Novelty Journals

ISSN 2394-9694

International Journal of Novel Research in Humanity and Social Sciences
Vol. 4, Issue 6, pp: (23-34), Month: November-December 2017, Available at: www.noveltyjournals.com

An Empirical Comparison of the effects of Unidimensional and Multidimensional Poverty on Wellbeing

Aisha Mohammed Abubakar

Lecturer, Department of Economics, Sokoto State University, Sokoto – Nigeria

Abstract: **The persistence of poverty, inequality and ill-being in many developing countries, despite economic progress, has revived interest in academic and policymaking circles. Before recent decades, poverty and well-being was conceived primarily as a matter of income and methodological debates centred naturally around what was perceived to be the best method of identifying and measuring deprivation. There is a fairly general agreement among both academics and development practitioners that poverty is a multidimensional phenomenon. Some confusion seems to exist in certain quarters, regarding the precise nature of this multidimensionality and the viability of univariate and multivariate indicators in influencing policy decisions. This paper attempts to review and analyse the effect of poverty on wellbeing from a multidimensional lens. In order to achieve this, the paper focuses on Income Poverty as it is the most widely used and criticized form of unidimensional poverty measurement. For the multidimensional strand, we will refer to the Multidimensional Poverty Index (MPI). This study employed Ordinary Least Squares regression technique on 106 countries between 2000 and 2010. Our results deduce that the effect of poverty on wellbeing depends on the poverty measure. The MPI revealed more significant effects on wellbeing in all the regressions compared to the unidimensional measure of poverty.**

Keywords: **Development Economics, Multidimensional Poverty, Poverty Headcount Ratio, Wellbeing.**

1. INTRODUCTION

Poverty, Inequality and Wellbeing are the focal points of development policies in contemporary development conjectures. Nevertheless, there have been heated debates on the stance in use of unidimensional and multidimensional indicators to influence policy decisions ranging from the works of Amartya Sen, Martin Ravallion to Sabina Alkire, James Foster and the likes. Moreover, it is widely and theoretically accepted that poverty and wellbeing is multidimensional; the idea of human capability funtionings proposed by Sen (1976) in the poverty realm and the need to ground poverty reduction strategies on the reality of the poor's experience are some of the common themes permeating multidimensional indices. Sen (1976) argues that poverty headcount ratio (PHCR) is not sufficiently informative because it does not reveal exact income distribution among the poor. Hence, income may not adequately represent poverty. Some researchers have however claimed that multidimensional indices are not necessary for poverty analysis.

For this reason, this paper addresses the debate on the effect of poverty on wellbeing by posing a research question: Does a multidimensional measure of poverty better explain wellbeing than a unidimensional one? In other words, which poverty indicator better explains the effect of deprivation on certain proxies of wellbeing? This study will use Poverty Headcount Ratio (henceforth, PHCR) as the unidimensional system because it is the most widely used and criticized form of unidimensional poverty measurement (Sen, 1976; Tsui, 2002; Bourguignon and Chakravarty, 2003). For the multidimensional strand, I will refer to the recently introduced Multidimensional Poverty Index (henceforth, MPI) by

Alkire and Santos (2010). This is because it is an improved form of the Human Development Index (HDI) that captures poverty dimensions other than income. Therefore, this work will attempt to investigate and suggest which approach to poverty measurement better explains wellbeing. This will be achieved through specification tests as well as regressing PHCR and the MPI on three different proxies of wellbeing: improved sanitation, adult mortality rate and school enrolment.

The paper is further segmented into four parts. Section 2 will present a comprehensive review of existing literature. Section 3 gives the methodology of the research. While section 4 presents the data analysis, the final section offers summary and concluding remarks.

2. LITERATURE REVIEW

2.1 Conceptual Background:

To begin with, Tsui (2002) defines Income poverty as a measure that aggregates income shortfalls from a predetermined poverty threshold of income while multidimensional indices involve a numerical representation of basic needs from pre-set minimum levels. Tsui (2002) further confirms that increase in income can allow a person to better meet basic needs, but markets for basic needs do not always exist. For instance, money becomes useless in the middle of the dessert or for a rich but sick person with no access to health services. As such, Alkire and Foster (2011) see poverty as multiple deprivations that are simultaneously experienced and that multidimensional indices measure the extent of these simultaneous disadvantages.

Several streams of ideas have informed and shaped the new thinking on poverty and the multidimensional indices of poverty. A major common theme underlying the ideas shaping MPI is diversity— diversity of ways in which people perceive and experience poverty, diversity in how poor people strive either to escape poverty or to cope with it, and diversity of policy interventions needed for combating poverty (Sidiqur, 2010). A convenient starting point for understanding multidimensional poverty is the notion of capability functionings developed by Sen (1976). In his understanding of Development as freedom, argued that the philosophical basis for the idea of human welfare as perceived in economic and political discourses is best provided by the concept of capability as compared with other concepts, such as utility or material possessions. The concept of capability has led to the recognition that poverty is intrinsically multidimensional in nature, consisting of the failure of several kinds of basic capabilities or "the failure of basic capabilities to reach certain minimally acceptable levels" (Sen, 1992:109).

The multidimensionality of poverty therefore called for new approaches to poverty assessment: vulnerability, social exclusion and Participatory methods of Poverty Assessments (PPAs). There is some debate in the theoretical literature on precisely how the basic capabilities are to be identified. Sen's own analysis leaves the list open-ended on the grounds that it should be up to the individuals of specific communities concerned to decide what is to be counted as basic. In contrast, Sidiqur (2010) argues that it is possible to identify, from the basic principles of moral and political philosophy, the full set of capabilities that should qualify as basic—for policy purposes—from any community's point of view.

However, the univariate approach to poverty measurement is not sufficient enough to observe multidimensional poverty as argued by Alkire and Santos (2010b). Additional indicators are required to adequately gauge multiple deprivations across countries. Similar to other multidimensional methods like the Human Development Index (HDI), the MPI was introduced in 2010 to capture the complexities of human circumstances in relation to poverty and wellbeing by excluding income in the analysis. Due to these complexities, it is difficult to adequately reflect human capabilities using a unidimensional index. In Alkire and Santos (2010a), a person is considered multidimensionally poor if the weighted indicators of a dimension which they are deprived add up to at least 33%. The MPI reflects acute poverty in 104 developing countries using a set of ten indicators across three dimensions.

With discrete measures of wellbeing in their analysis, Duclos et al (2006) revealed that a null hypothesis was not rejected using income poverty index but was rejected using multivariate analysis. Although they admit that the use of multidimensional indicators may be quite demanding, their conclusions lend credence to the fact it can provide more robust and subtle conclusions than poverty comparisons centred on income alone. More so, the PHCR may not be viable in every country's case. For instance, one may have up to $5 per day but is still deprived multidimensionally. It becomes significant to examine how much of an indicator is required by the poor in order to survive malnourishment, solve health concerns, etc.

2.2 Unidimensional versus Multidimensional Indices of Poverty Debates:

The ideas of diversity in the experience of poverty and the need to ground poverty reduction strategies on the reality of the poor's experience are some of the common themes permeating multidimensional indices. Some researchers have however, claimed that multidimensional indices do not necessarily capture multiple realities of poverty. Yet, unidimensional indices such as the headcount ratio and Income poverty gap are criticized for not sufficiently capturing the exact income distribution among the poor. The dimensions and respective indicators of the Alkire-Santos MPI are depicted below:

Table 1: Multidimensional Poverty Indicators and Poverty Dimensions

Poverty Dimensions	Indicators
Health	-Nutrition -Child Mortality
Education	-Years of schooling -Child Enrolment
Living Standard	-Cooking Fuel -Sanitation -Water -Electricity -Floor -Assets

Source: Alkire and Santos (2010a).

Referring to the above indicators, the MPI like any other poverty measure is fraught with data constraints. On this ground, Ravallion (2011) criticised the MPI indicators for not reflecting the overall welfare of the poor particularly in the living standard dimension. Ravallion (2011) further criticizes Alkire-Santos' MPI by quoting a blog comment that the MPI excludes "conflict, personal security, domestic and social violence, issues of power/empowerment and intra-household dynamics" which are important in poverty measurement. However, Alkire and Santos (2010a) explicitly indicated that the choice of dimensions was limited by data constraints due to restrictions on a single household data survey on which figures for the aforementioned "non-income" dimensions are absent. The authors further suggest that with the AF methodology on which the MPI is based alongside data availability, individuals will serve as the unit of analysis comparing across gender and age groups while also accounting for intra-household dynamics. Moreover, Ravallion (2011) admits that multidimensional indices can be acknowledged for providing a joint distribution of the multiple dimensions of poverty and that all poverty measures capture multidimensionality because they reflect consumption. However, he further claims that standard univariate poverty measures like Income Poverty Index is more reliable as it incorporates prices in analysis and uses shadow prices to estimate welfare on marketed and non-marketed goods during market failures.

Arguing in the same vein, Sidiqur (2010) argues that the income approach has the advantage of simplifying poverty assessment by collapsing a complex multidimensional phenomenon along a single dimension. For practical purposes, the income approach retains some relevance as an approximation, making it easier to maintain comparability which is especially important for the purpose of national-level policymaking. The multidimensional indices he argued, also involve a lot of intricacies and approximations given the inherent difficulty of capturing a complex reality. He further argued that many dimensions of a multidimensional view of poverty can in principle, be captured through income based estimates as there exists a rich tradition of estimating poverty-line income by seeking information on people's perception of their own well-being. For example, hunger by estimation of calorie intake which is determined by individual income.

On the contrary, one-dimensional indices like the dollarized index ($1/$2 per day) mask poverty and inequality thereby giving a general view of a country's condition which does not sufficiently inform poverty reduction policies. In addition, the $1/$2 per day income poverty measure may not work for every country. This is evident in Alkire and Santos (2010b)

ISSN 2394-9694

International Journal of Novel Research in Humanity and Social Sciences
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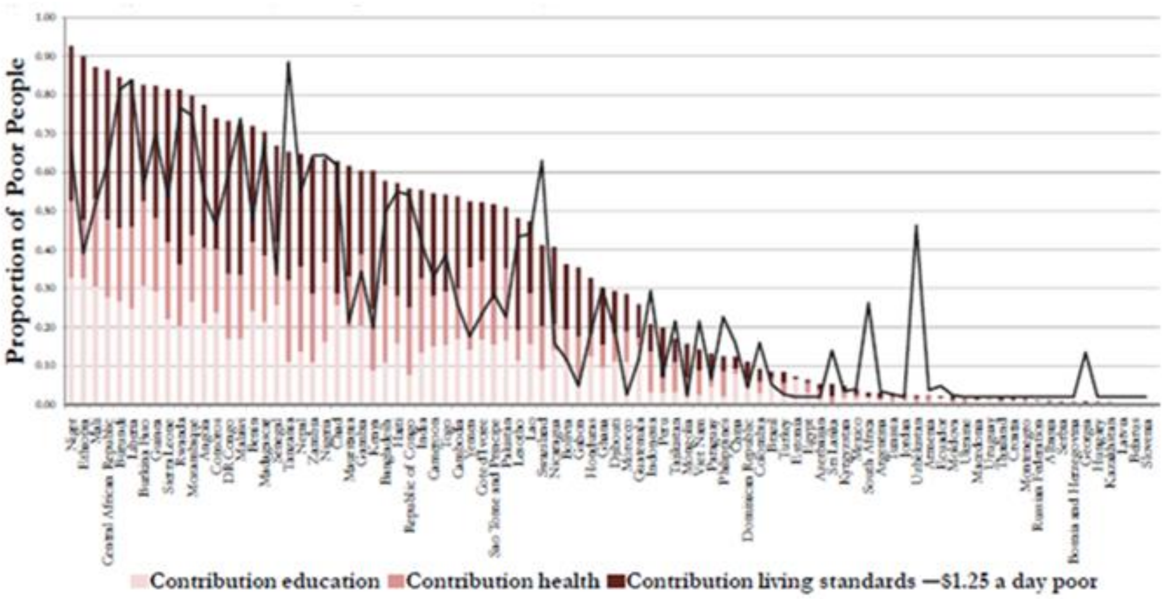
where there is the possibility that people are MPI poor but not necessarily income poor. They found that only two-thirds of people in Niger Republic are income poor whereas 93% are multidimensionally poor. Similarly, in Ethiopia, 90% of people are MPI poor relative to 39% extreme income poor. They also realized that India has experienced strong economic growth in recent years; nonetheless the MPI reveals that acute multidimensional poverty is still prevalent. The following graph summarizes the difference between MPI and Income poverty across 93 countries.



Source: Alkire and Santos (2010a).

Fig. 1: MPI levels relative to Income Poverty across 93 countries.

Fig. 1 above shows that Niger Republic has the highest MPI poverty relative to income poverty. For Tanzania, highest income poverty is prevalent compared to other countries, the multiple deprivation index is lower; this is also the case for Swaziland. Uzbekistan records a very low MPI value but has a high income poverty value. The list of evidences is endless. It is however worth noting that there is no significant difference in rankings between MPI and income poverty in Nigeria, Malawi and Ghana. In spite of this, Reyes (2004) confirms that multidimensional indices will show how various groups are vulnerable to 'varying forms' of poverty and ways can be easily suggested on how best to tackle deficiencies in such dimensions and regions. The government of any country can use the above MPI results to formulate policies that will help in improving the most deficient aspects of a specific dimension such as improvement in living standards in Niger, more investment in education in Chad, better health service delivery in Yemen, etc which the income approach does not articulate.

Duclos et al (2006) emphasized that subjective value judgements on dimensions may be carried out using univariate measures of wellbeing. They argued that the use of multidimensional indicators tends to provide more accurate conclusions regarding poverty and wellbeing. This is because a subgroup of households can experience a decline in income poverty but this may not necessarily be same for the overall household population within the region. Therefore, the poorest part of a country may be absolutely deprived while other parts are not really affected. This means that one may wrongly conclude that overall poverty has increased, not considering the part that is unaffected. This scenario is what Sen (1976) considers as 'violation of the transfer axiom'. It is also worth arguing that MPI provides a robust measure and basis for observing long run inter-temporal poverty amongst individuals over time. Alkire and Foster (2011) explained that the Alkire-Foster methodology employed in MPI can show variations in poverty over time in an integrated and consistent framework. It also provides precise insights on specific household deprivations which are contained in dimensional decompositions and partial indices.

Banerjee and Duflo (2007) conducted cross country analysis on selected developing countries revealing that poverty does increase death rate. Thus, higher poverty means poorer health status, hence higher *mortality rates*. On the relationship

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between education and poverty, Case, *et al* (2004) investigated the effects of orphan-hood and poverty on the enrolment of children in school. They found that poor orphans are less likely to be enrolled in school than non-orphans. Therefore, poverty leads to low *school enrolment* in children, with orphans facing greater non-enrolment risks. On sanitation, Landsberg (2009) finds strong correlation between low levels of improved *sanitation* and high incidence of poverty in Uganda. Although, poorer households lack the incentive to invest in improved sanitation access, this relationship is quite ambiguous due to other factors like hygiene awareness, culture, etc. These form the rationale for the variables used in this paper. The following section will provide an explanation for the methodology of this research.

3. DATA AND METHODOLOGY

The pooled cross-sectional data was obtained from a number of sources. Data on MPI were derived from the OPHI database 2011. The remaining data set was extracted from World Development Indicators (WDI) 2011 database. For the purpose of this study, the pooled cross-sectional sample covers 106 countries with variations in years between 2000 and 2010. These variations in years are as a result of inadequate data for the MPI variable for which only different years for different countries were available. This coupled with the fact that there are no huge secular differences in values across years. Pooled cross-sectional analysis according to Wooldridge (2009) can help examine how a key relationship has changed over time and help investigate the effectiveness of a variable-related policy strategy, a poverty reduction strategy for instance. The following presents a table of variables for the empirical analysis:

Table 2: Variable definitions and measurement

Definition	Measurement	Abbreviation
Unidimensional (Income) Poverty Measure	Poverty headcount ratio at $2 a day (PPP) (% of population)	phcr
Multidimensional Poverty Measure	Multidimensional poverty index (MPI)	mpi
Adult Mortality Rate	Mortality rate, adult, total (per 1,000 total adults)	admort
School Enrolment	School Enrolment, primary (% gross)	schenrl
Improved Sanitation	Improved Sanitation Facilities (% of population with access)	impsan

3.1 Model Specification and Estimation Method:

To achieve the objectives of this research, the ordinary least squares (OLS) technique will be applied. Though not suitable for probability models and criticised for sporadically providing biased estimates, it is used as a tool for analysing linear relationships among variables and serves as a benchmark approach to more rigorous empirical analysis (Greene, 2002). The OLS Models are given by:

$$\text{Wellbeing} = \beta_0 + \beta_2 \text{mpi} + \mu \qquad (1)$$

$$\text{Wellbeing} = \beta_0 + \beta_1 \text{phcr} + \mu \qquad (2)$$

$$\text{Wellbeing} = \beta_0 + \beta_1 \text{phcr} + \beta_2 \text{mpi} + \mu \qquad (3)$$

Where:

β_0, β_1 and β_2 are the estimated parameters of the model and μ is the disturbance term capturing other variables not included in the model. It is worth noting that wellbeing is proxied by adult mortality rate (admort), school enrolment (schenrl) and improved sanitation (impsan) for the respective regressions. The two poverty measures: poverty headcount ratio (phcr) and multidimensional poverty index (mpi) form the independent variables influencing wellbeing.

3.2 Research Hypotheses:

Hypothesis one

H_0: there is no significant relationship between Poverty and Wellbeing.

H_1: there is a significant relationship between Poverty and Wellbeing

Hypothesis two

H_0: Poverty headcount ratio has no significant effect on wellbeing.

H_1: Poverty headcount ratio has a significant effect on wellbeing

Hypothesis three

H_0: MPI has no significant effect on wellbeing

H_1: MPI has a significant effect on wellbeing

4. DATA ANALYSIS AND INTERPRETATION

Before delving into the main econometric analyses, it is imperative to present a descriptive summary and perform specification tests on the data under study.

Table 3a: Descriptive Statistics based on Regional Divisions

Region	Freq.	Percentage	Cum.
Arab States	9	8.49	8.49
East Asia and the Pacific	11	10.38	18.87
Europe and Central Asia	24	22.64	41.51
Latin America and Caribbean	18	16.98	58.49
South Asia	7	6.60	65.09
Sub-Saharan Africa	37	34.91	100.00
Total	106	100.00	

Source: Author's computation

The table above presents a concise summary on the data used in this paper and is centred on regional segmentations. There are 106 countries selected for the analysis, of which 9 constitute Arab countries and 11 countries are from East Asia and the Pacific. While 24 countries are from Europe and Central Asia, Latin America reports 18 countries in the study. South Asia and Sub-Saharan Africa present 7 and 37 countries respectively. The highest percentage of data (35%) comes from Sub-Saharan Africa possibly because of data availability alongside poverty being a recurrent issue in that region.

Table 3b: Descriptive Statistics for Mean, Variance, Standard Deviation, Skewness and Kurtosis

Variable	Obs	Mean	Std. Dev.	Min	Max	Variance	Skewness	Kurtosis
admort	106	496.1335	254.2716	143.1706	1302.676	64654.04	.9985695	3.435051
schenrl	103	103.763	18.21371	32.45448	154.1525	331.7393	-1.029042	5.998955
impsan	106	58.84906	30.02627	9	100	901.577	-.1544871	1.583685
phcr	94	42.20989	31.00677	.02	95.15	961.4196	.0641727	1.592997
mpi	106	.2062453	.1889416	0	.652	.0356989	.5596805	1.949431

Source: Author's computation

Table 3b depicts results on measures of central tendency and dispersion for the variables under study. Adult mortality rate has a mean of 496 and standard deviation of 254 per 1000 adults across countries in the data. School enrolment has a mean value of 104 and a standard deviation of 18.21 as a gross percentage of the population. The PHCR and the MPI have mean values of 42.21 and 0.21 respectively alongside standard deviations of 31.0 and 0.19 respectively. The coefficients of skewness for adult mortality, PHCR and the MPI are positively skewed to the right of the distribution whereas those of school enrolment and sanitation have negatively skewed distributions. On kurtosis, the values for adult mortality and school enrolment are greater than 3 showing that the distributions are leptokurtic: a very high peak relative to a normal distribution. For improved sanitation, PHCR and the MPI, the peakedness or kurtosis values are platykurtic: the distribution exhibits a flat top relative to a normal distribution. These imply that the distributions are not perfectly symmetrical.

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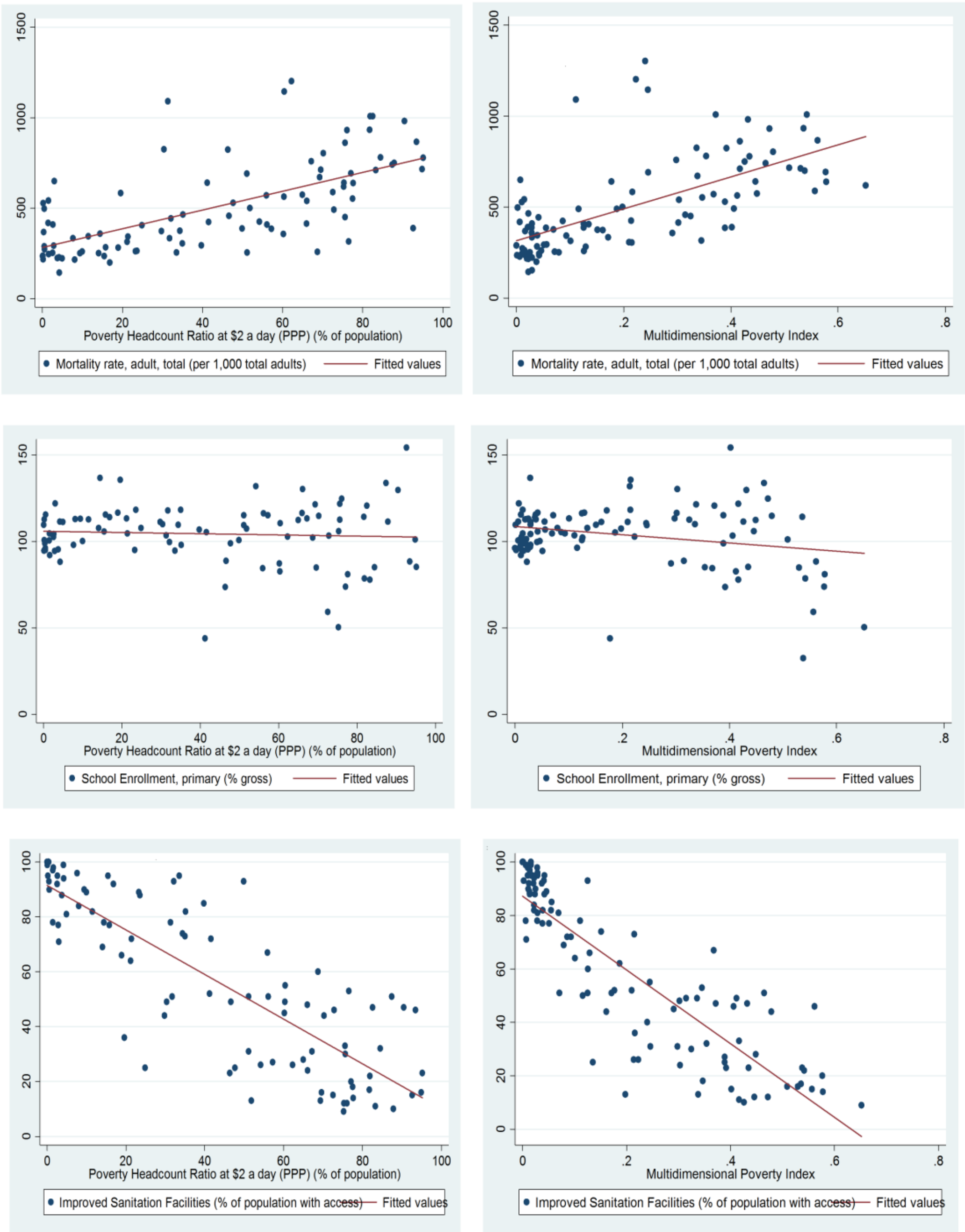
4.1 Checking for Linear Relationships:

We will show whether there are linear relationships between the dependent variables and the independent variables by presenting scatter plots with best fit lines, thus satisfying the Gauss-Markov theorem.



Source: Author's computation

Fig. 2: Scatter Plots for Linear Relationships

The scatter plots above do not show significant differences between the slopes for the PHCR and the MPI for the dependent variables. However, differences in outliers or residuals and magnitudes of effect on the wellbeing proxies may likely exist. We will therefore proceed to the regression results and investigate whether there are significant differences between the two poverty measures.

4.2 Regression Results:

Table 4a: Adult Mortality as a wellbeing measure, PHCR as the regressor

admort	Coeff.	Std. Err.	t	P>|t|	
phcr	5.195846	.6379573	8.14	0.000	N= 94 R-squared = 0.4189
constant	282.0369	33.35039	8.46	0.000	F (1, 92) = 66.33 Prob > F = 0.0000

Source: Author's computation

Table 4b: Adult Mortality as a wellbeing measure, MPI as the regressor

admort	Coeff.	Std. Err.	t	P>|t|	
mpi	880.0141	99.83968	8.81	0.000	N=106 R-squared =0.4276
constant	314.6348	27.86569	11.29	0.000	F (1, 104) = 77.69 Prob > F = 0.0000

Source: Author's computation

Table 4a and 4b present regression results based on the data for adult mortality as a wellbeing measure for the PHCR and the MPI respectively. Adult Mortality rate was regressed against PHCR in order to see the single effect of a unidimensional poverty measure on wellbeing. For table 4a, the estimated effect of income poverty is positive and significant even at 1% significance level. The value of the coefficient shows that an increase in income poverty by 1%, ceteris paribus, increases adult mortality by 5%. The coefficient of determination R^2 (0.41) indicates that 41% of the variations in the mortality rate is explained by variations in PHCR. The remaining 59% are explained by variables not included in the model. The F-value 66.33 indicates that the model is adequate: the estimated parameters are significant at all levels of significance. For table 4b, the estimated effect of the MPI is also positive but higher than that of income poverty, an increase in MPI by 1% will increase mortality rate by 880%. There is little difference in the R^2 values and F statistic.

Table 5a: School Enrolment as a wellbeing measure, PHCR as the regressor

schenrl	Coeff.	Std. Err.	t	P>|t|	
phcr	-.03505	.0599687	-0.58	0.560	N = 92 R-squared = 0.0038
constant	105.8551	3.094813	34.20	0.000	F (1, 90) = 0.34 Prob > F = 0.5604

Source: Author's computation

Table 5b: School Enrolment as a wellbeing measure, MPI as the regressor

schenrl	Coeff.	Std. Err.	t	P>|t|	
mpi	-23.65118	9.210431	-2.57	0.012	N= 103 R-squared = 0.0613
constant	108.569	2.560505	42.40	0.000	F (1, 101) = 6.59 Prob > F = 0.0117

Source: Author's computation

Table 5a and 5b depict results on the effect of income poverty and multidimensional poverty on school enrolment respectively. As in the preceding results, PHCR is regressed against school enrolment in table 5a. Therefore, the effect of income poverty on school enrolment is very low, negative (-0.035) and not significant. The R^2 (0.0038) is extremely low indicating that 0.38% of the variations in school enrolment is explained by the regressor, while the remaining 99.62% are accounted for by variables not included in the model. The F value of 0.34 indicates that we do not reject the null hypothesis that the slope coefficients are equal to zero at all levels of significance. Contrary to table 5a, MPI results in table 5b show F-value of 6.59 and therefore rejects the null hypothesis of no significant difference in slope coefficients from zero. The R^2 here is also very low, which is largely due to other factors not included in the model. The value of the coefficients for the MPI regressor on school enrolment is -23.65 showing a decrease in school enrolment by 23.65% when the MPI increases by 1%.

Table 6a: Improved Sanitation as a wellbeing proxy, PHCR as the regressor

impsan	Coeff.	Std. Err.	t	P>|t|	
phcr	-.8136164	.0562446	-14.47	0.000	N = 94 R-squared = 0.6946
constant	91.53415	2.940292	31.13	0.000	F (1, 92) = 209.26 Prob > F = 0.0000

Source: Author's computation

Table 6b: Improved Sanitation as a proxy for wellbeing, MPI as the regressor

impsan	Coeff.	Std. Err.	t	P>|t|	
mpi	-138.0274	7.72325	-17.87	0.000	N = 106 R-squared = 0.7544
constant	87.31657	2.155593	40.51	0.000	F (1,104) = 319.40 Prob > F = 0.0000

Source: Author's computation

Here, the results are quite interesting with high R^2 and F-statistic as well as highly significant p-values and coefficients. In table 6a, results for improved sanitation and PHCR are presented. The coefficient is negative as expected: 1% increase in income poverty is likely to reduce sanitation by 8.1%. The coefficient of determination R^2 (0.69) indicates that 69% variations in the dependent variable are explained by the regressor. The remaining 31% are accounted for, by the variables not captured in the model. The F-statistic of 209.26 is greater than critical F-value indicating that the model is adequate and therefore statistically significant at 1% level of significance. For the MPI in table 6b, the coefficient of -1.38.02 shows high effects of MPI on improved sanitation. The R^2 is also higher with 75% impact and an F-statistic of 319.4 thereby proving the adequacy of the model.

Table 7: Multiple regression results for Adult Mortality rate versus the Joint effects of PHCR and the MPI

admort	Coeff.	Std. Err.	t	P>|t|	
phcr	1.961236	1.345556	1.46	0.148	
mpi	589.0086	217.7309	2.71	0.008	N = 94 R-squared = 0.4622
constant	291.2621	32.44074	8.98	0.000	F (2, 91) = 39.10 Prob > F = 0.0000

Source: Author's computation

Table 7 depicts multiple regression results in order to estimate the joint effect of a unidimensional measure and multidimensional poverty measure. The coefficients are quite intriguing with differences in values. Mortality rate increases only by 1.96% due to a 1% change in income poverty but increases by over 500% using the MPI. The coefficient of PHCR is however not significant. Moreover, the effects of both poverty measures on adult mortality are smaller than it was in the simple regressions. However, the R^2 is higher in this multiple regression than it was for the simple regression meaning that multiple regression analysis is able to explain higher variations in the explained variable. We will conduct specification tests in the following sub-section to check for problems that are likely to affect research findings.

4.3 Specification Tests:

4.3.1 ***Test of Joint Significance:*** phcr + mpi = 0, F (1, 91) =7.45, Prob > F = 0.0076. The test indicates that both MPI and PHCR are jointly significant with an F-statistic of 7.45 at 1% significance level.

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4.3.2 ***Multicollinearity*****:** The correlation coefficient of 0.8886 in the multiple regression indicates existence of multicollinearity. To confirm the presence of multicollinearity, we determine the Variance Inflation Factor which is 4.75. It is very close to 5 meaning that multicollinearity exists between the MPI and PHCR. The auxiliary regressions also show higher R^2 of 0.78. This is possibly because they are sometimes considered as mutually exclusive alternatives in terms of measurement. Since co-linearity between the two variables is not our focus of interest, we will give more weight to the simple regression findings.

Table 8: Multicollinearity Test Results

Correlation Matrix

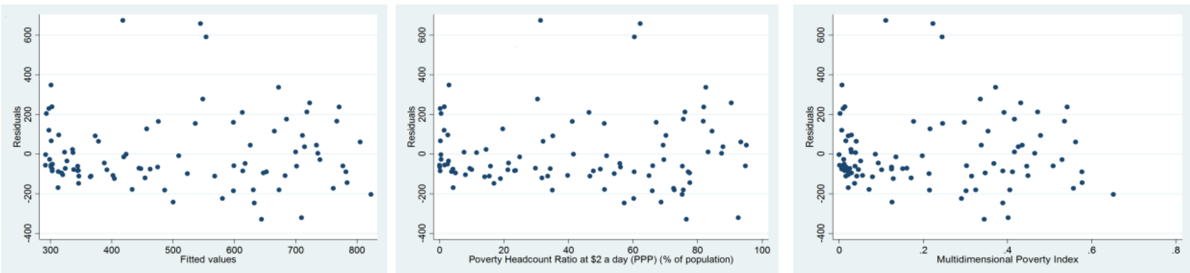
	phcr	mpi
phcr	1.0000	
mpi	0.8886	1.0000

Variance Inflation Factor

Variable	VIF	1/VIF
mpi	4.75	0.210346
phcr	4.75	0.210346
Mean VIF	4.75	

4.3.3 ***Heteroscedasticity:*** In figure 3, residuals were plot against fitted values of Y and Xs, it showed heteroscedasticity but this is rather subjective. Therefore, we conducted another test of heteroscedasticity.

rvfplot **rvpplot** **rvpplot**

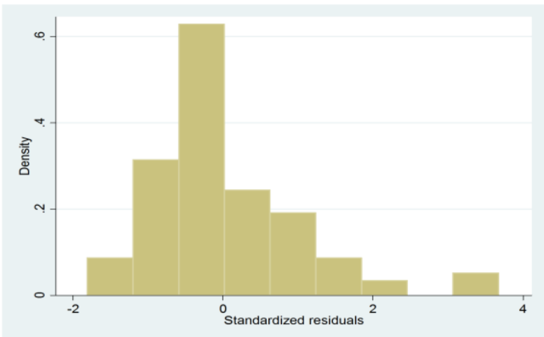


Source: Author's computation

Fig. 3: Heteroscedasticity Test Results

However, the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity does not reject the null of homoscedasticity: chi2 (1) =1.37 and Prob > chi2 =0.2411. Though heteroscedasticity is not a problem here, robust standard errors were however used as a precaution.

4.3.4 ***Normality Test*****:** The shapiro-wilk test for normal data does not reject the null hypothesis that the distribution of the residuals being tested is normal (w=0.88594). The following histogram for standardized residuals presents a shape very close to a normal distribution.



Source: Author's computation

Fig. 4: Histogram for Standardized Residuals

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5. SUMMARY AND CONCLUSION

The paper attempted to review and analyse the effect of poverty on wellbeing. The study finds significant effects of poverty on wellbeing which is in line with our expectations. It was revealed that poverty increases mortality rate, reduces school enrolment and sanitation relative to those who are somewhat better-off. Our results also established that the effect of poverty on level of wellbeing depends on the poverty measure. Compared to the income measure, multidimensional poverty revealed better significant effects on wellbeing in all the regressions. We therefore conclude that MPI is a viable measure of poverty explaining wellbeing. The unidimensional poverty headcount ratio (PHCR) might not adequately reflect wellbeing due to its restriction on income alone, neglecting other dimensions of poverty and wellbeing which is evident in our results. This is also consistent with the findings of Duclos et al (2006) and Alkire and Santos (2010).

This research is limited by the nature and quality of data which involves pooled cross-sections with heterogeneity in terms of years. In addition, the choice of variables selected may not be appropriate measures of ‘subjective’ wellbeing for the countries under study. These may affect the quality of the research findings. These results have some important policy implications. Consistent with our findings, a better understanding of the complex dynamics of poverty dimensions is crucial in the design of effective programs and budgetary allocations meant to relieve poverty within a development context. Future research shall attempt to test the effects of other determinants of wellbeing such as conflict, violence, human rights, etc.

In sum, it is worth acknowledging that both unidimensional and multidimensional indices are significant for understanding the nature and dynamics of poverty. In view of the fact that both methods have their own strengths and weaknesses, it would seem more practical to use them in tandem to complement each other rather than viewing both as mutually exclusive alternatives. The complementarity of indicators in a multidimensional sense is however imperative in the effort to tackle poverty because no single indicator or group of indicators can capture adequately the multiple aspects that constitute deprivation. Attempts have been made since the 1960s to identify indices to tackle the multidimensional nature of poverty. The current MPI is heir to this tradition. There is nothing inherently wrong in developing indicators useful for resource allocation. However, indicators should be cost-effective (or economic), relevant (or appropriate), simply measurable, achievable and realistic.

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