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Multidimensional poverty reduction among countries in Sub-Saharan Africa

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ABSTRACT
This paper focuses on changes in multidimensional poverty, as measured by the Global Multidimensional Poverty Index (Global MPI) in Sub-Saharan Africa. Using data for 35 countries, we describe the changes in level, intensity and composition of multidimensional poverty at the national level. For a subset of countries we discuss results at the sub-national level and provide a brief comparison to changes in income poverty. Our findings suggest that 30 countries, home to 92% of the population in our sample, significantly reduced multidimensional poverty as measured by the Global MPI for at least one comparison and significantly reduced the share of poor people. Looking within countries, we find different patterns of poverty reductions, with some countries reducing poverty for the poorest regions, while poorer regions in other countries do not seem to benefit from the general reduction in poverty to the same extent. When comparing trends in income and multidimensional poverty reduction we find significant differences, indicating that a holistic approach to poverty reduction should look at both, multidimensional and income poverty.

KEYWORDS
Sub-Saharan Africa, multidimensional poverty, Global MPI, Alkire-Foster method

1. Introduction

The measurement of poverty is not an end in itself. Instead, we measure poverty to help us substantiate claims of levels or changes, to evaluate poverty reduction programmes or to incentivise certain anti poverty actions. As the Expert Advisory Group on a Data Revolution for Sustainable Development states: "Without high-quality data, providing the right information on the right things at the right time; designing, monitoring and evaluating effective policies becomes almost impossible" (Independent Expert Advisory Group on a Data Revolution for Sustainable Development, 2014, p. 2). In this line, the present research exemplifies with a case study on the development of multidimensional poverty in Sub-Saharan Africa, how data from the Global Multidimensional Poverty Index (Global MPI), published by the Oxford Poverty and Human Development Initiative[1], can be used to assess and describe the evolution of multidimensional poverty.

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The paper is structured as follows: We first set forth the Global MPI, the data, harmonisation process and methodology of data analysis. Subsequently we present MPI changes at the national level, followed by sub-national poverty reductions by regions, and the decomposition by indicators. We will continue with a comparison of trends in income and multidimensional poverty reduction, and relationships with economic growth, before concluding.

2. The Global MPI and changes over time

Our analysis of the development of multidimensional poverty in Sub-Saharan Africa is based on the Global MPI (Alkire & Santos, 2014; United Nations Development Programme, 2015) The Global MPI is an internationally comparable measure of acute multidimensional poverty for developing countries based on the Alkire-Foster method (Alkire & Foster, 2011; Alkire, Foster, et al., 2015). In order to identify the poor, the Alkire-Foster method uses a counting procedure and two different cutoffs. Firstly, people are identified as deprived in each indicator according to a dimension specific deprivation cutoff. In a second step the number of weighted deprivations (the deprivation score)[2] is calculated for each individual and based on a poverty cutoff, which determines the number of weighted deprivations a person has to experience to be identified as poor. After identifying each person as either poor or non-poor, an aggregate measure is computed, in case of the Global MPI the adjusted headcount ratio M0. M0 is the product of two partial indices, the headcount ratio H and the intensity of poverty A. The headcount ratio H is simply the share of poor people in the population. The intensity A, the average deprivation share among the poor, is calculated by taking the average of the deprivation scores of poor people, and shows how many weighted deprivations poor people experience on average.
The Global MPI is based on the above procedure using specific deprivation cutoffs and a poverty cutoff of 1/3. It has three dimensions, health, education, and living standards. The dimensions health and education are measured using two indicators each, and living standards is measured with six indicators. All the dimensions are weighted equally (1/3) and the indicators within each dimensions receive equal weights as well. The dimensions, their indicators and respective deprivation cutoffs can be found in Table A1 (for a detailed discussion see Alkire and Santos (2014)).

3. Countries, data, and analyses

The paper applies the methodologies set out in Alkire, Roche, and Vaz (2015). We use data from this paper for 19 previously published countries; for nine out of these 19 we append more recent data. We add to this, harmonised data for further 16 countries. In total we have results for 35 countries, which were home to around 92% of the population in Sub-Saharan Africa in 2012.[3] For ten out of the 35 countries we have data for more than two periods and thus calculate the changes for three time periods, leading to overall 55 year-to-year comparisons. [4]

All data used by Alkire, Roche, and Vaz (2015) were Demographic and Health Surveys (DHS) data. For the present study, we include different surveys (see Table A2 in the appendix). Still most - 40 out of 55 - of the comparisons use DHS data in both time periods. The effective sample size ranges from 10,258 for Sao Tome and Principe in 2000 to 173,218 in Nigeria in 2013, while the average sample size is 41,135.

Published results for the Global MPI for the single surveys of each country take the maximum available information in each dataset into account. For the present analysis, data and indicators were strictly harmonised across time periods for each country to permit intertemporal comparisons. Harmonization assures the comparability of the results for each country across years and can involve either dropping an indicator, if the indicator is not available in one of the comparison years, and/or adjusting the definition of the indicator if there were changes in the questionnaires.[5]

In what follows we focus on the discussion of annualized rates of change, as the number of years between the included surveys varies (see Alkire, Foster, et al., 2015, p. 264ff.).[6] However, for each poverty estimate, the absolute change was tested for its significance using mean difference tests.[7] All our surveys use complex survey designs and ignoring the design features can lead to biased population estimates and incorrect statistical inference (for example Kish, 1995; Lehtonen & Pahkinen, 2004). In order to obtain unbiased variance estimates, the clustering and stratification of each survey was taken into account, viewing the two surveys of the specific country as two super-strata. As the survey design was taken into account, the standard errors in the tables are linearized standard errors. Similarly, the reported t-statistics and their respective p-values are survey analysis equivalents of a simple two-sample t-test (compare StataCorp, 2013, p. 110).

The Global MPI is calculated for observations that do not have missing values for any of the indicators. If the decrease in sample size was high, a bias analysis was also undertaken in form of t-tests, in order to assess whether we find significant and systematic differences in the deprivations of the remaining indicators between those who are missing the indicators with highest frequencies of missing values and those who are not missing these indicators. In line with Alkire and Santos (2014) we undertook bias analyses for the entire country if we lost 13% or more of the sample, and for subnational analyses if the sample size was reduced by 13% or more in this specific region. This type of test is similar to tests of whether or not data are missing completely at random (MCAR). Although no support for the alternative-hypothesis, implying that the data are not missing at random, cannot be interpreted as evidence of MCAR, as the probability of missingness can still be related to the values of the actual variable Allison (2002); Enders (2010), it allows us to assess if we can expect some sort of bias in our estimates. Among the surveys for which we have large shares of missing values, we find indication of a slight underestimation of poverty for Mauritania in 2007 and 2011, Namibia in 2007 as well as Gabon in 2000, and of a slight overestimation for Sao Tome and Principe in 2000. None of the subnational regions, showed any indication of bias.

The annualised growth rates of GDP per capita (in constant 2005 US Dollars) were calculated using GDP per capita information from the World Development Indicators of the World Bank (2015).[8] Data for the poverty headcount ratio at $1.90 a day (2011 PPP) were taken from the same source. In order to obtain estimates of the income poverty levels for countries for which the World Bank does not provide data for the same year, we interpolated or extrapolated the numbers from the information we have following the procedure of Alkire, Roche and Vaz (2015 and forthcoming).[9]

4. Changes in multidimensional poverty

Table A3 in the appendix reports the main statistics for the changes in MPI at the national level. The countries in our sample have very different initial levels of poverty, with MPI ranging from .076 for South Africa in 2008 to .696 for Niger in year 2006. We find significant absolute reductions in MPI for most countries.[10] Around 85.5% of the comparisons show significant progress in reducing multidimensional poverty and 92% of the population in our sample lives in a country that experienced poverty reductions for at least one comparison. Exceptions are Zimbabwe, Togo, Sierra Leone and Senegal.[11] Nigeria reduced multidimensional poverty between 2003 and 2008, but did not make significant progress between 2008 and 2013. For Madagascar, our data support the conclusion that multidimensional poverty significantly increased between 2004 and 2008/9.

Based on the annualised absolute changes, we find that the four countries with the highest reductions are Rwanda for the time periods 2005 - 2010 and 2005 - 2014/15, Liberia, Ghana for the period 2003 - 2008, and the Comoros, which all have annualised rates of reductions above -0.02. Rwanda shows the fastest national poverty reduction at a rate of -0.026 and clearly outperforms other countries.

[Figure 1 about here.]

MPI can be reduced by reducing H, reducing A or reducing both. In our sample, as in the case of MPI, 85.5% of comparisons of H show significant absolute reductions, and 76.4% of comparisons of A. Figure A1 shows the annualised absolute changes in H and A. Countries in the lower left corner reduced both, A and H, strongly. Countries in the upper left corner would have reduced H rather more than A, while those in the lower right corner have reduced A rather more than H. Finally countries in the upper right corner showed increases in both H and A. The graph additionally distinguishes between countries with significant absolute changes in MPI and those without. The light circles close to the origin denote countries for which our data do not support the conclusion of a significant absolute change in MPI. The dark circle in the upper right corner is Madagascar, which had a significant increase in MPI. This increase is mainly due to an increase in H, while the increase in A is statistically non-significant (results for H and A can be found in Tables A4 and A5 in the appendix). The graph suggests that countries generally have higher annualised reductions in H than A, as expected, and that there is more variation in the annualised changes of H. All countries with significant reductions in MPI also significantly reduced H and those without reductions in MPI also did not reduce H.[12]

We find the highest reduction in H for Comoros, which reduced the share of people living in multidimensional poverty by over 40% percentage points between 2000 and 2011, from 73.9% to 32.8%. Rwanda reduced H by nearly 30% percentage points in the time between 2005 and 2014/15, from 82.9% to 53.9%. For both countries, the large improvement in H outpaced population growth, thus leading to a reduction in the absolute number of poor.

The data of 32 countries can be disaggregated by subnational regions.[13] We have thus representative sub-national data for 272 regions in 32 countries, and 386 sub-national comparisons overall.[14] We find great sub-national disparities within countries. For Kenya in 2003, we have a range in MPI of 0.633, where the capital Nairobi is by far the least poor region (MPI = 0.048), while the North Eastern region is the poorest with an MPI of 0.681. In contrast, the three sub-national regions of Malawi show minimum much smaller range of 0.096, with levels of MPI between 0.298 and 0.393.

When looking at the sub-national level, 67.6% of the regions, home to 62% of the population in the 32 countries, show significant reductions in MPI for at least one comparison. We find that ten countries significantly reduced poverty in all sub-national regions for at least one comparison. These countries are Benin, Ethiopia for 2000 - 2011, Gabon, Gambia, Ghana for 2003-2008 and 2003-2014, Liberia, Malawi, Mozambique, Niger and Rwanda for 2005 - 2010 and 2005 - 2014/15. Five countries on the other hand, Madagascar, Senegal for 2010/11 - 2012/13, Sierra Leone, Togo and Zimbabwe, have not made progress in any sub-national regions.

[Figure 2 about here.]

Figure A2 shows the annualised absolute sub-national reductions in MPI versus MPI in the initial period for Mauritania, Benin, Mali and Guinea. These four countries show two different types of poverty reductions. For Mauritania and Benin we find that, in general, sub-national regions with higher initial poverty levels reduced poverty the most. In contrast, for Mali and Guinea we find that, even though there were many similarly poor regions in the initial period, the pace of poverty reduction between the regions varies and some of the equally poor regions originally did not make significant progress. Thus we find that some of the countries experienced types of poverty reductions that generally benefited the poorer regions more, helping those to catch up, while for other countries, not all the poor regions benefited equally from the general progress in terms of poverty reductions. When looking only at the comparisons between the earliest and most recent data available for each country, we find that 71.9% of the countries, home to 69.9% of the population of this study, reduced the gap between the poorest and the least poor regions. Eight countries have the largest reductions for the poorest sub-national region. The countries are Cote dIvoire, Kenya (2003 - 2008/9 and 2003 - 2014), Liberia, Mozambique, Malawi, Namibia (2000 - 2006/7 and 2000 - 2013), Niger and Nigeria (2008- 2013).

The analysis of sub-national regions allows us to identify regions that are outstanding regarding their reduction of multidimensional poverty. By outstanding we mean regions that perform better in terms of the annualised absolute changes in MPI than the leading country at the aggregate level, Rwanda. We find that 20, home to 6% of the population in our countries, regions perform better.[15] These regions and a range of related statistics can be found in Table A6 in descending order according to their annualised absolute reductions in MPI. We find that they vary regarding MPI in the initial period between 0.269 to 0.681. But most of them have a high MPI and incidence of poverty in the initial period (60% of these regions have an initial H of 80% or above).
When looking at the annualised absolute rate of change in MPI, four out of the five best performing regions are in the Republic of the Congo for the comparison between 2009 and 2011/12. In that time period, MPI was reduced from 0.389 to 0.273 in

the region of Likouala, leading to an annualized absolute reduction of -0.046. Seven regions have annualised absolute reductions in MPI larger than -0.03.
Nord-Kivu in the DR Congo shows the highest absolute reduction in H from 94.4% to 67% between 2007 and 2013/14. However, while Nord-Kivu had the highest absolute reduction, we find even higher annualised absolute rates of reduction in the incidence for other regions because their comparisons were for shorter time periods. By far the biggest annualised absolute reduction can be found in Likouala in the Republic of the Congo with a value of -0.079, which translated into a reduction of the initial headcount ratio from 73.9% to 54.1% for the years compared here.

The Global MPI can further be decomposed by indicators. Out of the 32 countries, 9 countries reduced the share of people who are poor and deprived in a specific indicator for all indicators. These countries are Zambia, Kenya, Ethiopia, Burkina Faso, Mozambique, Comoros, Ghana, Rwanda and Gabon. For Madagaskar, the data do not show a significant reduction in the censored headcount ratios for any of the indicators. 14 regions in six countries (Benin, Ethiopia, Ghana, Kenya, Mali and Rwanda) reduced the censored headcount ratios of all indicators. Table A7 in the appendix shows the ranking of the significant reductions among the indicators for each countries. The indicator that is most often reduced the most is toilet, followed by assets.

5. Multidimensional poverty, income poverty and economic growth

Due to the novelty of the multidimensional approach, a natural question to ask is how far we arrive at the same conclusion as when using the income approach. This section presents a brief comparison between reductions in multidimensional poverty and income poverty as measured by $1.90 a day.
We restrict the discussion to countries for which we have information on both, multidimensional and income poverty, after extra- or interpolation of the income data, leaving us with an effective sample size of 27 countries and 37 comparisons. [16]

[Figure 3 about here.]

Figure A3 gives a graphical comparison of the annualised relative changes in the headcount ratios for income and multidimensional poverty. We find that there are countries for which the trends are fairly similar, like Mali, Malawi or Burkina Faso. However, for many countries the rates differ markedly.17 Guinea and Niger, for example, experienced large reductions in income poverty, but slow reductions in terms of multidimensional poverty. On the other hand, for quite a few countries, looking only at income poverty reductions would mask achievements in multidimensional poverty. This is particularly striking in the case of South Africa, which experienced an increase in income poverty but is the leader in relative terms in multidimensional poverty reduction.

Table A8 in the appendix reports the compound annual growth rate of GDP per capita in constant 2005 US$. We find that the countries are very diverse regarding their economic development with South Africa being by far the richest, as measured by GDP per capita in the initial time period, followed by Namibia. The countries with the lowest GDP per capita in the first period are Ethiopia and Malawi. We also find very different growth rates. Nigeria experienced economic growth of over 8% for the time period between 2003 and 2008, while Ethiopia also had a growth rate of 8% for the period between 2005 and 2011. South Africa on the other hand had the lowest growth rate, followed by Benin (2001 and 2006) and Mali. Four countries had negative growth.

[Figure 4 about here.]

Figure A4 shows the relation between the annualised relative reductions in the multidimensional headcount ratio and the income headcount ratio versus growth in GDP per capita. Despite the differences in the conclusions when comparing reductions in multidimensional and income poverty within countries, the graphs seems to indicate for both that there is no clear, strong relationship between growth and either of the headcount ratios. Although the estimated regression lines have different signs, the estimated relationships are far from statistically significant.[17] Thus, our data do not support the conclusion that higher growth in GDP is associated with smaller reductions in multidimensional poverty. For multidimensional poverty, the conclusion does not change when looking at MPI or A. The data also do not support the conclusion that higher economic growth is associated with higher reductions in income poverty. However, despite the impression of a similar conclusion from the scatter plots, the one for income poverty seems to indicate that there are some potentially influential cases, like Guinea and Mauritania, which could drive the results, while the graph for multidimensional poverty does not indicate influential cases.

6. Conclusions

Our results support the conclusion that most of the countries in Sub-Saharan Africa in our sample made progress in terms of multidimensional poverty, with a few exceptions. When looking at the reduction in multidimensional poverty at the sub-national level, we find great disparities within and between countries. While many countries reduced the gap between the poorest and the least poor region, only few countries had the highest reduction for the poorest region. Looking at the sub-national level, we find huge within country differences across regions. These sub-national results can be used as the starting point for in-depth analyses of the causes of success in poverty reductions, which might otherwise be hidden behind national averages.

When comparing the results of the changes in multidimensional poverty to the changes in income poverty, we find that the two approaches give slightly different answers to the question where poverty was reduced. While some countries reduced both, we find many countries for which multidimensional poverty decreases and income poverty increases. If monetary and multidimensional poverty measures moved together, and if they both identified the same people as poor, there would be no need for two separate measures. Due to the kind of data we use, our results cannot give us any further clue as to whether or not we identify the same people or not. Nonetheless, we find that the measures do indeed not necessarily go in the same direction. The right policy interventions need to be then oriented to reduce all forms of poverty and having separate poverty measures provides the right information for policy makers. Despite the different picture in terms of absolute reductions, similar to other studies (Donaldson, 2008; Ferreira, Leite, & Ravallion, 2010), we do not find a clear relation between economic growth and poverty reduction. Our findings suggest that economic growth alone might not be sufficient to reduce multidimensional poverty.

Notes

[1]Data can be accessed online at http://www.ophi.org.uk/multidimensional-poverty-index/global-mpi-2016/.

[2]Weights are usually assumed to sum up to one. In this case, the weighted sum of deprivations is the share of weighted deprivations a person experiences.

[3]Population data are from the 2012 revision of the United Nations World Population Prospect (2015).

[4]If the comparison is ambiguous because there are several for one country, we additionally report the time periods which we refer to.

[5]See Alkire, Roche, and Vaz (2015) and Alkire, Jindra, Robles, and Vaz (2016) for a detailed description of the harmonisation process. Results for countries with more recent data can additionally differ from Alkire, Roche, and Vaz (2015), because countries have then been strictly harmonised across three surveys. Thus, although most of the surveys are published as part of the Global MPI, results here can differ from previously published results due to the harmonization.

[6]Denote X_{t1} as the achievement matrix in t_1 and X_{t2} as the achievement matrix in t_2. The annualised absolute rate of change is the absolute rate of change divided by the difference between the two years $\bar{\Delta} MPI = \frac{MPI(\boldsymbol{X}_{t_2}) - MPI(\boldsymbol{X}_{t_1})}{t_2 - t_1}$. The annualised relative rate of change is the compound rate of reduction in MPI between the starting and the end period $\bar{\delta} MPI = \left[\left(\frac{MPI(\boldsymbol{X}_{t_2})}{MPI(\boldsymbol{X}_{t_1})} \right)^{\frac{1}{t_2 - t_1}} - 1 \right] \times 100$. The formulas apply to each of the partial indices as well.

[7]The statistical analysis was done using Stata Version 13.1 (StataCorp, 2013).

[8]We use the dataset provided by the Quality of Government Institute (Teorell et al., 2016) to merge GDP and income poverty data to the multidimensional poverty data. The world development indicators in this dataset were downloaded on the 02.11.2015 from http://go.worldbank.org/2EAGGLRZ40.

[9]In case the headcount ratio H (or poverty gap) is missing, the value in year t is calculated by finding the two closest points (H_0, t_0) and (H_1, t_1) where $t_0 < t$ and $t_1 > t$ for which we have observed H_{t0} and H_{t1} and H_t is then interpolated using $H_t = \frac{H_1 - H_0}{t_1 - t_0}(t - t_0) + H_0$. Extrapolation uses the two closest points on the same side of t and the same formula.

[10]If not mentioned otherwise, we use $\alpha = 0.05$.

[11]The timing of the surveys seems to matter for whether or not we find a significant reduction in M_0. Countries with significant reductions have on average surveys which are 6.8 years apart, while countries with non-significant reductions have surveys which are on average 4.5 years apart. The difference is statistically significant ($t(53) = 2.42$, p-value $= 0.019$).

[12]Again based on $\alpha = 0.05$.

[13] Assuming we have m groups and the population share of group l is given by $v^l = \frac{n^l}{n}$, we can express MPI at the national level, given a specific achievement matrix X, as the population share weighted subgroup poverty levels: $MPI = \sum_{l=1}^{m} v^l MPI(X^l)$.

[14]The survey design does not allow to decompose by region for Zambia, South Africa, and the Comoros.

[15]The results are descriptive as the data do not allow significance tests for the annualised changes.

[16]We only extra- or interpolate the income headcount ratio if we have information on income poverty available that is less than four years apart from the years of the surveys used for estimating multidimensional poverty.

[17]In case of the relationship between the multidimensional H and growth in GDP per capita we get $\hat{\beta} = 0.12, s.e. = 0.18$, t-value$= .65$. For income poverty we get $\hat{\beta} = -0.16, s.e. = 0.31$, t-value$= -.05$.

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