being

From the estimated parameters of the household well-being generating function, factual and counterfactual distributions are simulated to inform analysis of inequality in well-being across households. Three factual distributions are simulated—the overall distribution, circumstance-based distribution and the effort-based distribution.

Similarly, three counterfactual bench-marking scenarios are simulated under the ceteris paribus assumption.

(1) The first counterfactual distribution of well-being is achieved by equalising circumstance-based variables, while allowing in the function, the effort-based variables as observed. Inequality due to circumstances is thereby eliminated in the counterfactual distribution. Inequality in this counterfactual distribution of well-being is entirely attributable to variations in effort-based variables. The variability in the factual distribution of well-being depends on the circumstance- and the observed and unobserved effort-related variables, whereas variation in this counterfactual distribution of well-being is attributable entirely to the observed and unobserved effort-related variables. This scenario is constructed to ensure that circumstances beyond the household control do not determine differences in life outcomes.
(2) The second counterfactual distribution is obtained by equalising years of schooling in the overall distribution. Inequality in the resulting counterfactual distribution is free of any variations attributable to education.
(3) The third counterfactual is achieved by equalising years of schooling in the effort-related distribution. The resulting effort-based inequality is void of education-related components.

Gini indices for the overall factual distribution and the circumstance and effort related distributions, by year

As Table 5 shows that the measured inequality as captured by the Gini coefficient was about 0.41 for the factual distribution; 0.125 (=0.159 × 0.786) for the factual circumstance distribution; and 0.286 (=0.364 × 0.786) for the overall factual effort distribution over the

Table 5. Gini Inequality for the Factual Distributions in Cameroon

Group	Estimate	Standard Deviation	Lower Bound	Upper Bound
		Factual overall distribution		
2007	0.3902	0.0061	0.3782	0.4023
2014	0.4190	0.0060	0.4071	0.4309
Pooled data	0.4113	0.0043	0.4028	0.4197
		Factual circumstance distribution		
2007	0.1625	0.0030	0.1565	0.1685
2014	0.1549	0.0021	0.1506	0.1592
Pooled data	0.1590	0.0019	0.1552	0.1628
		Factual effort distribution		
2007	0.3312	0.0048	0.3216	0.3408
2014	0.3775	0.0049	0.3678	0.3872
Pooled data	0.3640	0.0035	0.3570	0.3709

Source: Computed by authors.

Table 6. Impacts of Equalising Circumstances-Based Variables on Gini Inequality in Cameroon

Group variable	Gini index		Difference
	Factual	Counterfactual	
Area of residence			
Overall	0.4113***	0.3640***	−0.0472***
	(0.0043)	(0.0035)	(0.0023)
Urban	0.3515***	0.3476***	−0.0039
	(0.0077)	(0.0071)	(0.0034)
Semi-Urban	0.3350***	0.3326***	−0.0024
	(0.0111)	(0.0117)	(0.0056)
Rural	0.3134***	0.2961***	−0.0173***
	(0.0070)	(0.0070)	(0.0035)

Source: Computed by authors. Values in parenthesis are standard errors. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ are 1%, 5% and 10% levels of significance, respectively.

period 2007 to 2014. This is an indication that over the period of analysis, effort-based sources of the well-being accounted for over 70% of measured inequality. The 30% of measured inequality attributable to circumstances beyond the control of the household is non-negligible even though measured inequality is largely effort-based and perhaps justifiable. Between 2007 and 2014 measures inequality increased by 0.03 points, whereas inequality attributable to circumstances declined marginally by 0.01 points, inequality due to effort increased by 0.05 points.

Impact of circumstances on overall inequality, by location

When circumstance-based variables are equalised across households, Table 6 shows that the counterfactual Gini of 36.4% is about 4.7% significantly lower than the overall measured inequality of 41.1%. This is an indication that levelling the playing field in terms of equalisation of circumstances is inequality reducing. Although the counterfactual distribution registered lower inequalities by location than the factual distribution, the decline was only statistically significant in rural areas. These results show that over the period of study circumstance-based variables were inequality augmenting in the actual distribution. Furthermore, inequality decreases from the urban to the rural areas in both the factual and counterfactual distributions.

Table 7. Gini Inequality Impacts of Equalising Years of Schooling in Cameroon

Group variable	Gini index		Difference
	Factual	Counterfactual	
Area of residence			
Overall	0.4113***	0.3550***	−0.0562***
	(0.0043)	(0.0034)	(0.0038)
Urban	0.3515***	0.3146***	−0.0369***
	(0.0077)	(0.0055)	(0.0044)
Semi-urban	0.3350***	0.3051***	−0.0298***
	(0.0111)	(0.0087)	(0.0079)
Rural	0.3134***	0.2973***	−0.0160***
	(0.0070)	(0.0068)	(0.0026)

Source: Computed by authors. Values in parenthesis are standard errors. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ are 1%, 5% and 10% levels of significance, respectively.

Table 8. Gini Inequality Impacts of Equalising Education in the effort-Related Distribution in Cameroon

Group variables	Gini index		Difference
	Factual	Counterfactual	
Area of residence			
Overall	0.3640***	0.3257***	−0.0382***
	(0.0035)	(0.0032)	(0.0027)
Urban	0.3476***	0.3169***	−0.0306***
	(0.0071)	(0.0059)	(0.0045)
Semi-urban	0.3326***	0.3055***	−0.0270***
	(0.0117)	(0.0104)	(0.0085)
Rural	0.2961***	0.2847***	−0.0113***
	(0.0070)	(0.0073)	(0.0028)

Source: Computed by authors. Values in parenthesis are standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ are 1%, 5% and 10% levels of significance, respectively.

Impact of education on overall inequality by location, 2007–2014

In Table 7, equalisation of educational achievements (counterfactual distribution), other things being equal, reduces inequality overall, across urban, semi-urban and rural areas. Thus, improving broad-based educational opportunities does have a well-being inequality mitigating effect.

Impact of education on effort-based inequality, by location

Table 8 shows that equalising educational endowments in the effort-based distribution engenders a significant decline in effort-based inequality overall and by location. This suggests that observed educational endowments tend to reinforce effort-based inequality. Thus, leveling schooling opportunities through increases in the density of schools would be inequality reduction.

Pro-poor growth and inequality

Panels A and B of Table 9 show no relative pro-poor growth for total expenditures per adult equivalent over the period 2007 and 2014, whereas observed growth in household economic well-being expanded over the study period, poor households appear to have witnessed a well-being contraction attributable to dynamics of inequality. The contraction in expenditure per adult equivalent for the poorer households between the surveys was driven

Table 9. Pro-Poorness of Growth for Cameroon: Relative Pro-Poor Growth Due to Kakwani *et al.* (2006)

Period	2007	2014	Counterfactual versus factual outcomes 2007 (I)	Counterfactual versus factual outcomes 2014 (II)	Changes over time (II)-(I)
Factual total expenditure per adult equivalent	Ln	Ln			
A) Actual growth rate	13.21	13.41	—	—	0.2
B) Pro-poor growth rate	10.70	10.68	—	—	−0.02
Outcome [gain (+)/loss (−)]	Loss in growth of 0.22 percentage points due to increase in inequality				
Counterfactual total expenditure per adult equivalent (when we equalised circumstances)					
C) Simulated actual growth rate	13.10	13.31	−0.11 (line C- line A)	−0.10 (line C- line A)	−0.01
D) Simulated pro-poor growth rate	10.67	10.66	−0.03 (line D–line B)	−0.02 (line D–line B)	0.01
Outcome [gain (+)/loss (−)]	Gain in growth of 0.02 percentage points attributable to a decline in equality.				
Counterfactual total expenditure per adult equivalent (when we equalised Education)					
E) Simulated actual growth rate	13.18	13.19	−0.03 (line E–line A)	−0.22 (line E–line A)	−0.19
F) Simulated pro-poor growth rate	10.68	10.66	−0.02 (line F-line B)	−0.02 (line F–line B)	0.00
Outcome [gain (+)/loss (−)]	Gain in growth of 0.19 percentage points attributable to a decline in inequality				
Factual distribution of effort					
G) Simulated actual growth rate	0.32	0.53	—	—	0.21
H) Simulated pro-poor growth rate	6.59	7.13	—	—	0.54
Outcome [gain (+)/loss (−)]	Gain in growth in the effort distribution of 0.33 points distribution.				
Counterfactual distribution of effort (when education is equalised amongst the effort related variables)					
I) Simulated actual growth rate	0.32	0.35	0.00 (line I–line G)	−0.18 (line I–line G)	−0.18
J) Simulated pro-poor growth rate	6.68	6.64	0.09 (line J–line H)	−0.49 (line J–line H)	−0.58
Outcome [gain (+)/loss (−)]	Loss in effort endowments of 0.40 percentage points attributable to its uneven distribution.				

Source: Computed by authors.

by an increase in inequality among the households at the bottom of the distribution. The decrease in poverty between 2007 and 2014 of 2.4 percentage points was not accompanied by a decline in inequality among the poor.

Eliminating the inequality associated with circumstance-based sources; increases household expenditure over the period under review. In terms of the differences in outcomes (between the factual and counterfactual growth and the pro-poor growth rates), it is observed that when we eliminate inequality due to circumstances, total expenditures for 2007 and 2014 witness a decline of 0.11 and 0.10 percentage points, respectively. Overtime, while average growth decreased by 0.01, pro-poor growth increased by 0.01 percentage points—the net effect being a gain in growth of 0.02% attributable to a decline in inequality (panels C and D of Table 9). This finding reveals the importance of improving access

Table 10. Impact of Circumstances on Mean Well-Being Among 40% of Least Well-Off Households in Cameroon

Location	2007			2014		
	Factual	Counter-factual	Impact Abs. [Rel.]	Factual	Counter-factual	Impact Abs. [Rel.]
Urban	396,145.3	286,857.1	−109,288.2 [−0.28]	358,257.2	308,463.4	−49,793.8 [−0.14]
Rural	202,771.8	239,936.7	37,164.9 [0.18]	209,291.2	241,917.3	32,626.1 [0.16]
Cameroon	234,517.8	252,235.7	17,717.9 [0.08]	252,809.5	267,313.2	14,503.7 [0.06]

Source: Computed by authors. Values are reported in FCFA (1 Euro equals 656.51FCFA). Relative values in brackets.

Table 11. Impact of Circumstances on Shared Prosperity Among 40% of Least Well-Off in Cameroon

Location	Shared prosperity		
	Factual (2007–2014)	Counterfactual (2007–2014)	Impact Abs. [Rel.]
Urban	−1.43	1.04	2.47 [−1.73]
Rural	0.45	0.12	−0.33 [−0.73]
Cameroon	1.08	0.83	−0.25 [−0.23]

Source: Computed by authors. Relative values in brackets.

for poorer households to circumstanced-based opportunities and of promoting pro-poor policies.

Elimination of education-based inequality between 2007 and 2014 would have occasioned an average total expenditure declined of 0.19% and zero pro-poor growth. This indicates gains in pro-poorness of 0.19 percentage points attributable to a decline in inequality at the bottom of the distribution of well-being (see, panels E and F of Table 9).

The last panel of Table 9 shows the pro-poor analysis of the effort-based distribution. The distribution of effort witnessed pro-poor growth between 2007 and 2014, with gains in growth accompanied by decreases in inequality for households situated at the bottom of the effort distribution. The effort distribution increased slightly over the period under review when the effect of education on inequality is eliminated. This indicates that poor households are likely to experience an expansion in their effort endowments if interventions are put in place that would eliminate inequality in terms of education for households situated at the bottom of the distribution. Over the period under review, both average growth and pro-poor growth decreased by 0.58 and 0.18 percentage points, respectively—generating a net loss of 0.40 percentage points, which is attributable to an increase in inequality in the effort distribution among the least endowed. This finding reveals the importance of improving access for poorer households to educational opportunities and encouraging pro-poor policies in terms of education.

Shared prosperity analysis for Cameroon

In this section, we report results from shared prosperity analysis (Tables 10-12) and the Palma ratio (Table 13) for Cameroon and by location. Table 10 suggests that in 2007 and 2014, average household expenditure of the bottom 40% of the population was lower overall, and in rural areas in the factual distribution compared with the counterfactual

Table 12. Impact of Circumstances on Shared Prosperity Premium in Cameroon

	Shared prosperity premium		
Location	Factual (2007–2014)	Counterfactual (2007–2014)	Impact: Abs. [Rel.]
Urban	−2.17	−0.98	1.19 [−0.55]
Rural	−3.64	−3.43	0.21 [−0.06]
Cameroon	−1.85	−2.28	−0.43 [0.23]

Source: Computed by authors. Relative values in brackets.

Table 13. Impact of Circumstances on Palma Ratio in Cameroon

Group variables	Factual (2007–2014)	Counterfactual (2007–2014)	Impact: Abs [Rel.]
Urban	1.87	1.74	−0.31 [−0.16]
Rural	1.79	1.65	−0.14 [−0.92]
Cameroon	2.01	1.71	−0.30 [−0.15]

Source: Computed by authors.

distribution. In this context, circumstances are well-being reducing among the least well-off. However, urban areas posted lower values for the counterfactual distribution compared with the factual distribution. This is an indication that in urban settings circumstances were well-being augmenting in the factual distribution over the period under analysis. These results suggest that interventions that level the playing field in circumstance-related variables would increase well-being overall and raise it higher in rural than in urban areas.

Table 11 shows the shared prosperity indices nationally and by location. In particular, circumstances were shared-prosperity improving in the overall factual distribution. Looking at the urban–rural dynamics, circumstances were shared-prosperity increasing in rural areas, but shared-prosperity dampening in urban areas in the factual distributions of the least well-off households. This finding suggests that designing interventions that equalize circumstances would enhance shared-prosperity more in urban than rural settings.

Table 12 presents results of the shared prosperity premium for Cameroon. The shared prosperity premium is negative in both the factual and circumstance equalising distributions. The shared prosperity deficits are seen in both distributions (with and without the policy scenario). However, although the share of benefits from growth accruing to the population increased over the period under review, the 40% least well-off households benefited less from the country's rising prosperity. While circumstances were mitigating deficits in the overall shared prosperity, they were exacerbating the deficits in the urban and rural settings.

Gauging other dimensions of inequality between the tails of the distributions, Table 13 reports the Palma ratios associated with household expenditure for the factual and counterfactual distributions over the period 2007 to 2014. Results indicate that nationally and by location (urban versus rural) circumstances are Palma ratio increasing in the factual distribution. This is an indication that the circumstances are increasing disparities between the top and bottom of the distributions of household well-being—implying that they are inequality increasing in the factual distribution. This finding suggests that eliminating differences in circumstances would decrease the Palma ratio over time. Thus, levelling the playing field in terms of equalising circumstances would have an inequality reducing tendency between the tails of the distribution of well-being.

4.2. Results for Kenya

Tables 14 to 25 present estimation and simulation results for Kenya whilst Table 3A in the Appendix contains sample selection estimates of the wage employment status. For Kenya,

Table 14. Determinants of Household Expenditure per Adult Equivalent—Kenya

Variables	Reduced form equations		Structural equation	
	Sickness equation (column 1)	Sickness times year dummy (column 2)	OLS estimates (column 3)	Control function estimates (column 4)
Sickness (1 = yes and 0 = otherwise)			0.0450***	−2.2158***
			(0.0061)	(0.1194)
Sickness times year dummy			0.0480***	−2.6651***
			(0.0092)	(0.1988)
Employed (1 = yes and 0 = otherwise)			0.0621***	0.0566***
			(0.0059)	(0.0059)
Primary education	−0.0384***	−0.0185***	0.165***	0.0115
	(0.0043)	(0.0028)	(0.0057)	(0.0072)
Secondary education	−0.0539***	−0.0246***	0.376***	0.1631***
	(0.0060)	(0.0040)	(0.0081)	(0.0102)
Tertiary education	−0.0427***	−0.0220***	0.560***	0.3529***
	(0.0082)	(0.0054)	(0.0112)	(0.0124)
Married (1 = yes and 0 = otherwise)	0.0508***	0.0153***	0.0390***	0.1710***
	(0.0045)	(0.0030)	(0.0062)	(0.0083)
Age	−0.0063***	−0.0028***	−0.00793***	−0.0543***
	(0.0003)	(0.0002)	(0.0004)	(0.0012)
Age squared	0.0001***	0.0001***	8.07e-05***	0.0007***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Female (1 = yes and 0 = otherwise)	0.0490***	0.0231***	0.0171***	0.2375***
	(0.0029)	(0.0019)	(0.0040)	(0.0069)
Rural areas (1 = yes and 0 = otherwise)	−0.0076	0.0024	−0.355***	−0.3697***
	(0.0057)	(0.0037)	(0.0076)	(0.0077)
Coast	−0.1026***	−0.0639***	−0.702***	−1.1111***
	(0.0175)	(0.0116)	(0.0237)	(0.0266)
North Eastern	−0.1865***	−0.1301***	−0.897***	−1.5966***
	(0.0324)	(0.0214)	(0.0437)	(0.0491)
Eastern	−0.0507***	−0.0685***	−0.520***	−0.8543***
	(0.0171)	(0.0113)	(0.0231)	(0.0253)
Central	−0.1451***	−0.0884***	−0.307***	−0.8694***
	(0.0173)	(0.0115)	(0.0235)	(0.0282)
Rift Valley	−0.1406***	−0.1057***	−0.491***	−1.1037***
	(0.0170)	(0.0113)	(0.0231)	(0.0291)
Western	0.0052	−0.0578***	−0.618***	−0.7288***
	(0.0173)	(0.0115)	(0.0234)	(0.0253)
Nyanza	−0.0024	−0.0477***	−0.556***	−0.6809***
	(0.0171)	(0.0113)	(0.0232)	(0.0243)
Year-dummy (1 = 2015 and 0 = 2005)	−0.0574***	0.2646***	0.194***	0.6779***
	(0.0065)	(0.0043)	(0.0047)	(0.0450)
Log of land	−0.0348***	0.0017		
	(0.0031)	(0.0021)		
Log of land times year-dummy	0.0068	−0.0348***		
	(0.0050)	(0.0033)		

(Continued)

Table 14. Continued

Variables	Reduced form equations		Structural equation	
	Sickness equation (column 1)	Sickness times year dummy (column 2)	OLS estimates (column 3)	Control function estimates (column 4)
Non–self-cluster proportion for employment	−0.0003	0.0031		
	(0.0139)	(0.0092)		
Residual for sickness				2.1556***
				(0.1181)
Residual for sickness times year dummy				3.0601***
				(0.1837)
Sickness times its residual				0.1581***
				(0.0531)
Sickness times year dummy times its residual				−0.4619***
				(0.1580)
IMR				−0.1843***
				(0.0062)
Constant	0.4091***	0.0763***	8.937***	10.6759***
	(0.0175)	(0.0116)	(0.0226)	(0.0521)
Fisher [n, n-k]	258.5	839.5	904.6	809.1
Prob > F	0.0000	0.0000	0.0000	0.0000
R-squared/adjusted R-squared	0.0553/0.0551	0.1597/0.1595	0.1699/0.1698	0.1879/0.1876
Observations	83,974			

Source: Computed by authors. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ are 1%, 5% and 10% levels of significance, respectively. Notes: Nairobi is the omitted province dummy.

the main effort variables driving the level and distribution of household economic well-being are levels of education and sickness, both of which are dichotomous. Descriptive statistics are in appendix Table 2B.

4.2.1. Determinants of the well-being generating function for Kenya

Reduced form parameter estimates for the health status model

Columns 1 and 2 of Table 14 indicate that a percentage increase in the total acreage is associated with a 3.5% reduction in the probability of reporting an illness. However, this finding is context-specific because individuals from poor households can be accustomed to common ailments and therefore report sickness less frequently than those from rich households (Akin *et al.*, 1986).

Other variables of importance in sickness reporting are education, marital status, age in quadratic form, gender and location (columns 1 and 2 of Table 14). Educated persons are less likely to report sickness than the uneducated. Married persons were 5.0% and 1.5% more likely to report sickness than the singles in 2005 and between 2005 and 2015, respectively. Older persons are more likely to report sickness than younger ones. In particular, for 2005, below 31 years of age, any additional year reduces the likelihood of reporting sickness, and above 31 years of age, any additional year increases sickness reporting. Women are more likely to report sickness than men. Compared with dwellers in the Nairobi Province, those in the other counties are less likely to report sickness.

The effects of effort-based variables on economic well-being

The ordinary least squares estimate of the well-being generating function in column 3 of Table 14 are likely to be biased and inconsistent because of the potential endogeneity of sickness and employment status. Column 4 of Table 14 corrects for endogeneity, unobserved heterogeneity associated with sickness and sample selection bias emanating from the non-randomness of wage employment uptake. Column 4 of Table 14 hosts the preferred control function estimates because they simultaneously control for endogeneity of sickness, unobserved heterogeneity and sample selection biases. This is depicted by statistical significance of the coefficients on reduced form residual for the sickness equation, and by the significance of the coefficients on the interaction of residual with sickness, plus the coefficient on the IMR.

In Table 14, we report coefficients on sickness, employment and level of education. Households reporting sickness suffered economic well-being deficits compared with those not reporting sickness in 2005 and suffered deeper welfare deficits relative to those who did not report sickness between 2005 and 2015. This disparity arguably comes from unobserved factors associated with acute and chronic illnesses (Akin *et al.*, 1986; Mwabu, 1986).

The indirect effect of poor health captured by the coefficient on the interaction of sickness with its residual is working contrary to the direct effect in 2005. In particular, unobservable variables predicted from the sickness equation are mitigating the negative direct effect of sickness on economic well-being by 16%. Meanwhile, between 2005 and 2015, the indirect effect works in tandem with the negative direct effect, worsening it by 46%. This is evidence of unobserved heterogeneity originating perhaps from differences in socioeconomic or genetic endowments inherited from earlier generations. Over the period under review, those reporting sickness registered a large well-being loss compared to the non-reporting sample.

Column 4 of Table 14 reveals that those employed register a premium in well-being of 6% compared to those without market employment. Some level of education is positively correlated with well-being, but non-significantly among those with primary education. However, post primary education holders register monotonic gains in well-being, compared with the uneducated (16% and 35%) for secondary and tertiary education, respectively. In terms of marital status, those who are married enjoy an economic well-being premium of about 17% over single persons.

Regression-based decomposition analysis

The regression-based decomposition of the Shapley Value-based Gini index shows that effort components positively accounted for inequality, unlike the circumstance components (Table 15, column 3). Considering the effort component, health (sickness) accounted for 33% of total inequality. Education and employment posted 18% and 6% of overall observed inequality, respectively. The combined share of all effort components in the well-being inequality was about 57%.

Regarding the circumstances related components, we observe that they were inequality reducing. Nonetheless, the negative shares of about 14% of the circumstance-based sources suggest that their inequality mitigating effects were largely outweighed by both the effort-based and the residual-based sources.

The estimated residual income sources account for 55% of total inequality. This suggests that the unobserved sources play an important role in accounting for inequality in Kenya. Thus, health, education and labor market interventions aiming at reducing inequality should be complemented with other programs that level the playing field.

Marginal contributions for the efforts and circumstances are presented in Table 16. For the health (not reporting sickness), the first-to-third levels of entries suggest that the impact of health on overall inequality is negative. However, when we incorporate policies associated

Table 15. Regression-Based Decomposition for Kenya

Income Sources	Analytical Approach		Shapley value Approach
	Income shares (1)	Gini index (2)	Gini index (3)
Effort component			
Being sick (1 = yes and 0 = otherwise)	0.5357	0.0491 (0.1392)	0.1181 (0.3348)
Schooling	0.1150	0.0075 (0.0214)	0.0650 (0.1843)
Employed (1 = yes and 0 = otherwise)	0.0519	0.0070 (0.0199)	0.0207 (0.0587)
Married (1 = yes and 0 = otherwise)	−0.0144	−0.0009 (−0.0027)	0.0037 (0.0107)
Circumstance component			
Combined circumstance variables	0.2897	0.0109 (0.0309)	−0.0495 (−0.1402)
Residual		0.2369 (0.6713)	0.1946 (0.5516)
Total value		0.3529 (1.0000)	0.3529 (1.0000)

Source: Computed by authors using the DASP software by Araar and Duclos (2009). Values in brackets are the relative contributions.

Table 16. Marginal Contributions of the Income Sources Based on the Shapley Value Approach—Kenya

Estimated Sources	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Being sick (1 = yes and 0 = otherwise)	0.1455	0.0737	0.0245	−0.0135	−0.0438	−0.0682
Schooling	0.0362	0.0158	0.0077	0.0036	0.0016	−0.00001
Employed (1 = yes and 0 = otherwise)	0.0140	0.0032	0.0014	0.0010	0.0008	0.0001
Married (1 = yes and 0 = otherwise)	0.0147	0.0002	−0.0014	−0.0015	−0.0028	−0.0052
Combined circumstance variables	0.1057	0.0398	−0.0043	−0.0382	−0.0652	−0.0871
Residual	0.1020	0.0537	0.0269	0.0107	0.0019	−0.0007

Source: Computed by authors.

with the other sources in addition to health from the fourth level, then inequality worsening effects manifest themselves thereafter.

When education is considered alone (level 1), the weighted marginal impact on inequality (Gini) is 0.0362. Inequality increasing effects of education continue to the fifth level when complementary policies are at play. Wage employment posts similar trends for all six levels of the policy scenarios.

For the circumstance-related components, their inequality reducing effect reported in Table 16 is not evident in the first and second entry levels (Table 16). However, from the third level, the inequality reducing effect is seen in the presence of other policy mixes.

Gini indices for the overall factual, circumstance- and effort related distributions, by year

Table 17 reports changes in inequality as measured by the Gini coefficient. Over the period 2005–2015, inequality indices were about 0.353 for the factual distribution, 0.167(=0.3786* 0.4398); for the factual circumstances' distribution; and 0.186(=0.4238*0.4398) for the overall factual effort distribution. Over this time frame, circumstance-based sources of the well-being accounted for about 47% of measured inequality. Effort variables under the household control accounted for 53% of the measured inequality. In the case of Kenya as

Table 17. Gini Inequality for the Overall, Factual and Counterfactual Distributions for Kenya

Sample groups	Estimate	Factual distribution Standard Deviation	Lower Bound	Upper Bound
2005	0.3640	0.0060	0.3521	0.3759
2015	0.3311	0.0060	0.3193	0.3430
Pooled data	0.3529	0.0044	0.3442	0.3617
Circumstances associated factual distribution				
2005	0.3224	0.0086	0.3054	0.3395
2015	0.3279	0.0081	0.3119	0.3439
Pooled data	0.3786	0.0069	0.3648	0.3923
Effort associated factual distribution				
2005	0.4181	0.0055	0.4071	0.4290
2015	0.3822	0.0044	0.3735	0.3908
Pooled data	0.4238	0.0042	0.4155	0.4321

Source: Computed by authors.

Table 18. The Impact on Gini of Equalising Circumstances, Kenya

Group variables	Gini index		Difference
	Factual	Counterfactual	
Impacts by area of residence			
Overall	0.3529***	0.4238***	0.0709***
	(0.0044)	(0.0042)	(0.0039)
Urban	0.3340***	0.4180***	0.0840***
	(0.0039)	(0.0042)	(0.0032)
Rural	0.3899***	0.4829***	0.0930***
	(0.0117)	(0.0182)	(0.0138)

Source: Computed by authors. Values in parenthesis are standard errors. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ are 1%, 5% and 10% levels of significance, respectively.

opposed to Cameroon's, measured inequality is about evenly split between circumstance-based and effort-based variables. Between 2005 and 2015 measured inequality (Gini) decreased by 0.033 points on a 0–1 scale. In addition, both the inequality attributable to circumstances and the inequality due to effort declined by 0.006 points and 0.036 points, respectively.

Impact of circumstances on overall inequality for Kenya, by location

Equalising circumstance-based variables across households (Table 18) yields a counterfactual Gini of about 0.424 points (on 0–1) scale, which is about 0.071 points higher than the overall inequality of 0.353. The suggestion here is that circumstance-based variables are inequality reducing in the factual distribution.

The counterfactual distribution registers higher inequalities in urban and rural areas than the factual distribution. These results show that over the period of study circumstance-based variables were inequality reducing in the factual distribution. Thus, leveling the playing field by equalising circumstances-based sources of household economic well-being may not be an effective way reducing inequality in Kenya.

Table 19. The Impact on Gini of Equalising Sickness Probabilities, Kenya

Group Variable	Gini Index		Difference
	Factual	Counterfactual	
	Area of residence		
Overall	0.3529***	0.8869***	0.5340***
	(0.0044)	(0.0017)	(0.0042)
Urban	0.3340***	0.8836***	0.5495***
	(0.0039)	(0.0015)	(0.0038)
Rural	0.3899***	0.8657***	0.4757***
	(0.0117)	(0.0060)	(0.0124)

Source: Computed by authors. Values in parenthesis are standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ are 1%, 5% and 10% levels of significance, respectively.

Table 20. The Impact on Gini of Equalising Sickness in the Effort-Related Distribution, Kenya

Group Variable	Gini Index		Difference
	Factual	Counterfactual	
	Area of residence		
Overall	0.4238***	0.8511***	0.4272***
	(0.0042)	(0.0019)	(0.0048)
Urban	0.4180***	0.8477***	0.4297***
	(0.0042)	(0.0020)	(0.0049)
Rural	0.4829***	0.8591***	0.3761***
	(0.0182)	(0.0061)	(0.0200)

Source: Computed by authors. Values in parenthesis are standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ are 1%, 5% and 10% levels of significance, respectively.

Impacts of sickness on overall inequality by location

Table 19 shows that when sickness probability is equalized, Gini inequalities increased overall and across urban and rural areas. Moreover, these impacts of sickness on inequalities increased between urban and rural areas. This effect was higher for urban than rural areas. This finding is an indication that a generalised shock would likely reduce rural–rural and urban–urban remittances, as well as urban–rural transfers and because of the resilience of the rural people—income distribution may worsen. This can be exacerbated by the impaired productivity of the self-employed.

Impacts of sickness on effort-related inequality by location

As depicted in Table 20, equalising sickness probabilities (counterfactual distribution), other things being equal, effort-related inequality significantly increases overall and across urban and rural areas. These results show that observed sickness likelihoods have inequality diluting tendencies overall and across locations. This is indication that maintaining the status quo in sickness reporting is well-being inequality mitigating. This finding is perhaps pointing to the truism that once acquired; health status can hardly be redistributed. Only the redistribution of soft and hard infrastructures can improve health outcomes.

In Table 20, equalisation of sickness probabilities may amount to improving health across the board, making it possible for previously ill individuals to earn unusually large incomes and thus worsen income distribution. Equalisation of health status can thus increase both incomes and the Gini coefficient. This seemingly counterintuitive finding is plausible.

Equalisation of health status in childhood, via vaccinations for example, can increase both income and its inequality in successive generations. Given that illness has an intrinsic disutility, it seems that equalisation of health status that improves household income, while worsening its distribution is welfare improving. However, the welfare outcome is dependent on how equalisation is done. If equalisation increases probability of sickness for those who previously reported illness infrequently, equalisation can reduce welfare, even as it improves income distribution.

Pro-poorness of growth and inequality for Kenya

The simulation results for pro-poor growth rates are reported in Table 21. Panels A and B show that there was a 0.02 percentage point loss in the growth of per capita household consumption expenditure between 2005 and 2015—implying that growth was marginally anti-poor. An interesting finding from panels C and D is that equalisation of health endowments—that in this case entails equalisation of sickness probabilities is associated with a gain in average growth in consumption expenditure of 2.53 percentage points and with a pro-poor growth rate gain of 0.07%. The net effect is a loss in growth in the order of 2.46 percentage points attributable to an increase in inequality. The simulation result suggests that healthy, high productivity individuals were assigned the same illness probabilities as the previous ill people, and this had the effect of increasing overall incomes and the pro-poorness of growth probably associated with other unobservable variables captured by the residual of the reduced form equation for sickness. The finding suggests that it is very important to ensure that policies designed to reduce inequalities are adequately implemented to include community characteristics associated to issues of sickness like soft and hard health infrastructures that affect growth or productivity.

Panels E and F indicate that equalisation of circumstances in Kenya would result to a loss in growth in household consumption by 0.71% and in pro-poor growth by 0.01%. In this case, re-distribution of circumstanced-based incomes in favour of the poor is welfare eroding, and deficits in pro-poor are marginal, thereby engendering a marginal net gain in growth of 0.61 percentage points. This indicates that equalisation of circumstances or effort would focus on scaling up opportunities of less endowed individuals and communities without disrupting incentives for innovation and enhancing productivity at the top of the income distribution.

In addition, panels G and H, and panels I and J of Table 21 depict the simulated effort growth and pro-poor growth rates, as well as the simulated effort counterfactual growth and its pro-poor growth counterparts. Results show that there is a loss in effort endowments of 0.67% between 2005 and 2015, but a gain in pro-poor effort endowments growth of 0.47% in the same period. These opposing tendencies engendered a net gain in effort endowments of about 1.14% attributable to a decline in effort inequalities. When sickness probabilities are equalized, simulated effort endowments expand by 2.18%, but its pro-poor counterpart contracted by 0.86%, thereby engendering a net loss in effort endowments of 3.04% provoked by increasing inequality in the distribution of effort.

Shared prosperity analysis

In this section, we present shared prosperity analysis (Tables 22-24) and the Palma ratio (Table 25) for Kenya. In 2005 average household expenditure of the bottom 40% of the population was higher overall and in rural areas in the counterfactual distribution than the factual distribution (Table 22). In urban areas, circumstances were well-being augmenting in the factual distribution. Average household expenditures of the bottom 40% of the counterfactual distributions was lower than the factual distributions. This suggests that circumstances were well-being reducing among the least well-off.

Table 23 assesses shared prosperity in Kenya. Circumstances were shared-prosperity increasing in the factual distributions nationally and by location. Table 24 indicates that

Table 21. Pro-Poorness of Growth in Kenya: Relative Pro-Poor Growth Due to Kakwani *et al.* (2006)

Period	2005	2015	Counter factual versus factual outcomes 2005 (I)	Counter factual versus factual outcomes 2015 (II)	Changes over time (II)–(I)
Factual total expenditure per capita	Ln	Ln			
A) actual growth rate	7.93	7.97	—	—	0.04
B) pro-poor growth rate	11.79	11.81	—	—	0.02
Outcome [gain (+)/loss (−)]	loss in growth of 0.02 percentage points due to an increase in well-being inequality among the under privileged.				
Counterfactual total expenditure per capita (when we equalised Health)					
C) Simulated actual growth rate	8.16	10.73	0.23 (line C–line A)	2.76 (line C–line A)	2.53
D) Simulated Pro-poor growth rate	11.77	11.88	3.84 (line D–line B)	3.91 (line D–line B)	0.07
Outcome [gain (+)/loss (−)]	Loss in growth of 2.46 percentage points due to an increase in household well-being inequality.				
Counterfactual total expenditure per capita (when we equalised circumstances)					
E) Simulated actual growth rate	8.33	7.66	0.40 (line E–line A)	−0.31 (line E–line A)	−0.71
F) Simulated pro-poor growth rate	11.82	11.77	3.9 (line F–line B)	3.8 (line F–line B)	−0.1
Outcome [gain (+)/loss (−)]	Gain in growth of 0.61 percentage points attributable to a reduction in well-being inequality.				
Factual distribution of effort					
G) Simulated actual growth rate	−0.95	−1.62	—	—	−0.67
H) Simulated pro-poor growth rate	9.29	9.76	—	—	0.47
Outcome [gain (+)/loss (−)]	Gain in effort endowments of 1.14 percentage points in the effort distribution attributable to a reduction in effort-based inequality.				
Counterfactual distribution of Effort (when sickness probabilities are equalised amongst the effort related variables)					
I) Simulated actual growth rate	−0.71	0.80	0.24 (line I–line G)	2.42 (line I–line G)	2.18
J) Simulated pro-poor growth rate	9.51	9.12	0.22 (line J–line H)	−0.64 (line J–line H)	−0.86
Outcome [gain (+)/loss (−)]	Loss in effort endowments of 3.04 percentage points attributable to increasing inequality in the effort distribution.				

Source: Computed by authors.

the shared prosperity premium index was positive in both the factual and circumstance equalising distributions. This indicates that the 40% least well-off households benefited more from the country's rising prosperity compared to the well-off households overall and across locations. Furthermore, levelling the playing field in terms of circumstances enhances shared prosperity premium overall and in urban areas.

Table 25 portrays the Palma ratios for the factual and counterfactual household expenditure distributions between 2005 and 2015. Circumstances were Palma-ratio reducing in the factual distributions nationally and by location, with reduction being deeper in urban areas than in the rest of the country. Equalising circumstances may not reduce inequality

Table 22. Impacts of Circumstances on Mean Well-Being Among 40% of Least Well-Off Households in Kenya

Location	2005			2015		
	Factual	Counter-factual	Impact: Abs. [Rel.]	Factual	Counter-factual	Impact: Abs. [Rel.]
Urban	3090.5	2712.1	−378.4 [−0.12]	3320.7	1447.2	−1873.5 [−0.56]
Rural	1853.5	2333.9	408.4 [0.25]	2494.5	1618.6	−875.9 [−0.35]
Kenya	1,880.4	2,346.9	466.5 [0.24]	2,559.9	1,594.1	−965.8 [−0.37]

Source: Computed by authors. Values are reported in Kenyan Shillings (1 US dollar = 101.25 ShS). Values in brackets are relative values.

Table 23. Impacts of Circumstances on Shared Prosperity Among 40% of Least Well-Off in Kenya

Location	Shared prosperity		
	Factual (2005–2015)	Counterfactual (2005–2015)	Impact: Abs. [Rel.]
Urban	0.72	−6.09	−6.81 [−9.45]
Rural	3.01	−3.59	−6.60 [−2.19]
Kenya	3.13	−3.79	−6.92 [−2.21]

Source: Computed by authors. Relative values in brackets.

Table 24. Impacts of Circumstances on Shared Prosperity Premium in Kenya

Location	Shared prosperity premium		
	Factual (2005–2015)	Counterfactual (2005–2015)	Impact: Abs. [Rel.]
Urban	1.18	1.41	0.23 [0.19]
Rural	1.28	1.23	−0.05 [−0.03]
Kenya	0.97	1.11	0.14 [0.14]

Source: Computed by authors. Relative values in brackets.

Table 25. Impacts of Circumstances on Palma Ratios by Location in Kenya

Group Variable	Factual distribution	Counterfactual distribution for Circumstance	Difference in Palma ratio Abs [Rel.]
Kenya	1.50	2.14	0.64 [0.42]
Urban	1.73	2.97	1.24 [0.71]
Rural	1.32	2.00	0.68 [0.51]

Source*:* Computed by authors. Values in brackets are relative values.

between the richest 10% and the poorest 40% of the distribution of well-being in Kenya. Equalising circumstances would perhaps enhance well-being across the board, but with some economies of scale occurring among the well-to-do individuals and households.

5. Conclusion

Using household surveys from Cameroon and Kenya, this paper investigated how an income generating function (with effort and circumstances as its main arguments) is linked to poverty, inequality of opportunities, pro-poor growth and shared prosperity.

The results showed that human capital variables, education—for Cameroon and health—for Kenya, significantly affect the level and inequality of household economic well-being. Specifically, education human capital (years of schooling) is positively associated with household economic well-being in Cameroon, whereas an alternative measure of human capital in Kenya (sickness reporting rate) was negatively correlated with household well-being. Equalising education in Cameroon had the tendency to reduce inequality between 2007 and 2014. For Kenya, we found that sickness reporting mitigated inequality in the factual distribution in Kenya over the period 2005–2015, suggesting that its equalisation is inequality-augmenting. Thus, in both countries human capital improvements are good for welfare and for overall equity. The pro-poor growth findings showed that equalising education would generate a gain in growth attributable to a decline in inequality in Cameroon. For Kenya, gains in growth in household income are attributable to reductions in sickness reporting among the under-privileged, suggesting that better health strongly reduces poverty among individuals at the bottom of income distribution.

The regression-based decomposition results further corroborated the high absolute and relative shares of the effort components of welfare when we consider education for Cameroon and health for Kenya. In terms of shared prosperity, eliminating disparities in circumstances in the factual distributions improves shared prosperity, despite the differences observed by location, implying that horizontal economic inequalities can be addressed via public policies that reduce inequalities in opportunities. The changes in Palma ratios revealed that, whereas circumstances are Palma-ratio increasing in the factual distributions for Cameroon, they are Palma-ratio decreasing in Kenya, implying that country-specific contexts can affect effectiveness of redistributive policies in unexpected ways.

Supplementary material

Supplementary material is available at *Journal of African Economies* online.

Data availability

The data used in this paper can be provided by the authors upon reasonable request.

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