Applying Relativity in Understanding Poverty and Promoting Economic Development in Rural Africa

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Abstract
Combating poverty remains a major hindrance to economic development across Africa, even though it is well known that the poor are generally concentrated in rural areas. Paradoxically, identifying and targeting development efforts to the (very) poor remains a major challenge, mainly due to data deficiency and the wide application of popular but poorly adapted absolute poverty assessment approaches. This paper succinctly revisits the comparative advantages of relative over absolute poverty measures, and their prospects for application in rural Africa. Claims in favour of the relative approach are then substantiated by its application to empirically elicit poverty distribution among households in rural Cameroon. Analytical results fundamentally based on principle component analysis strengthen our advocacy for a dominant application and better prospects for relative poverty assessments over absolute ones, especially in rural areas of developing countries such as Cameroon, where data unavailability persists. In addition, the holistic and multi-dimensional attributes embedded in the relative approach oblige an atonement of its overarching prospects for identifying and targeting the poor in order to fight poverty and enhance economic development, especially in rural areas in Africa, as demonstrated in the Cameroonian case study.

Key words: Poverty, relative assessment, economic development, rural areas, Africa, Cameroon

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1. Introduction

The global importance of the fight against poverty and its influence on economic development especially in developing countries cannot be overemphasized. For many decades now, fighting poverty has remained an important global objective and features permanently as a policy goal in many developing countries. Its importance was reflected for instance in the Millennium Development Goals (MDGs) endorsed by 198 UN member states and 23 International Development Organizations in New York in September 2000, which became the overarching global development policy framework between 2000 and 2015. Halving extreme poverty by 2015 was the first MDG (Stewart, 2015). Eliminating poverty is still a key goal in the currently globally elaborated (17) Sustainable Development Goals (SDGs) that have succeeded the MDGs and will run until 2030 (Le Blanc, 2015), and remains a prominent policy objective of many sovereign states, particularly in Africa. In spite of the progress made in the fight against poverty over the years, over two billion people in the world still currently live in poverty (based on the World Bank's poverty line of US $ 2/day), with the bulk of them living in Africa (Bruton et al., 2013).

In spite of renewed global commitment to the fight against poverty demonstrated in the SDGs, achieving such a lofty goal is likely to remain largely unachievable and illusionary, mainly as a result of (but not limited to) many perverse factors such as societal decay, emanating from increasing natural and manmade disasters(Edoun et al, 2015); the relevance attributed to poverty reduction and economic development by public and private policies demonstrated for instance through good governance, transparency and accountability, research and extension, technological innovations, diffusion and adoption (Eastwood et al., 2017); and livelihood diversification (Senger et al., 2017).

Econometric and environmental modeling for instance suggests that disasters will continue to escalate in the future. In fact, sea levels rose up to 20cm in the twentieth century. Temperatures are expected to globally increase up to 5.8ºC by 2100 (Nicholls, 2002, ISDR, 2015). These changes in environmental factors provide favorable conditions for the upsurge of natural disasters. Rising natural and manmade disasters (such as economic crises, insurgency and terrorism) will further increasing poverty, impede economic development and create so called poverty traps (Carter and Barrett, 2006, Malmin, 2016). De-commitment to address climate issues by some major governments such as the United States of America will arguably further complicated the climate change-poverty reduction-economic development nexus.

It is a truism that the fight against poverty and slower than expected economic development in the last two decades or so across Africa has been largely caused by combined upsurge of natural disasters such as floods, droughts, volcanic eruptions; and manmade ones, such as violent conflicts, political instability and terrorism (Holzmann et al, 2003, Edoun et al., 2015,ISDR, 2015, Malmin, 2016). However, the rather disappointing achievements in reducing poverty cannot be limited to these factors. A critical factor widely accepted in the topical literature to have impeded progress in the poverty reduction front especially in African countries has been the ability to identify and adequately target services to the poor (Zeller et al., 1998, IFAD 2003, Balgah et al., 2015). For a long time now poverty in these countries has largely been identified as a rural phenomenon (Ellis, 1999, Fambom and Baye, 2002). Even when resources and policies have favored the course, adequately directing services to the poorest even in rural areas has remained a daunting task. Identifying and implementing approaches that efficiently identify the poor, assess endogenous contributing or impeding factors, improve targeting efficiency and foster economic development can greatly support global poverty reduction efforts especially in rural areas across Africa, where many households are still caught in poverty traps (Carter and Barrett, 2006); and where absolute approaches to measure poverty are still unfortunately dominant.

Contemporary poverty assessments are often grouped into absolute and relative approaches. From a general perspective, absolute measures of poverty on the one hand will determine a money-related poverty line, often constructed from income or consumption data. Those who fall below the line are considered poor and those above non-poor, irrespective of context (Atkinson, 1970, Dasgupta et al., 1973). The data demands for such measures are sometimes rigorous and difficult to obtain in most rural African communities. Its general context insensitivity has been a subject of criticism (Zeller et al., 1998, IFAD 2003). Proponents of this approach have attempted to address this shortcoming by applying context-specific Purchasing Power Parity (PPP) measures (Fambom and Baye, 2002). Relative poverty approaches on the other hand allow poverty levels to be computed based on a number of well defined (often context-specific) poverty indicators (Henry et al, 2003, Bourguignon and Chachravarty, 2003). While it has attracted criticism for its lack of generalization especially for comparison across countries and for the choice of selected indicators, it tends to capture context-specific poverty dynamics, especially in developing countries where money metric data is highly deficient (IFAD, 2003).

This paper concisely revisits this discourse and the relevance of each group of approaches for assessing poverty in rural areas especially in developing countries. Using an empirical case study from rural Cameroon the paper attempts a demonstration of the comparative advantage of the relative approaches over absolute measures for identifying and targeting services to the poor especially in rural areas of developing countries where hard data can be very difficult to elicit. A fundamental assumption here is that it is relative and not absolute measures which are crucial for identifying and directing resources to the poor in Africa, as the conceptualization of poverty in many African countries transcends absoluteness. The policy implications for an agenda biased towards relative poverty assessments in rural areas in Africa and the consequences for global poverty reduction are commented.

The paper will continue as follows. Section 2 briefly reviews the literature on poverty assessments Section 3 presents the materials and methods applied in the case study. Section 4 presents and discusses the results. Section 5 concludes the paper.

2. Topical Literature Review

Perhaps one of the reasons why measuring poverty especially across Africa is often described as devastating, extremely difficult, inaccurate and daunting may resonate from the limited understanding of how poverty is conceived within Africa; and the complex ramifications emerging for instance from its specific history, and contemporary influences of colonization (Jerven, 2014, Tem, 2016). One point of conversion on the poverty discourse however is that comparatively low availability of data renders the task of measuring (especially absolute) poverty in many African countries quite difficult. This section provides a historical snapshot of absolute and relative poverty assessment instruments, and concisely indicates their potentials or limitations for poverty research in Africa. The relative poverty approach which is the focus of this study will then be concisely introduced and prospects for its application in rural areas of Africa stimulated.

2.1. A Concise Historical Overview of Poverty Assessment Approaches

Living standard measurement surveys (LSMS) have remained the most dominant global approach to measuring absolute poverty for close to half a century now. History holds that LSMS are traceable to Atkinson's (1970) seminal paper on the measurement of poverty; and strengthened by the works of Amartya Sen and colleagues around the same period (see for instance, Dasgupta et al., 1973, and Sen, 1976). LSMS were conceptualized with the objective of identifying the poor, mainly based on a money-metric variable, the poverty line, which will be constructed using income or consumption data. Since this construction is based on a basket of goods and services required for a "normal" life, those who had incomes below the poverty line were considered poor, while those above it were non-poor (Sen, 1976). The philosophy behind LSMS was so appealing that it was adopted by the World Bank in 1980 as a major approach to assess poverty in member countries and to facilitate the implementation of poverty alleviation decision making policies (Grosh and Glewwe, 1995).

Perhaps, the most interesting period in the historical evolution of poverty measures is the 1980s. In fact, various attempts to consolidate LSMS and the poverty line concept in measuring (absolute) poverty or to further improve the robustness of this and related concepts emerged during this period (Forster et al., 1984, Atkinson, 1987). Interestingly, an alternative measure, the relative poverty approach, was conceived almost concomitantly. Contrary to the predominantly money-metric focus of absolute poverty measures, relative poverty advocates proposed a newer conceptualization of poverty based on wellbeing in a wider sense. The relative abundance of capabilities and entitlements that should go beyond income and consumption to include aspects of deprivation, social justice, equity and dignity, were considered more acceptable in understanding and measuring the poverty dynamics, as compared to a single, absolute, money-related dimension (Sen 1983). In other words, poverty was increasingly construed, conceived and measured from different dimensions constituting it, and not necessarily from an isolated and mono-directional money-related poverty line, computed based on income or consumption expenditures. The relative poverty assessment approach was experimented in the 1990s by those who found it appealing (e.g. UNDP 1990).

However, the absolute approach overshadowed the relative poverty assessments, due to its measurability, comparability within and across countries and the strong, proven correlation between poverty levels and income or consumption expenditures (Atkinson, 1991, Ravallion 1992, Grosh and Glewwe, 1995, Deaton, 1995).Traditionally therefore, LSMS and poverty lines have been the first choice of planners seeking to analyze poverty within and across countries. Contemporary attempts to improve on this approach abound (e.g. Carter and Barrett, 2006), and empirical applications are overwhelming (e.g. Datt and Ravallion, 1992, Jorgensen, 1998, Chen and Ravallion, 2001, Fambom and Baye, 2002, Deaton, 2005, Odzi, 2018).

Notwithstanding, a number of popular criticisms have been levied against the validity of formal surveys and poverty lines especially in Africa where data unreliability is high, mainly due to the complexity in compiling incomes and/or consumption expenditures in the absence of regular records (Ellis, 1993).The response has been to develop and apply relative poverty assessment approaches that allow for poverty indices to be computed based on a number of easily accessible, well defined poverty indicators, identified to strongly measure poverty (Henry et al, 2003, Bourguignon and Chachravarty, 2003). Examples include the Human Development Index and the Human Security Index of the United Nations Development

Program (UNDP 1994) and the International Food Policy Research Institute's (IFPRI's) Poverty Index (Henry et al., 2003). Multidimensional approaches to poverty assessments have proven to be quite useful in targeting services to the poor, in capturing intra-household and intra-community poverty differences, and in assessing the impacts of development projects, programs and policies (Zeller et al., 2006, Balgah et al., 2015). As part of advocacy efforts towards illuminating the relevance and appropriateness of this approach for application in developing countries, we apply the relative Poverty Assessment Tool (PAT) to assess and compare relative poverty among households benefitting from state and non-state support in the North West Region of Cameroon after a natural disaster, and those who did not. The Poverty Assessment Tool (Henry et al., 2003, Zeller et al., 2006) is specifically applied in the empirical case study. This tool is briefly reviewed in the following section.

2.2. The (Relative) Poverty Assessment Tool – PAT: A brief Introduction

The Poverty Assessment Tool (PAT) has been chosen to illustrate our support for relative assessments in developing countries. We apply it to comparatively assess rural poverty across different household types in our empirical case study from Cameroon. The choice for the tool is due to its proven capacity to differentiate poverty in communities where data on income and consumption expenditures that form the basis for poverty lines are difficult to collect (Irungu, 2002, Henry et al., 2003).

This tool was developed by the International Food Policy Research Institute (IFPRI) with the technical and financial assistance of the Consultative Group to Assist the Poor, CGAP (Henry et al., 2000). PAT has proven to be very appropriate for assessing poverty levels of beneficiaries of development policies and projects in relation to the general population in any area of intervention, well beyond the microfinance sector for which it was initially developed (Balgah, 2004, Zeller et al., 2006). It has been empirically applied for instance to assess how far policies and project services are targeting the poor in the Eastern and Southern Africa (IFAD, 2002), and in the Near East and North Africa (IFAD, 2003). Many country-specific case studies exist (see for instance and Zeller et al. (1998)for relative assessment of Microfinance impacts in Malawi, Minten and Zeller (2000) on the same issue in Madagascar, Irungu (2002) for outreach and performance of development NGOs in Kenya, and Balgah and Buchenrieder (2011) for technology adoption in Cameroon). Isolated components have also been consciously or unconsciously applied empirically. A contemporary example is the work of Odozi (2018), who appropriated the food poverty component to elicit poverty distribution and its determinants amongst rural households in southern Nigeria.

The prolific and diverse use of the PAT has been motivated by its multiple favorable characteristics such as practicality under developing country situations, accuracy in measuring relative poverty, easy applicability, a relatively short time needed for application, lower implementation costs and comparability of treatment and control groups under different circumstances, regardless of location, structure and context (Henry et al, 2000, Balgah and Buchenrieder 2011).Its theoretical and empirical foundations are underpinned by the entitlements and capabilities approach to understanding poverty, and by the conception of poverty as a multifaceted and multidimensional phenomenon (Sen, 1983).

Basically, PAT consists of a number of indicators that reflect poverty levels powerfully and for which credible information can be quickly and inexpensively obtained (Zeller et al., 2006).Unlike the poverty lines approach, it does not oblige the compilation of all food and non-food expenditures of a household since some types of expenses are closely related to the level of household poverty and others are not. As such, biases introduced by recall methods are reduced. Studies have shown for example that the proportion of clothing expenditure in the household budget remains stable, between 5 and15 percent of the total expenses (Minten and Zeller, 2000, Irungu, 2002, Balgah and Buchenrieder, 2011). Since clothing, unlike food commodities usually means the purchase of a finished good, and is not as variable as the latter, households in rural areas of many developing countries are more likely to recall such expenses (Henry et al., 2000, 2003). Household clothing expenditures are therefore benchmarks for comparative analysis in the application of PAT. Due to these numerous advantages for capturing relative poverty (at least over the absolute poverty line), we contend that the tool is quite appropriate for measuring poverty especially in rural areas of Africa. The prospects however are higher, inasmuch as capturing poverty is important for local, context-specfic policy implementation and economic development. The shortcoming of comparisons across communities and countries abound, as the strength and importance of the selected poverty indicators are likely to vary from one case study to another. We assume *apriori* that the strengths supersede the weaknesses, given that in many African societies, differences in poverty levels is likely to be attributed to a comprehensive assessment of implicit and explicit “livelihood” differences, which go beyond money-metric measures. We support our contention with an empirical case study from rural Cameroon.

3. Materials and Methods

3.1. Background of the study

The Republic of Cameroon is often described as Africa in miniature, due to its wide cultural and agro-ecological diversity. Poverty rates in the country are estimated to be increasing, in spite of the abundance of resources in this country (Balgah, 2016). About 48% of its entire population lives below the poverty line; with 55% of all the poor located in the rural areas (Heifer International, 2014). Some major reasons for persistent poverty in Cameroon include increasing frequency of natural disasters, inadequate policies, poor governance and widespread corruption (Bang, 2013).

With around two million inhabitants, its North West Region (NWR) is one of the most populated regions in the country. This represents an estimated 11% of total population (Gur et al., 2015). About 80% of North Westerners live in rural areas, where poverty is concentrated (Fambom and Baye, 2002).The population growth rate in the region (4.5%) is higher than the national average of 3.3% (Innocent et al., 2016). The North West region has witnessed an increasing upsurge of natural disasters in recent decades. Perhaps the most devastating natural disaster on record is still the 1986 lake Nyos natural gas explosion.

On August 21st 1986, a limnitic eruption at Lake Nyos, located in the North West Region of Cameroon was responsible for the emission of large amounts of carbon dioxide and minimal amounts of hydrogen sulphide that suffocated and killed about 2,000 inhabitants and almost all livestock in three villages (Cha,Nyos and Subum) located within a diameter of about 25km around the lake. Geomorphologic investigations after the gas explosion revealed potentially releasable300 million M^3Carbon dioxide in the deeper layers of the lake (Halbwachs et al., 2004). As an outcome of an international conference on Lake Nyos in Yaoundé – Cameroon, it was resolved that the over 5500survivorsshould be resettled immediately into safer areas (Sigvaldson, 1989). Between 1987 and 1988, all survivors were moved into seven newly constructed resettlement camps in the neighboring villages of Buabua,Kimbi, Yemngeh, Kumfutu, Esu, Ipalim, and Upkwa. Since then, the poverty stricken households have naturally received biased support from state and non-state actors, in an attempt to reduce the level of poverty and step up their livelihoods at least to the levels of matching non-victims in the recipient communities. Such a selective targeting gives us justification to assess the performance of policy interventions, and to identify the prospects of the relative approach for poverty assessments in rural areas of developing countries. By examining the relative poverty among the two household types, we are assuming that the poverty levels of both household types were more or less the same before the disaster stroke.

3.2. Methodology

In the absence of panel data, only ex-post, cross sectional analysis could be carried out.It should be mentioned here that like with many other rural areas in the country, consumption and expenditure data was conspicuously absent, rendering any attempts to apply absolute poverty measures futile. Qualitative and quantitative data were then obtained at household level for both household types, based on the relative PAT. Six villages generally close to each other (Cha, Nyos and Subum,Kimbi, Bua-bua and Kumfutu) were purposively selected for data collection (see figure 1). We assume apriori that closeness minimizes the effects of extraneous factors not measured by our research, which could affect poverty levels differently.

Similar data on multiple dimensions of povertywas obtained from both victims and non-victims using a structured questionnaire, developed mainly on the basis of the Poverty Assessment Tool (PAT) (Henry et al., 2000&2003).The questionnaire contained demographic, economic, human, social, dwelling and food security variables.

Data was obtained from a total of 300 households, consisting of a census of 198 victims and 102 randomly selected non-victims. The sampling frame for victims was obtained from the local disaster management institution, while that for matching non-victims was constructed with the help of local traditional authorities. Both the household head and spouse were present during the questionnaire administration, which was done by trained enumerators. Experience suggests that this reduces data collection errors, especially when recall is the dominant approach for obtaining data (Fisher et al., 2009). Participatory Rural Appraisal methods, particularly key informant interviews, focus group discussions and field observations complemented the standardized questionnaire. Field data collection took place in October 2014.

Collected data was entered and analyzed using SPSS (Statistical Package for Social Sciences), version 17.0. Both descriptive statistics and econometric analysis were performed, generally adopting a5% significance level ($\alpha = 0.05$). Results are presented and discussed in the next section. Specific household indices were econometrically computed using the principle component analysis (PCA) technique and used to comparatively analyze the poverty distribution by household type. Further specifications will be provided in the next section.

4. Results and Discussion

This section presents and discusses the research results in a comparative manner. It commences with the descriptive statistics before proceeding to the econometric analysis.

4.1. Descriptive statistics

Human capital was captured using literacy rate, the mean age of household head and the household size, as informed by the PAT guidelines. These variables were judged to be appropriate, considering that subsistence farming is the dominant livelihood strategy in the research region (Balgah and Buchenrieder, 2011). Although the mean literacy rate of 50% (assessed as the percentage of household heads in the sample who could read and write) is generally low compared to the national average of 94% for Cameroon (World Resource Institute, 2006), over 60% of victimized household heads could read and write, compared to only around 39% for heads of the matching non-victimized households (X^2=0.081). This can be attributed to disaster policy interventions biased towards victims, if one assumes that the literacy rate was more or less the same among the two household types before the disaster. Non-victimized households are significantly younger on average than victims (Mean= 44.22 and 49.58 years respectively, p=0.00). This is logical, as the bulk of those who were suffocated by the gas explosion in 1986 were children (Shanklin, 1988). However, the mean household size of victims is significantly larger than for non-victims (8 and 6 persons respectively; p=0.002). Higher household sizes for victims could be interpreted as a logical outcome of the disaster. It is likely that the experience of loosing loved ones to the disaster could have stimulated a higher proliferation rate amongst victims, in a bit to (at least psychologically and numerically) compensate for household members lost during the 1986 disaster. This process is likely to have benefitted from selective targeting by state and non-state actors, which probably exposed victims to more resources than non-victims. At this level, there is reason to conjecture that the biased policy intervention improved the human capital of beneficiary households.

Additional descriptive statistics are presented in Table I below. Victims have slightly higher annual household incomes, number of plots and logically more land than the non-victims. Non-victims on the other hand have larger per capita expenses on clothing and footwear than victims. These differences are not statistically significant. Both households reported eating a mean of about two meals per day. This is one meal short of the expected number of meals a day. This may suggest a deeper examination and research on food security issues in the community, which goes beyond the current frame of this work.

An analysis of dwelling indicators is presented in Tables II and III. Over 90% of all households own the houses in which they live, while the remaining households mostly live in houses offered by relatives, or are renting. This result supports previous research outcomes in North West Cameroon, where house ownership was reported to be very important indicator of wellbeing (see for instance Balgah and Buchenrieder, 2011). Over 95% of all houses are permanent, with walls constructed mainly from sun-dried bricks and roofed with Zinc. In general however, the houses are of poor quality, with almost 60% of all the houses seriously dilapidated and/or are in need of major repairs. However, victims generally live in better houses than non-victims (almost 46% and less than 40% respectively). This difference is not statistically significant. Nevertheless, a housing edge for victims over non-victims is attributable to the selective targeting policy, considering that the houses in which victims currently live were constructed by state and non-state actors after the disaster (Sigvaldson, 1989, Ngwa and Balgah, 2016).

Table I: Socioeconomic analysis of sample by household type

	Household type	Mean	Std. Deviation	Std. Error Mean	significance
Total household size	Victim	7.89	5.013	.356	0.002
	Non victim	6.13	4.068	.403	
Estimated annual household income(FCFA)	Victim	29365	28100	1995	
	Non victim	27680	21970	2175	0.598
Per capita annual expenditures on clothing and footwear (FCFA)	Victim	2635	3685	265	
	Non victim	4625	12080	1225	0.218
How many plots does the household has access to	Victim	3.01	3.790	.272	0.903
	Non victim	2.96	2.369	.238	
Total area of land (Ha)	Victim	4.192	6.9226	.4970	
	Non victim	3.212	3.1543	.3170	0.182
Mean number of meals served in the household per day	Victim	2.09	1.87	0.13	
	Non victim	2.18	1.97	0.20	0.449

Source: Own field data analysis

Table II: Comparative analysis of House ownership by household type

Household type	Percentage type of ownership reported				Total (%)	X^2
	Household/ Household head	Friend/ relative	Landlord	Government		
Non victim	90.20	5.80	4.00	0.00	100	.294
Victim	95.00	3.00	1.50	0.50	100	
Sample mean	92.60	4.40	2.75	0.25	100	

Source: Own field data analysis

Table III: Comparative analysis of structural condition of house by household type

Household type	Structural condition of house (%)			Total (%)	X^2
	seriously dilapidated	In need of major repairs	In good condition		
Non victim	16.67	44.11	39.22	100	0.484
Victim	13.13	40.91	45.96	100	
Sample mean	14.90	42.50	42.60	100	

Source: Own field data analysis

The descriptive statistics reveal a mixed picture. With the exception of household size and house construction, where victims claim a significant edge over non-victims, there is alternation of comparative advantage of each household type over the other, even if the differences are not statistically significant. At this stage, it is difficult to make strong statements about the distribution of poverty amongst and between household types. In fact, the descriptive analysis does very little to vouch for relative assessments and a prospective dominant approach for assessing rural poverty in Africa.

To draw relevant conclusions, further econometric analysis is required. One way to do this (as stipulated in the PAT methodology) is to construct unique household poverty indices, following the poverty assessment tool (Henry et al., 2003, Zeller et al., 2006, Balgah and Buchenrieder, 2011). The approach applied in this paper is further explained below.

4.2. Econometric analysis

The Principal Component Analysis (PCA) was econometrically applied to compute poverty indices at household level. PCA isolates and measures the poverty component embedded in the various poverty variables to create a household-specific poverty score or index, following procedures explained in the Poverty Assessment Tool (Henry et al., 2000; 2003). In the first step, bivariate analysis was performed between the dependent variable, per capita expenditure on clothing and foot wear, and all (independent) ordinal and ratio-scale variables in the data set, as prescribed in the PAT approach. This procedure generates correlation coefficients which are used to select relevant variables for further analysis. Only independent variables correlating with the bench mark indicator with a significance level less than 10% were selected for use in computing unique household poverty indices through the application of the PCA. The objective is to compute a new variable, $P*$, which linearly combines relevant indicators, and therefore maximally accounts for the total variance in the individual indicators. The econometric model used to compute the household poverty index takes the following form:

$$P^* = P_1X_1 + P_2X_2 + P_3X_3 + \ldots + P_nX_n \qquad (1)$$

Where the weighted contribution of each individual variable to poverty (Pn) are specified such that the newly computed poverty index ($P*$) accounts for the maximum variances in the individual variables (Xn). A poverty index constructed in this manner provides a better measure of relative poverty, considering that different dimensions of poverty are considered in the process of computing the household-specific indices. According to Henry et al. (2003), amongst other conditions, an accepted model should develop poverty indices with a mean of at least zero and a standard deviation of one, and a KMO measure of at least 0.60. Our model meets these requirements (see table IV and figure I below).

Table IV. KMO and Bartlett's Test of model

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.674
Bartlett's Test of Sphericity	Approx. Chi-Square	241.494
	df	36
	Sig.	.000

Source: Own field data analysis

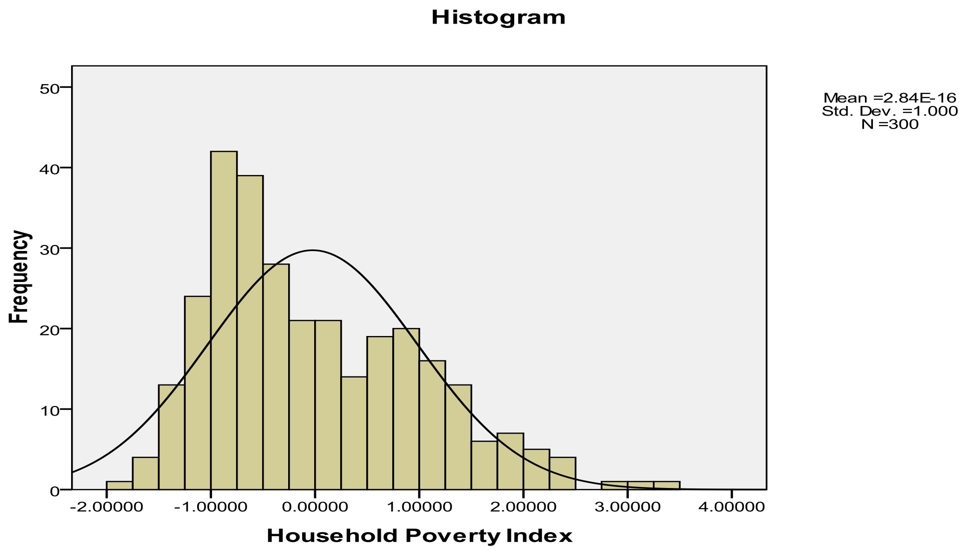

Figure I. Distribution of poverty indices across all sampled households
Source: Own field data analysis

An additional way of testing the strength of the model employed in PCA is by closely examining the explained common variance. This is presented in table V. The explained common variance table displays the Eigen values calculated for each component included in the model. In the PAT methodology, the larger the Eigen value, the more that component is explained by the model. Since the model applied here has been carefully screened to include only poverty indicators, the first component is likely to explain the variance in the test and matching samples associated with poverty (Henry et al, 2003). As a rule, a minimum value of 1 is needed for a component to be accepted as an explanatory factor in the model. As can be seen in table V, the first component (in this case the poverty index) explains about 24% of the variance between victims and non-victims. Cumulatively, the first four components with Eigen values above 1 allow the model to explain over 66% of the variance in the sample.

Table V. Explained Common Variance

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.106	23.399	23.399	2.106	23.399	23.399
2	1.564	17.373	40.772			
3	1.238	13.759	54.531			
4	1.048	11.649	66.180			
5	.869	9.652	75.832			
6	.708	7.871	83.703			
7	.646	7.175	90.878			
8	.476	5.287	96.165			
9	.345	3.835	100.000			

Extraction Method: Principal Component Analysis.
Source: Own field data analysis

Using the poverty index, the matching households (non-victims) were first grouped into terciles, consisting of the lowest one third of households (lowest), constituting the poorest households, the middle one third considered as just poor and the last (higher) one third constituting the nonpoor tercile, as prescribed by the methodology (Henry et al., 2003, Balgah et al, 2015). The middle tercile for matching households provided the cut-off indices for the three groups. On the basis of these cut-off indices, treatment households were also grouped accordingly. It is worth mentioning that the latter households had suffered losses from a natural disaster from Lake Nyos in the North West Region in 1986 (Shanklin, 1988, Sigvaldson, 1989). Poverty groups of matching (non-victim) households insure that they are equally represented in all groups. In fact if the treatment households (victims) would be equally distributed percentage wise in the terciles created based on the matching households, it would be assumed that they have fully recovered from the disaster, and that development efforts have been quite successful in this direction. Variability in distribution will then be interpreted accordingly.

The descriptive statistics of the middle tercile is presented in Table VI. The mean index of the middle tercile is negative, suggesting that poverty is still wide spread in the communities, irrespective of household type. However, since we are interested in relative poverty distribution, it becomes interesting to observe how the level of poverty differentiates victims from non-victims. This is done with the help of the middle tercile of non-victims displayed in table VI.

Table VI. Descriptive statistics of middle tercile of poverty index

Variable	Minimum	Maximum	Mean	Std. Deviation
Household Poverty Index	-.59020	.60636	-.0394349	.35706398

Source: Own field data analysis

Figure II presents the results. Treatment (victimized) households are significantly better-off compared to the matching ones, as 67.6 % of the former households belong to the just poor category (middle tercile), compared to 33.3% of matching (non-victimized) households in the same category. A higher percent of non-victims (33.3 %) are very poor (i.e. lowest tercile) compared to only around 20% of the victimized ones. However, there are almost three times less victimized households (around 13%) who are non-poor (higher tercile), compared to non-victims.

In the absence of baseline data, it is however difficult to attribute these differences to targeting efficiency of the development organizations that have selectively supported victims. One way to address the issue in this specific case study is to compare the mean values of livestock and household assets for both household types. This seems logical, as victimized households lost almost all of their livestock and household assets during the natural gas explosion (Shanklin, 1988, Balgah and Buchenrieder, 2011). If the mean is not significantly different between victims and non-victims, then one can assume that development partners did a great job to reduce poverty gap amongst the household types, by rapidly building up livestock assets for the victims. Contrary results will suggest a poor performance of development policy.

The comparative results are presented in table VII below. One observes that although the mean livestock and total household assets for non-victimized household (US$ 553 and US$ 1401 respectively) are higher than for victimized households (US$ 470 and US$ 1150 respectively), they are not statistically significant (0.74 and 0.63 respectively). In addition, livestock assets, that were almost zero after the 1986 disaster, currently represent almost 41% of the total value of household assets for these households. Higher asset values for non-victims resonate logically with the higher percentage of such households who are non-poor compared to the victims. The results suggest that development efforts in the research region that mainly targeted victimized households were able to reduce the poverty gap that locally existed with non-victims after the 1986 disaster, though not completely, as many households are still cut in the poverty trap (Carter and Barrett, 2006).

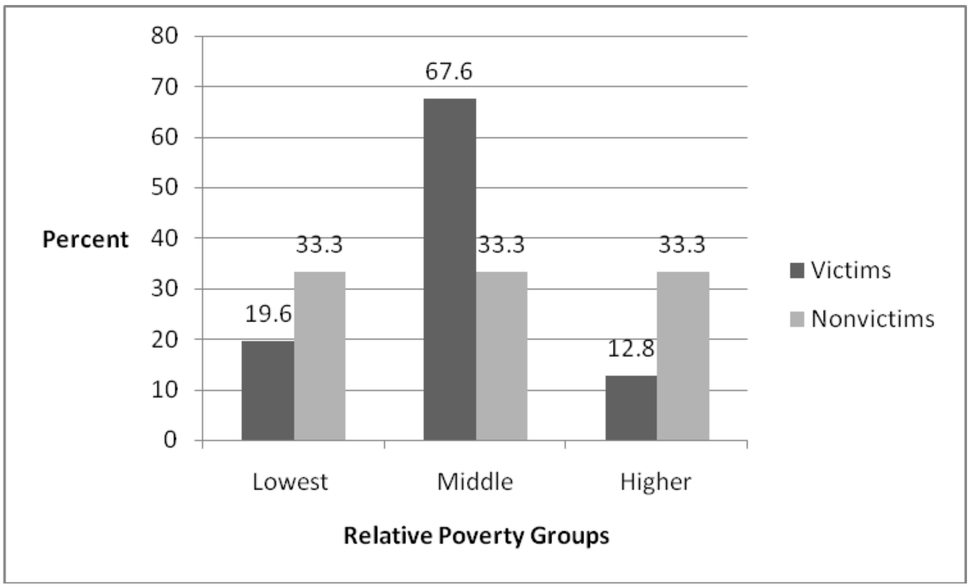

Figure II: Relative poverty distribution by household type
Source: Own field data analysis

Table VII. comparative analysis of livestock and household assets by household type

Variable	Household type	Mean (FCFA)	Std. Deviation	P value
Mean value of livestock assets	Non victims	332,355	1.42454E6	0.74
	Victims	281,840	1.17502E6	
Mean value of household assets	Non victims	840,730	2.94816E6	0.63
	Victims	690,075	2.32769E6	

Source: Own field data analysis

Notes:

1. All values have been rounded up to the nearest FCFA
2. 1 US S equals FCFA 600

5. Conclusions

The objective of this paper has been to stimulate reflections on the inappropriateness of absolute measures for assessing poverty in rural Africa; while propagating a narrative in favor of more relative poverty assessment approaches for identifying the (very) poor and targeting them with services; thereby fostering economic development in African economies. In addition to a concise overview of absolute and poverty measures, this paper has substantiated what can be considered a consciously biased preference for relative poverty assessments in rural Africa, by comparatively assessing relative poverty distribution among rural households based on a case study from Cameroon. Poverty was assessed by comparing individual socioeconomic variables correlating (significance better than 10%) with per capita expenditures on clothing and foot wear, which is a bench mark indicator in the relative poverty assessment tool (PAT) adopted for the study(Henry et al, 2003). These socioeconomic variables formed the basis for the computation of unique household poverty indices. An analysis of the results leads us to a number of conclusions. Firstly, with the exception of household size and age and house construction, the individual indicators did not significantly differentiate the treatment from the matching households. Secondly, and based on a comparison of the computed poverty indices, the percentage of victimized households that fell in the middle poverty tercile more than doubled those of the matching households. In addition, livestock and household assets of non-victims were slightly higher than for victims, although the differences were not significant at the 5% level. Thirdly, the overall sample mean poverty index for all the households was very low (mean=0.00), suggesting that poverty is a widespread phenomenon in the region, irrespective of household type. In fact the households are still caught in the vicious cycle of poverty.

These results lead us to a number of conclusions. (1) The biased targeting policy implemented by development partners in the region in favor of the disaster victims was successfully reduced the poverty gap between victims and non-victims, created by the 1986 Lake Nyos disaster in the North West Region of Cameroon. (2) Most households in the sample are currently still warbling in poverty, irrespective of type.

It is therefore recommended that broad based, holistic and unbiased poverty development approaches should be implemented in the research region, if fighting poverty and promoting sustainable (economic) development are explicit policy objectives in the region. Meanwhile, future research efforts should be directed on understanding why development policy interventions in this rural area in Cameroon could not succeed to eliminate poverty completely, or at least to fully bring back the livelihoods of victims to the same levels of their counterpart non-victims, even over a quarter of a century. Understanding such issues and addressing them can provide answers to policy efforts towards poverty reduction in rural Cameroon, which can contribute to the government's objective of the country becoming an emerging nation in 2035. It is further recommended to carry out similar research in other areas, to ascertain to what extent relative poverty assessments can be applied to disentangle differences in poverty in specific rural communities across Africa.

Drawing from the case study, one contends that relative approaches have higher prospects over absolute ones, for identifying and targeting services to the poor in rural areas in Africa, where hard data is often very difficult to elicit. This advantage however should be understood within the context of difficulty in comparisons across case studies and countries for that matter, considering that the indicators retained for econometric analysis are likely to vary from case to case. While further research is however needed to strengthen this contention and to improve the prospects of relative poverty assessments for rural African areas, one has to also question the need, given that the perception of poverty is largely context-specific. In any case, there seems to be a need to identify and gradually apply indicators that are robust across space and time to provide more scientific validity to the relative approach. This of course requires time and additional research efforts. In the meantime, and as long as poverty in many rural African societies remains a relative phenomenon, it would just be logical to assume that relativity in assessing poverty and economic development would be more appropriate than any absolute, money-metric approach.

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References

Atkinson, A. B. (1970) On the measurement of inequality, *Journal of economic theory*, *2*(3), pp. 244-263.

Atkinson, A.B. (1987) On the measurement of Poverty, *Econometrica* 55, pp. 749-764

Atkinson, A.B. (1991) Comparing Poverty Rates Internationally: Lessons from Recent Studies in Developed Countries,*World Bank Economic Review*, 5(1), pp. 3-22.

Balgah, R.A. (2004) *Poverty and resource Management for Fish Farming Households in North West Cameroon. A Comparative Analysis*, Goettingen: Institute of Rural Development.

Balgah, R.A. and Buchenrieder, G. (2011) Does technology adoption reduce risks for smallholder farmers in Cameroon?,*Pakistan Journal of Social Science* 8(1), pp. 13-22.

Balgah, R.A., Yenshu, E.V., Innocent, N.M. & Kimengsi, J.N. (2015) Rural Development NGOs and Service Delivery to the Poor: An Empirical Analysis of a Training Center in rural Cameroon,*Asian Journal of Agriculture and Rural Development* 5(4),103-115.

Balgah, R.A. (2016) Applying Participatory Rural Appraisal to Unlock Gender Group Differences in Some Communities in Rural Cameroon, *Asian Journal of Agricultural Extension, Economics & Sociology*, 12(3), pp. 1-11.

Bang, H. N. (2013) Governance of disaster risk reduction in Cameroon: The need to empower local government, *Jàmbá: Journal of Disaster Risk Studies*,*5*(2), 10-pages.

Bourguignon, F., & Chakravarty, S. R. (2003) The measurement of multidimensional poverty, *The Journal of Economic Inequality*, *1*(1), pp.25-49.

Bruton, G. D., Ketchen, D. J., & Ireland, R. D. (2013) Entrepreneurship as a solution to poverty, *Journal of Business Venturing*, *28*(6), pp.683-689.

Carter M. R. & Barrett C. B. (2006) The economics of poverty traps and persistent poverty: An asset-based approach, *The Journal of Development Studies*, 42(2), pp. 178-199,

Chen, S. & Ravallion, M. (2001) How did the world's poorest fare in the 1990s?, *Review of Income and Wealth*, 47(3), pp. 283-300.

Dasgupta, P., Sen, A. & Starrett, D. (1973) Notes on the measurement of inequality, *Journal of Economic Theory*, *6*(2), pp.180-187.

Datt, G., & Ravallion, M. (1992) Growth and redistribution components of changes in poverty measures: A decomposition with applications to Brazil and India in the 1980s, *Journal of Development Economics*, *38*(2), pp.275-295.

Deaton, A. (1995) Data and econometric tools for development analysis, .*Handbook of Development Economics*, *3*, pp.1785-1882.

Deaton, A. (2005) Measuring Poverty in a Growing World (or Measuring Growth in a Poor World), *The Review of Economics and Statistics*, 87(1), pp. 1-19.

Eastwood, C., Klerkx, L. & Nettle, R. (2017) Dynamics and distribution of public and private research and extension roles for technological innovation and diffusion: Case studies of the implementation and adaptation of precision farming technologies, *Journal of Rural Studies* 49(2017), pp.1-12.

Edoun, E. I., Balgah, R.A**.** & Mbohwa, C. (2015) The impact of effective management of natural disasters on Africa's development, *Economic Research*, 28(1), pp. 924-938.

Ellis, F. (1993) *Peasant Economics. Farm Households and Agrarian Development*, New York: Cambridge University Press.

Fambom, S. & Baye, F.M. (2002) Income Distribution and Poverty in Cameroon, Paper presented at the WIDER and Center for the Study of African Economies Conference on Spatial inequality in Africa, University of Oxford, 21-22 September, 2002.

Fisher, M., Reimer, J.J. & Edward, R. (2009) Who should be Interviewed in Surveys of Household Income?, *IFPRI Discussion Paper,* No. 949.

Forster, J., Greer, J. & Thorbecke, E. (1984) A class of decomposable Poverty Measures, *Econometrica,* 3(88), pp.215-251.

Grosh, M. & Glewwe, P. (1996) A guide to Living Standards Surveys and Their Data Sets, LSMS Working Paper No. 120, Washington DC: The World Bank.

Gur, A. S., Kimengsi, J. N., Sunjo, T. E., & Awambeng, A. E. (2015) The implications of climate variability on market gardening in Santa Sub-Division, North West Region of Cameroon, *Environment and Natural Resources Research*, *5*(2), pp.14-23.

Halbwachs, M., Sabroux, J. C., Grangeon, J., Kayser, G., Tochon-Danguy, J. C., Felix, A., & Hell, J. (2004) Degassing the "killer lakes" Nyos and Monoun, Cameroon, *Eos, Transactions American Geophysical Union*, *85*(30), pp.281-285.

Heifer International (2014) *The state of the African farmer,* New York: Heifer International.

Henry, C. Sharma, M., C. Lapenu, & Zeller M. (2000) *Assessing relative poverty of microfinance clients,* A CGAP tool, Washington DC: International Food Policy Research Institute.

Henry, C; M. Sharma, C. Lapenu, and Zeller M. (2003) *Microfinance Poverty Assessment Tool,* Washington DC: World Bank, CGAP.

Holzmann, R., Sherburne-Benz, L. & Telsuic, E. (2003) Social risk Management. The World Bank's approach to social protection in a globalized world, Social Protection Department, Washington DC: The World Bank.

IFAD (2002) *Assessment of Rural Poverty. Eastern and Southern Africa,* Rome: International Fund for Agricultural Development.

IFAD (2003) *Assessment of Rural Poverty. Near East and North Africa,* Rome: International Fund for Agricultural Development.

Irungu, C. I. (2002) *Outreach Performance of Non-governmental Development Organisations in eastern Kenya,*Kiel: Wissenschaftsverlag Vauk Kiel KG.

ISDR (2015) *The Pocket GAR 2015. Making development sustainable. The future of disaster risk management,* Geneva: United Nations Office for Disaster Risk Reduction.

Jerven, M. (2014) Measuring African Development: Past and Present. Introduction to the Special Issue, *Canadian Journal of Development Studies/Revue Canadienne d'études du développement* 35(1), pp. 1-8.

Jorgensen, D.W. (1998) Did we lose the battle on poverty?, ,*Journal of Economic Perspectives*, 12(1), pp. 79-96.

Innocent, NM., Bitondo, D. & Balgah, R.A. (2016), Climate variability and Change in the Bamenda Highlands: Perceptions, Impacts and Coping Mechanisms, *British Journal of Applied Science and Technology*, 12(5), pp. 1-18.

Le Blanc, D. (2015). Towards integration at last? The sustainable development goals as a network of targets, *Sustainable Development*, *23*(3), pp.176-187.

Malmin, M. (2016). Islam's Link to Terror—A Psychology of Denial. *World Journal of Social Science Research*, *3*(1), pp.92-113.

Minten, B., & M. Zeller (2000) *Beyond market liberalization. Income generation, poverty alleviation and environmental stability in Madagascar*, Aldershot: Ashgate Publishing Company.

Nicholls, R.J. (2002) Analysis of global impacts of sea level rise: A case study of flooding, *Physics and Chemistry of the Earth*, 27(32-34), pp. 1455-1466.

Ngwa, K. A., & Balgah, R. A. (2016). Determinants of Livelihood Security Among Disaster Victims in rural Cameroon, *International Journal of Recent Scientific Research*, 7(1), pp.8328-8334

Odozi, J.C. (2018) Food Poverty Dynamics and the Determinants across Households in Rural South South Nigeria. *African Journal of Economic Review* 6(2), pp. 135-151.

Sen, A. (1976) Poverty: an ordinal approach to measurement, *Econometrica*, 44(2), pp. 219-231.

Sen, A. (1983) Poor, Relatively Speaking, *Oxford Economics Papers* 35, pp. 153-169.

Senger, I., Borges, J.A.R. & Machado, J.A.D. (2017) Using the theory of planned behavior to understand the intention of small farmers in diversifying their agricultural production. *Journal of Rural Studies,* 49 (2017), pp. 32-40.

Shanklin, E. (1988). Beautiful deadly Lake Nyos: The explosion and its aftermath, *Anthropology Today*, *4*(1), pp.12-14.

Sigvaldason, G. E. (1989) International conference on Lake Nyos disaster, Yaoundé, Cameroon 16–20 March, 1987: conclusions and recommendations, *Journal of volcanology and geothermal research*, *39*(2), pp.97-107.

Stewart, F. (2015) The Sustainable Development Goals: a comment, *Journal of Global Ethics*, 11(3), pp. 288-293.

Tem P.M. (2016) Flaws in the native administration system in Southern Cameroons. A factor for the 1949 creation of local government, *Afro Asian Journal of Social Sciences*,7(1), pp.1-24.

UNDP (United Nations Development Program) (1990) *Human development report 1990,* New York: Oxford University Press.

UNDP (United Nations Development Program) (1994)*Human development report 1994*, New dimensions of human security, New York: United Nations Development Program (UNDP).

World Resource Institute (2006). Population, Health and Human well-being. Country Profile-Cameroon. http://earthtrends.wri.org/text/population-health/country-profile-32.html (accessed on 10.04.2016).

Zeller, M., Diagne, A., & Mataya, C. (1998) Market access by smallholder farmers in Malawi: Implications for technology adoption, agricultural productivity and crop income *Agricultural Economics*, *19*(1), pp.219-229.

Zeller, M., Sharma, M., Henry, C.& Lapenu, C. (2006). An operational method for assessing the poverty outreach performance of development policies and projects: Results of case studies in Africa, Asia, and Latin America, *World Development*, *34*(3), pp.446-464.