Journal of Economic Cooperation and Development, **42**, 3 (2021), 167-211

Grouping foreign aid and the Multidimensional Poverty Index: a cluster analysis

José María Larrú[1], Raquel Ibar[2] and Carlos Quesada[3]

The paper deals with the effects of foreign aid on the changes in the Multidimensional Poverty Index over time. The goal is to group data on foreign aid (considered under a variety of measures and instruments), the MPI and changes on their headcount and their intensity components, and public expenditure on education and health, for a sample of 60 observations (50 countries) and the period 1999-2014. As information is only available as a cross-country section, the methodology used is a three steps cluster and discriminant analysis. In the first step, the cluster was carried out with six different sectorial foreign aid, closely linked to the ten MPI indicators. In a second step, the clusters were performed among the changes in the ten MPI indicators. In the third step, aid, MPI indicators and public expenditures on education and health were considered. The main results are three groups of countries in each step. Only few countries remain always in the same group. Although there is a remarkable heterogeneity across countries and groups among the aid types allocated on them, all countries belonging to the second group received a significant amount of aid.

ملخص

تتناول الورقة آثار المعونة الخارجية على التغيرات في مؤشر الفقر المتعدد الأبعاد على مر الزمن. ويتلخص الهدف في تجميع البيانات المتعلقة بالمعونة الأجنبية (التي يتم النظر إليها في إطار مجموعة متنوعة من التدابير والأدوات)، ومؤشر الفقر المتعدد الأبعاد، والتغيرات التي تطرأ على عناصره الرئيسية

[1] Department of Economics, Universidad San Pablo-CEU, CEU Universities, Madrid, Spain.
E-mail: larram@ceu.es
[2] Department of Applied Economics, Rey Juan Carlos University, Madrid, Spain.
E-mail: raquel.ibar@urjc.es
[3] Department of Applied Mathematics to Information and Communication Technologies, Universidad Politécnica de Madrid, Madrid, Spain.
E-mail: carlos.quesada@upm.es

ومكونات كثافته، والإنفاق العام على التعليم والصحة، من أجل عينة تتكون من 60 ملاحظة (50 دولة) وعلى مدى فترة تمتد بين 1999 و 2014. وبما أن المعلومات متاحة فقط كفرع شامل لعدة بلدان، فإن المنهجية المستخدمة هي مجموعة الخطوات الثلاث والتحليل التمييزي. في الخطوة الأولى، نُفذت المجموعة بستة معونات خارجية قطاعية مختلفة، ترتبط ارتباطا وثيقا بالمؤشرات العشرة لمؤشرات الفقر متعدد الأبعاد. وفي خطوة ثانية، أُجريت المجموعات ضمن التغيرات التي طرأت على المؤشرات العشرة لمؤشرات الفقر متعدد الأبعاد. وفي الخطوة الثالثة، تم النظر في مسألة المعونة ومؤشرات الفقر متعدد الأبعاد والنفقات العامة على التعليم والصحة. والنتائج الرئيسية أفضت إلى ثلاث مجموعات من البلدان في كل خطوة.ولم يبق سوى عدد قليل من البلدان في نفس المجموعة. وعلى الرغم من وجود تباين ملحوظ بين البلدان والمجموعات من بين أنواع المعونة المخصصة لها، تلقت جميع البلدان المنتمية إلى المجموعة الثانية قدرا كبيرا من المعونة.

ABSTRAITE

L'article traite des effets de l'aide étrangère sur l'évolution de l'indice de pauvreté multidimensionnelle dans le temps. L'objectif est de regrouper les données sur l'aide étrangère (considérée sous une variété de mesures et d'instruments), l'IPM et les changements sur leur effectif et leurs composantes d'intensité, et les dépenses publiques d'éducation et de santé, pour un échantillon de 60 observations (50 pays) et la période 1999-2014. Comme l'information n'est disponible que sous forme de section transnationale, la méthodologie utilisée est une analyse en grappes et discriminante en trois étapes. Dans la première étape, le cluster a été réalisé avec six aides étrangères sectorielles différentes, étroitement liées aux dix indicateurs de l'IPM. Dans une deuxième étape, les clusters ont été réalisés parmi les changements des dix indicateurs de l'IPM. Dans la troisième étape, l'aide, les indicateurs de l'IPM et les dépenses publiques en matière d'éducation et de santé ont été considérés. Les principaux résultats sont trois groupes de pays dans chaque étape. Seuls quelques pays restent toujours dans le même groupe. Bien qu'il existe une hétérogénéité remarquable entre les pays et les groupes en ce qui concerne les types d'aide qui leur sont alloués, tous les pays appartenant au deuxième groupe ont reçu un montant d'aide significatif.

Keywords: Foreign Aid, Multidimensional Poverty Index, Cluster analysis

JEL Classification: F35, I32, C38

1. Introduction

Sustainable Development Goal 1 aims to end poverty in all its forms and dimensions (target 1.2). Poverty may be defined according to income but also under deprivations people face in their lives. The Multidimensional Poverty Index (MPI) is a synthetic index that scrutinizes personal deprivations across ten indicators in health (two indicators), education (two indicators) and standard of living (6 indicators). The sources used to compute MPI are national surveys (for instance Demographic and Health Surveys, Multiple Indicator Cluster Surveys or other). As every survey is conveyed in different years in different countries, there is no possibility to get an annual time series of MPI across countries, but it is possible to get different data points at different time period to perform a cross-country analysis.

The global MPI was launched in 2010 by the Oxford Poverty and Human Development Initiative (OPHI) at the University of Oxford and the UNDP for the Human Development Report. Figures are updated at least once a year using newly available surveys and data. In 2016. OPHI compiled up to 60 country cases and offered the changes in the MPI and its ten indicators for different time periods. Following the analysis made by Alkire, Roche and Vaz (2017) for 34 countries, Alkire et al. (2017) for 35 Sub-Saharan countries and Alkire et al. 2019 for ten countries, this paper tries to complement the analysis of the changes in multidimensional poverty across countries and to link them to Official Development Assistance (ODA) flows.

One of the main ODA purposes is to fight against poverty. Therefore, the aim of this paper is to analyze if ODA has incidence in poverty reduction when poverty is measured by a multidimensional method. As there is no time series for the evolution of multidimensional poverty, the methodology used in this paper is a cluster analysis. We perform groups of countries following three steps. In the first step, we consider MPI data and their ten indicators to get empirically the most accurate number of clusters (three). In the second step, we add the sectorial ODA data most closely related to each MPI indicator. We also get three clusters. In the third step we add the public expenditure in health and education (relative to each country GDP) to the MPI indicators and ODA sectors.

As far as we know this is the first time that a cluster analysis is used to analyze MPI and ODA flows. Our main findings are three heterogeneous clusters in each step. Neither geographical or income levels criteria explains the heterogeneity. There are some positive correlations among the ten indicators of the MPI. Electricity stands out among them, although it was the sector that received the lowest level of ODA. There is a positive trend (convergence) between MPI changes and the initial level of the MPI.

These results are interesting for future ODA allocations and the measure of the progress of SDG 1.

The rest of the article is organized as flows. In section 2 we motivate the paper and show the connected literature. Section 3 explains data and methodology. Section 4 describes results and the theory of change that may be behind our normative interpretation. Section 5 concludes.

2. Linking MPI and ODA

In 2010, the United Nations Development Program's flagship publication Human Development Report offered a new set of development indicators. One of them was the Multidimensional Poverty Index, developed by Alkire and Foster (2011a).

Any index related to multidimensional poverty requires determining the unit of analysis (the household surveyed in the case of MPI), selecting the main deprivations to be considered (health, education and standard of living), identifying the set of indicators in which each person is deprived (two in the case of education and health and six for standard of living)[4] at the same time and summarizing their poverty profile in a weighted deprivation score. Persons are identified as multidimensionally poor if their deprivation score exceeds a cross-dimensional poverty cutoff (33.3% for the equally weighted three dimensions)[5]. The proportion of poor people (H) and their average deprivation score (i.e. the 'intensity' of poverty or percentage of simultaneous deprivations they experience, A), become part of the final poverty measure (H*A)[6.]

---

[4] The indicators are: years of schooling and child school attendance (educational deprivations); child mortality and nutrition (healthy deprivation); access to electricity, improved sanitation and drinking water, flooring, cooking fuel and assets ownership (living standard deprivation). In the renewed version of MPI-2018 some changes in the definition of each indicator have been carried out. The details can be consulted in Alkire & Kanagaratnam (2018) and Alkire, Kanagaratnam & Suppa (2018).

[5] Two additional cut-offs are considered in analytical studies: people who are deprived between 20%-33.3% are considered as "vulnerable to poverty" and those who are deprived in 50% or more of the dimensions are qualified as under "severe poverty". When the deprivation cut-offs in eight of the ten indicators reflect higher thresholds, the category of "destitution" is used (see Alkire, Conconi & Seth 2014).

[6] A more formal explanations can be seen in Alkire & Santos (2014) and Alkire et al. (2015).

The methodological proposal for the elaboration of an MPI offered by Alkire & Foster (2011a, b) provides remarkable flexibility. Maintaining all the technical characteristics (axioms) and their capacity for decomposition under various criteria (spatial by region, urban-rural, by ethnic groups, by gender), the governments of each country can adapt this methodology to their own context and political priorities (Alkire et al. 2019b). Many governments in Latin America have done so[7].

Notwithstanding, the MPI has received some criticism. For instance, Burchi et al. (2018. 2019) have proposed the Global Correlation Sensitive Poverty Index (G-CSPI), that incorporates employment as a poverty dimension instead standard of living, though maintaining education and health. Authors remark as an advantage over MPI that it is an individual rather than a household-level measure of poverty, which is crucial for gender-disaggregated analysis and horizontal inequalities. Moreover, they criticize the Alkire, Roche and Vaz's (2017) article because sometimes there was not available information for some indicators in every country. Other drawbacks signaled by Burchi's et al. such as that the MPI is insensitive to inequality among the poor or that its variation over time is, due to the dual cut-off method, almost entirely due to changes in the headcount ratio and only minimally due to changes in the poverty intensity have been contested by Alkire & Foster (2019) and Alkire at al. (2019a).

Ravallion (2011, 2012a) has remarked the discretional equi-ponderation of the three dimensions of the MPI, qualifying the index as a "mashup index". Ravallion proposes the use of a dashboard indexes to evaluate the trends of poverty, including the MPI and the monetary poverty index based on the USD 1.90 a day PPP 2011, as the World Bank is doing. OPHI and UNDP has accepted this view and the targets selected to monitor the SGD 1 included in the 2030 Agenda for Sustainable Development has

[7] See, for instance, Government of Chile 2015. Government of Costa Rica 2015. Government of El Salvador 2015. Government of Honduras 2016, 2017. Government of Panama 2017. Government of the Dominican Republic 2017. There are methodological proposals for developed countries such as Alkire, Apablaza and Jung (2014) and Whelan et al (2014) for the countries of the European Union that produce a homogeneous survey; for five European countries (D'Ambrosio et al., 2011); for Spain (although focused on social welfare, rather than on poverty, de Argüeso et al., 2013); for Germany (Rippin 2016, Suppa 2016), and even for China (Wang et al 2016) OR Sierra Leone (OPHI & UNDP 2019b).

recognized it. While Target 1.1 concentrates on the eradication of income poverty, Target 1.2 goes beyond the income dimension and calls for a reduction of “poverty in all its dimensions according to national definitions”.

In 2017, a 1.3 billion people were identified as multidimensionally poor across 101 countries (OPHI and UNDP 2019a). A massive variation in multidimensional poverty within countries was identified (for instance, poverty in Uganda’s provinces range from 6% to 96.3%) and a quick poverty reduction was pointed out for countries such as Cambodia or India (more than 700 million people were out of poverty for 2005/06-2015/16). A wide variation across countries was not only identified in the incidence[8] but also in the intensity[9] and the inequality[10] of poverty experienced by each poor household. In 2017, the incidence of multidimensional poverty reached 23.1%, the intensity was 49.4% with a 10.5% of the population under severe poverty (that means a deprivation score of 50% or more) and 15.3% of population qualified as vulnerable to poverty (a deprivation score of 20-33%). Health deprivations contributed to poverty in 25.8%, whereas the contribution of education was 29.5% and standard of living 44.7%.

By regions, Sub-Saharan Africa was the region with highest incidence of multidimensional poverty (57.5%) followed by South Asia (31%), Arab States (15.7%), Latin America and the Caribbean (7.5%), East Asia and the Pacific (5.6%) and Europe and Central Asia (1.1%). The intensity of deprivation remarkably shows less dispersion: the higher value was 54.9% in Sub-Saharan Africa and the minimum was 37.9% in Europe and Central Asia.

[8] The incidence or poverty headcount is the population with a deprivation score of at least 33%, expressed as a share of the population in the survey year, the number of people in the survey year.

[9] The intensity of multidimensional poverty is the average deprivation score experienced by people in multidimensional poverty. The MPI is the product of the incidence times intensity of multidimensional poverty.

[10] Inequality among por people is measured using the variance, which is calculated by subtracting each multidimensionally poor person’ deprivation score from the average intensity, squaring the difference, summing the squared differences, and dividing the sum by the number of multidimensionally poor people (OPHI-UNDP 2019:13; Alkire and Foster, 2019).

The 2030 Agenda for Sustainable Development (United Nations 2015) pointed out the relevance of Official Development Assistance (ODA) flows to reach the SDGs. Number 43 of the United Nations' declaration states:

> *An important use of international public finance, including official development assistance (ODA), is to catalyze additional resource mobilization from other sources, public and private. ODA providers reaffirm their respective commitments, including the commitment by many developed countries to achieve the target of 0.7% of gross national income for official development assistance (ODA/GNI) to developing countries and 0.15% to 0.2% of ODA/GNI to least developed countries.*

ODA is defined as government aid designed to promote the economic development and welfare of developing countries. Aid may be provided bilaterally, from donor to recipient, or channeled through a multilateral development agency. Aid includes grants, "soft" loans (where the grant element is at least 25% of the total) and the provision of technical assistance. The OECD maintains a list of developing countries and territories; only aid to these countries counts as ODA. Although not every ODA disbursement has poverty reduction as its declared and main goal, most ODA flows might be considered as a financial contribution for poverty eradication[11]. Furthermore, tough ODA is not the highest financial flow to enhance economic development (it is private foreign direct investment but this flow is mainly focused in emerging countries), it is the main public (official) flow that has poverty eradication as its preferred purpose. This is the purpose of this paper. We want to know if ODA flows can be linked to MPI trends.

Related literature to this work is, on the one hand, Larrú (2017) who has offered a normative approach to link ODA and the MPI proposed by Santos & Villatoro (2018, 2019) for Latin American countries and, on the

[11] The Addis Ababa Action Agenda called for "strengthen international cooperation to support efforts to build capacity in developing countries, including through enhanced official development assistance (ODA)" to reach the sustainable development targets (United Nations 2015b; §22).

other hand, articles related to the analysis of the changes MPI over time such as Alkire, Roche and Vaz (2017) and Alkire et al (2019a).

The nature of data, gathered from different time periods, and scarcity of cases where the MPI was measured in the framework of ODA, inherently limits the scope of this study and forces to be selective with the appropriate methodology. In Section 3 it will be justified why not only we do not carry out a causal or regression analysis, but the reasons to select a cluster and discriminant analysis. It is important to bear in mind that the analysis has been done over discrete data points (changes in MPI and its ten components) and different time periods for each country due to the different years in which poverty surveys were conducted. This is the reason why poverty indexes and ODA flows are all annualized.

3. Data and Methodology

3.1. Data and correlations among variables

Our dataset for MPI comes from OPHI and the results for the "2016 Summer global MPI Resources" (Tables 6.1-6.6)[12]. The dataset offers information for 60 cases and 50 countries[13]. From the dataset, we selected these cross-section variables for the 60 available observations to maximize the sample size:

- MPI change in relative terms; this is the difference in levels across two periods as a percentage of the initial period;
- Headcount and intensity changes in relative terms;

[12] Data are available at https://ophi.org.uk/2016-summer-global-mpi-resources/
[13] Country names are added with a period length. This period reflects the first and final year in which a survey was conducted. For example, Armenia 2005-2011 means that a DHS survey was carried out in 2005 and other in 2011. The dataset offers the annualized difference between these two years. Sometimes, there is more than one data point for a country, because it could be computed the changes for different time periods. For example, there are three observations for Nigeria: 2003-2008; 2008-2014; 2003-2013. The other cases are Senegal 2005-2012/14; 2010/11-2012/14; 2005-2010/12 (the dash bar means that the surveys were conducted under those years); Bangladesh 2004-2008; 2007-2012; The Republic of Congo 2005-2011/13; 2009-2011/13; Peru 2005-2009 and 2008-2013; Zimbabwe 2006-2010/12; 2010/11-2015. Alkire, Roche and Vaz (2017) followed the same criteria and used 37 observations for the sample of 34 countries.

- the change in the number of multidimensional poor;
- the annualized absolute change in raw headcounts (in percentage points) of the ten MPI indicators[14].

Raw headcounts are the total proportion of the population who experience deprivations in each indicator. In other words, we have a [60x10] matrix (though there were 10 missing observations for nutrition and two for flooring and cooking fuel).

For the shake of completeness, all methods described below were carried out for two versions of the dataset. On one hand, the dataset was restricted to the 42 observations that had no missing values in any of the variables. On the other hand, the full dataset with N=60 was considered using the median for imputation of the missing values. The results in both cases were extremely similar so we just report the results obtained for the full sample hereafter.

In addition to the analysis of the MPI indicators, we wanted to know if some domestic resources could have an impact or influence in the selected countries and periods. We consider the public spending on education and health (relative to GDP) as relevant variables due to their link with the first two dimensions of the MPI. We extracted the values from World Bank's World Development Indicators and compute their average value for each country and time period.

Finally, data for ODA was extracted from OECD-DAC dataset. We computed the sum of Net ODA coming from "All donors" for each developing country of our sample. We use the Creditor Reporting System (CRS) dataset to match MPI-indicators with sectorial ODA. We considered ODA under gross disbursements, from 2002-2017 in current prices (US Dollar millions) for data availability. We selected six sectorial ODA that are closely related to the ten MPI indicators: education, health, energy, electricity, water and sanitation, and "other". The latter was computed as a "residual". It was the result of the difference between "ODA total sectors" minus ODA for social sector, economic sector, production sector, debt relief and humanitarian aid.

[14] See the footnote 1 for the 10 indicators.

Table 1 shows the main statistical indicators.

All the variables have 60 observations except for nutrition (50)15, floor and fuel (58)16 and public expenditure in education (55)17. All countries, except for Madagascar have achieved a negative MPI-change (reduction in multidimensional poverty)[18]. Poverty reduction was lower in nutrition (37 cases out of 50), cooking fuel (38 out of 58), flooring (44 out of 60) and water (46 out of 60) than in the rest on deprivations. Conversely, poverty increased in fuel (20 cases) and flooring and water (14 cases respectively). Means and median values show a higher poverty reduction in assets (-1.58%) and sanitation (-1.33%) than in fuel (-0.27%) and nutrition (-0.5%). The highest reduction happened in Rwanda 2005/2011 in sanitation (-7,38%) followed by The Republic of Congo 2005/2010 in assets (-6.51%). There was an increase of poverty in Sierra Leone in sanitation (+6.62%).

[15] The missing values were Burundi, Core d'Ivoire, Guyana, Indonesia, Pakistan, Sao Tome and Principe, Tanzania, the Republic of Congo - in three cases.
[16] The missing values were Central African Republic and South Africa for floor and Cote d'Ivoire and Egypt for fuel.
[17] The missing values were Nigeria -in three cases- Jordan and Haiti.
[18] Senegal 2010-2014 showed a 0.0% in her MPI-change, with +0.9% in the incidence of poverty and -0.9% in the intensity component.

Table 1. Main statistical indicators: components of the MPI (first panel) and the rest of the variables (second panel)

Name	Years of schooling	Child school attendance	Child mortality	Nutrition	Electricity	Improved sanitation	Drinking water	Flooring	Cooking fuel	Asset ownership
Mean	-0.74	-1.09	-0.98	-0.50	-0.96	-1.33	-0.91	-0.58	-0.27	-1.58
Median	-0.60	-0.90	-0.83	-0.46	-0.93	-1.10	-0.75	-0.53	-0.16	-1.28
Max	1.11	2.91	1.20	2.82	2.43	6.62	2.83	0.79	5.64	2.96
Min	-3.22	-5.46	-6.37	-2.77	-5.26	-7.38	-6.00	-3.84	-3.12	-6.51
Variance	0.62	2.02	1.39	0.95	1.29	4.33	2.71	0.65	1.47	3.14
St. deviation	0.79	1.42	1.18	0.97	1.14	2.08	1.65	0.81	1.21	1.77
C. Variation	-1.06	-1.30	-1.20	-1.95	-1.18	-1.56	-1.80	-1.40	-4.43	-1.12
Pov.reduction	52	50	53	37	52	52	46	44	38	52
Pov. Increase	8	9	7	13	8	8	14	14	20	8
Observations	60	60	60	50	60	60	60	58	58	60

Name	educ_Gov_exp	Health_public	ODA_ educ	ODA_ health	ODA_ energy	ODA_ electri	ODA water_sanit	ODA_ other	MPI_ change	poor_ change	Hcount_change	Intensity_change
Mean	4.06	10.24	79.41	82.66	36.53	10.61	40.16	157.22	-4.85	-341.34	-3.93	-0.95
Median	3.78	9.91	62.83	53.49	18.75	5.99	30.13	141.87	-4.04	-9.77	-3.00	-0.94
Max	11.07	17.72	342.93	347.93	296.51	61.50	145.23	682.68	2.30	11745.2	2.01	0.28
Min	1.43	4.31	4.37	2.75	0.05	0.00	0.99	4.66	-17.73	-26957.8	-17.60	-2.12
Variance	2.94	10.36	5519.69	7399.04	2394.26	181.51	1148.82	16586.27	13.80	23869671.10	12.97	0.31
St. Deviation	1.71	3.22	74.29	86.02	48.93	13.47	33.89	128.79	3.72	4885.66	3.60	0.56
CVariation	0.42	0.31	0.94	1.04	1.34	1.27	0.84	0.82	-0.77	-14.31	-0.92	-0.59
Pov.Reduc									58	31	57	58
Pov.increase									2	29	3	2
Observ	55	60	60	60	60	60	60	60	60	60	60	60

Source: Authors' elaboration.

There were 14 cases where the reduction of poverty happened in the ten MPI-indicators and 13 cases where the reduction occurred in 9 indicators. The minimum reduction happened in 4 cases where there was only a reduction in 4 indicators (Cote d'Ivoire 2005 - 2011/13; Madagascar 2004 - 2008/10; Senegal 2010/11 - 2012/14; Zimbabwe 2010/11 – 2015). Not every country shows a reduction in poverty under all its forms or dimensions. Even more, there is a remarkable heterogeneity among the results in the poverty indicators. Variance ranges from 4.33% (sanitation) and 3.14% (assets) to 0.62% (years of schooling) and 0.65 (flooring). Fuel shows the highest volatility when it is measured by the coefficient of variation (CV): +4.43% compared to years of schooling (-1.06%) that was the lowest.

Table 2 shows the country with the highest poverty reduction and the highest poverty increase for each poverty indicator.

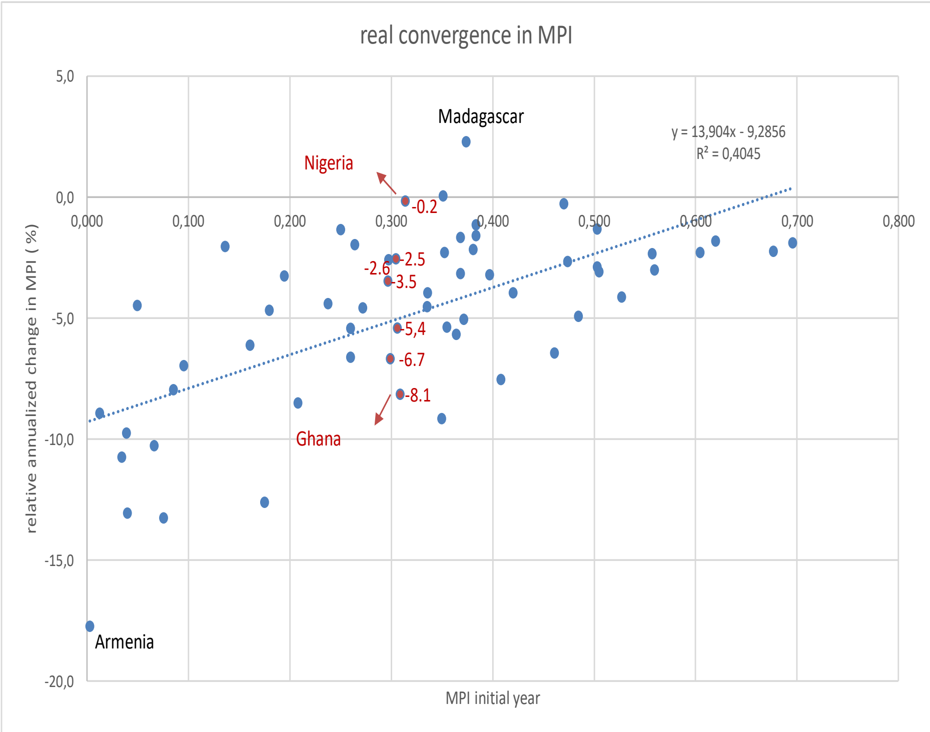
Table 2. The highest poverty reduction and poverty increase in each MPI indicator

Country/case	Reduction value (%)	Indicator	Country/case	Increase value (%)
Burundi 2005/2011	-3.22	Years of schooling	Madagascar 2004/2010	+1.11
Liberia 2007/2014	-5.46	School attendance	Jordan 2007-2010	+2.91
D.R. Congo 2007/2013	-6.37	Child mortality	Sierra Leone 2008-2014	+1.2
South Africa 2008/2013	-2.77	Nutrition	Madagascar 2004-2010	+2.82
Nepal 2006/2012	-5.26	Electricity	Senegal 2010-2014	+2.43
Rwanda 2005/2011	-7.38	Sanitation	Sierra Leone 2008-2014	+6.62
Ethiopia 2000-2006	-6.00	Water	Senegal 2010-2014	+2.83
Senegal 2010-2014	-3.84	Flooring	D.R. Congo 2007/2013	+0.79
Indonesia 2007/2013	-3.12	Fuel	D.R. Congo 2007/2013	+5.64
Congo, the Rep. of 2005/2010	-6.51	Assets	Senegal 2010/2014	+2.96

Note: Column 3 (Indicator) is valid for the other left-hand and right-hand columns.
Source: Authors’ elaboration.

MPI change shows a positive trend with the initial MPI value. The lower the initial MPI is, the higher change in MPI happens. Notwithstanding, Figure 1 shows the heterogeneity of the changes in MPI related to an initial MPI around 0.300. The cases ranges from -0.2% (Nigeria) to -8.1% (Ghana)[19].

Figure 1. Correlation between initial MPI and relative annualized changes in MPI



Source: Authors' elaboration.

Regarding public expenditure in education and health relative to GDP, all countries have invested more in health than education. Health shows more variance but lower volatility than education. Lesotho 2004-2010 was the

[19] Standard errors= 2.21 and t-stat=6.28. Regression includes a constant. Despite the positive trend the R^2 is only 40%. Ravallion (2012b) did not find poverty convergence using unidimensional monetary data. Regression of MPI change on the number of years for each country-period was only significant at 94% of confidence: the coefficient=0.44; se=0.23; t-stat=1.93; p-value=0.0589. R^2=0.06.

case with the highest expenditure in education (11.07%) followed by Colombia (17.22%) and Malawi (17.11%) in health, whereas the lowest cases were Central African Republic 2000 – 2011 in education (1.43%) and Pakistan 2006-2014 in health (4.31%). The correlation between the two public expenditures is very low (0.1746; R^2=0.0087). Furthermore, there is no correlation between the sum of public expenditure in education and health and the change of MPI (-0.054; R^2=0.0034)[20].

A significant but low pair-wise Pearson correlation was found between *public expenditure in education* and school attendance (0.288*) and between *public expenditure in health* and child mortality (0.319*). *Total health expenditure* is also correlated with child mortality (0.322*), public expenditure in education (0.338*) and public expenditure in health (0.547**).

Regarding ODA measures, some bilateral correlations between variables are interesting enough. For instance, total expenditure in health (public and private, relative to GDP) is statistically significantly correlated with the six sectorial types: -0.387* with ODA-education; -0.458** with ODA-health; -0.385** with ODA-energy; -0.369** with ODA-electricity; -0.298* with ODA-water; -0.268* ODA-other[21]. We interpret these results as a substitution effect or fungibility of ODA. While donors finance a variety of public services, partner countries (recipients) may allocate less resources to public health.

All ODA types are correlated to each other. The highest coefficients are 0.798** between ODA-education and ODA-energy; 0.770** between ODA-energy and ODA-other. The lowest coefficients are between ODA-energy and ODA-electricity (0.479**); and ODA-energy and ODA-health (0.566**). Table 3 shows the correlation matrix among sectorial ODA variables.

[20] See Figure A.1 in the Annex.

[21] There are significant correlations between total health expenditure and the other measures of ODA: total ODA gross, total ODA net, ODA loans, ODA grants, Multilateral ODA, CPA, ODA social, economic, production, debt and humanitarian aid. Values ranges from -0.452** (ODA loans) to -0.271* (ODA debt). Significant correlations remain between public expenditure in health (relative to GDP) and ODA-education (-0.330*), ODA-health (-0.377**) and ODA-energy (-0.385**) and the other total measures of ODA: gross, net, loans, multilateral, CPA, humanitarian and ODA-economic. All values are available to readers upon request.

Table 3. Correlation matrix among sectorial ODA variables.

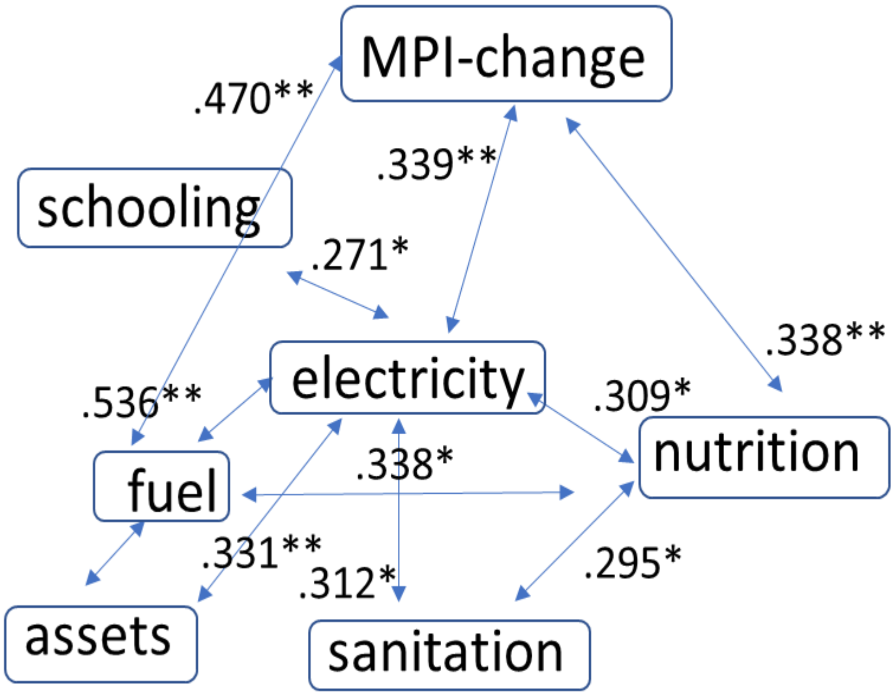
	ODA-education	ODA-health	ODA-energy	ODA-electricity	ODA-water&santitation	ODA-other
ODA-education	1					
ODA-health	.581**	1				
ODA-energy	.787**	.527**	1			
ODA-electricity	.632**	.653**	.492**	1		
ODA-water&santitation	.593**	.607**	.613**	.584**	1	
ODA-other	.745**	.508**	.755**	.523**	.701**	1

Note: ** stands for 99% of confidence. Source: Authors' calculations.

There are also interesting correlations among the ten MPI indicators and with MPI-change (Figure 2). As it can be seen, electricity is the MPI indicator that is more correlated with the other deprivations. We may infer that, due to higher spillover effects, donor might consider enhancing investment in ODA for electricity.

In a nutshell, we focus our analysis in the changes of the ten indicators that make up the MPI and six sectorial ODAs that are closely related to the MPI components. We also take into account the public expenditure and education and health relative to GDP. All data are annualized.

Figure 2. Correlations between MPI components



Note: ** stands for statistically significant at 99% of confidence and * at 95%. Each Pearson correlation was computed using the available data for each variable. The number of observations varies between each pair. For sensitivity analysis, results for a sample including imputed values (N=60) and for a restricted sample (N=42) with no missing value, see Figure A.2. in the Annex.
Source: Authors' calculations.

3.2. Methodology

In order to go beyond descriptive statistics, both supervised and unsupervised analyses were conducted in R, with very different performance in each case[22].

Several supervised learning methods were used in order to assess whether the MPI-change could be predicted by means of the six ODA variables and also whether MPI-change could be predicted in terms of health expenditure and education expenditure. The results were no good in both

[22] R 3.6.1 was used under the frontend RStudio 1.2.5001.

cases for any of the methods that were implemented23. For each of them, several configurations of parameters were tried and the performance of each of those cases was evaluated by 100 iterations of Monte Carlo cross validation[24] obtaining a median R^2 always below 0.25 (Figure A.3. in the Annex). Given the different nature of the techniques, the result strongly suggests that prediction of MPI-change is not viable by means of ODAs, health expenditure or education expenditure.

Furthermore, regressions on each of the MPI indicators were also run to see if any of the indicators does have a relation with the ODAs (although a description of the whole MPI-change was not possible) with an equally discouraging result.

Since no reliable prediction seems possible, unsupervised learning was carried out in order to extract groups of similar countries and therefore deepen the insight on the topic. Again, several methods and configurations were implemented although this time with excellent results. Three different problems were studied; clustering the countries in terms of their similarity considering only MPI indicators, clustering the countries in terms of ODAs and finally clustering the countries considering both MPI indicators and ODAs.

When clustering, there are three main choices to make; firstly, the distance to create the dissimilarity matrix (and/or an appropriate method for reduction of dimensionality), secondly, what clustering method to select and finally the number of clusters to select. Of course, all the above should be considered altogether in order to explore all possible combinations. The best dissimilarity matrix for all the three cases[25] was

---

[23] The full list of implemented methods is: Linear Model, k-Nearest Neighbors, 3-layer Neural Networks (using neuralnet package), Least Angle Regression (using lars package), Polynomial Kernel Regularized Least Squares (using KRLS package), Lasso Regression and Ridge Regression (using elasticnet package), CART (using rpart package), bagged CART (using e1071 package), Boosted Generalized Additive Model (using mboost package), eXtreme Gradient Boosting (using xgboost package), L2 Regularized Support Vector Machine with Linear Kernel (using LiblineaR package), Multi-Layer Perceptron (using RSNNS package) and Random Forests (using randomForest package).

[24] The cross-validation was implemented with the caret package using train() with the train control trainControl(method="LGOCV", number=100. p=0.8).

[25] For each problem of clustering, Euclidean, Chevyshev, Manhattan, Canberra and Mahalanobis distances were tried using the *base* and *philentropy* packages as well as

found with the KODAMA algorithm[26] using k-Nearest Neighbors with k=2.

In all three cases, Agnes clustering (Hierarchical clustering with Ward D2 linkages) was selected to carry out the studies with three clusters, although several others were implemented. The selection of clustering algorithm and optimal number of clusters was done attending to internal measures (to check that inside a group observations are close to each other and to check that groups are well separated) and stability measures27 (to check the consistency and the robustness of the results, that is, checking whether observations are classified in the same groups even if a variable is removed). Agnes was typically the choice with a best trade-off of all measures although in many cases other methods performed similarly28, even finding exactly the same clusters in some case (this is a great and uncommon sign of robustness, as two different techniques arrive to the same result). Finally, in very few cases a different clustering might arguably be better attending to one or some of the specific measures, but we stick to Agnes with three groups so that the results can be compared with significance and no extra inconstancies that could arise from comparing different methods are introduced.

4. Cluster and discriminant analysis: results

As a first approach, we tried to verify if cross-country regression analysis offers some statistically significant results. As explained above, no method provided a significant model to associate MPI indicators and

PCA, KODAMA, ISOMAP and Shannon nonlinear mapping for dimensionality reduction. The best dissimilarity matrix was selected using the Hopkins statistic (clusterend package).

[26] The KODAMA algorithm is a novel learning algorithm for unsupervised feature extraction, is specifically designed for analyzing noisy and high-dimensional datasets. KODAMA works in a similar fashion to algorithms such as t-SNE, Shannon Nonlinear Mapping or ISOMAP, reducing the dimensionality of the dataset in a nonlinear way such that meaningful groups are identified.

[27] The internal methods are the silhouette width, connectivity and Dunn index whereas the stability methods are APN, AD and ADM indexes. All were implemented using *clValid*.

[28] In addition to Agnes, Hierarchical clustering with other linkages, Kmeans Clustering, Diana Clustering, Model Based Clustering and Self Organizing Tree Algorithms were computed using the *factoextra* package.

ODA variables[29]. We cannot attribute any causal relationship among MPI changes and ODAs. It should be noted that the sum of the six sectorial ODAs are only capturing an average of 36% of all gross ODA resources[30]. This implies that, besides our omitted variables problem for modeling changes in MPI, we are only considering a low proportion of the potential effect of the whole ODA flows. Moreover, the median value for the components of gross ODA are 7% for education, 6% for health and 21% for assets[31]. Even among all the ODA purposes (or sectors), very little resources are being committing for the components of MPI.

4.1. Cluster analysis

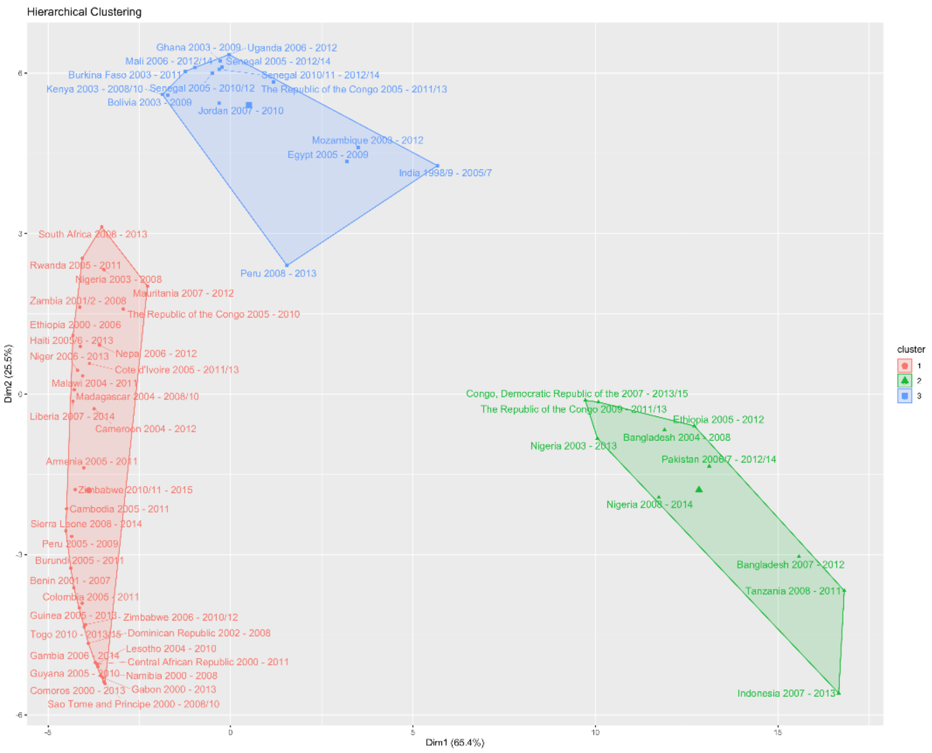
Then, instead of modeling MPI changes we look for groups of countries that share a profile regarding MPI components or sectors of ODA. A cluster analysis is the correct methodology to achieve this goal. As it was explained above, the clustering was conducted in three steps, firstly we made a cluster classification for the six sectorial measures of ODA. Secondly, we clustered the 10 MPI components. Thirdly, we carried out a cluster with ODAs, MPIs components and public expenditures in education and health. The results can be seen in Figures 3. 4 and 5.

Figure 3. Cluster amongst the six sectorial ODA.

[29] For instance, the result when we regress the six sectorial ODAs, and education and health as a share of GDP on MPI-change was that only ODAs for education and for energy were statistically significant (at 95%) with and Adjusted R^2=0.0928. The coefficient for ODA-education was 0.0034 (se=0.0015; p-value=0.0265) and for ODA-energy was -0.004 (se=0.0023; p-value=0.067).

[30] The values range from 55% of Indonesia and Jordan to 9% of Nigeria 2003-2008 and 16% of Guyana.

[31] The maximum values range from 21.4% in education (Gabon 2000-2013); 20.5% in health (Nigeria 2008 – 2014); and 49.1% in assets (Mauritania 2007-2012).



Source: Authors' elaboration.

Figure 3 shows the three groups when the six sectorial ODAs are used. It can be seen that there is not a continental pattern (there are countries from Africa, Asia and America in all groups). Cluster 1 (displayed in red) is the most numerous with 35 cases (58% of the whole sample). The ten cases of cluster 2 (green) showed higher values than the averages in all the ODA measures. In fact, the ten cases belong to the first quartile when the six sectorial ODAs are ranked. Cluster 3 (blue) is made up of 15 cases (25% of the sample).

When the ten indicators of the MPI are used, the three groups showed in Figure 4 are identified.

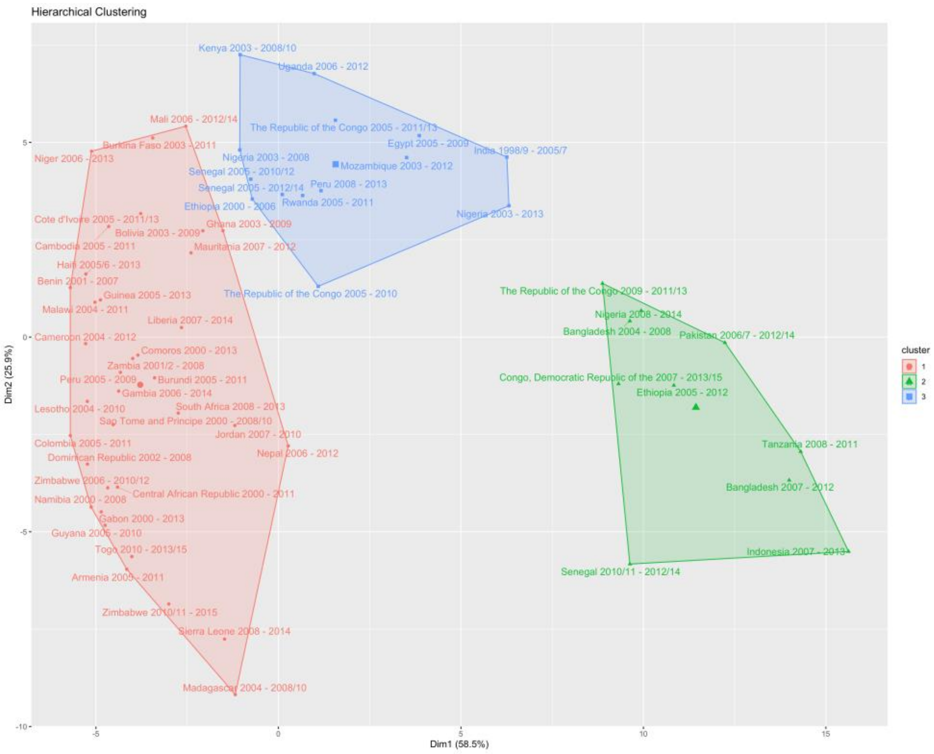
30 cases (50%) are clustered around cluster one. Madagascar, who is the only case where there was a positive MPI change (higher poverty) is classified in this first group. Cluster 2 is solely made up of five observations featuring four countries: Bangladesh, Senegal, Nepal and Rwanda. The remainder 25 cases (42%) are grouped in cluster 3.

Figure 4. Cluster amongst 10 MPI indicators

Source: Authors' elaboration.

The cluster analysis still offers three groups when public expenditures in education and health are added to the six ODAs measures and the 10 MPI indicators (Figure 5). This time, the groups are more diversified. Cluster 1 in red features 36 cases (60% of the sample). Distances between them are large. The opposite happens between the ten cases (17%) of cluster 2. The remainder 14 cases (23%) are grouped in cluster 3.

Figure 5. Cluster with ODA, MPI indicators and education and health expenditures



Source: Authors' elaboration.

In all cases, we identified three clusters as the benchmark results. There is a noticeable heterogeneity within and between clusters[32]. We interpret this result as a confirmation that there is no blueprint for poverty reduction.

We also identify some countries that remain in the same cluster in the three groupings. Fifteen cases remain in the first group: Armenia, Cameroon, Colombia, Cote d'Ivoire, Dominican Republic, Gabon, Guyana, Lesotho, Madagascar, Namibia, Peru 2005-2009. Sao Tome and Principe, Togo and Zimbabwe (in the two cases).

---

[32] See Table A.1. in the Annex for the classification of each country in each of the three steps.

Only Bangladesh (in the two periods) remains in the second group and Mozambique in the third group, remains in the same group in the three steps.

There are 15 cases that are grouped in the first cluster when ODA and all indicators are used, and they shifted to the third group when MPIs are included (Table 4)[33].

Table 4. Countries classified in cluster 1 under ODAs, cluster 3 under MPI indicators and cluster 1 when education and health public expenditures are added

Benin 2001 - 2007
Burundi 2005 - 2011
Cambodia 2005 - 2011
Central African Republic 2000 - 2011
Comoros 2000 - 2013
Gambia 2006 - 2014
Guinea 2005 - 2013
Haiti 2005/6 - 2013
Liberia 2007 - 2014
Malawi 2004 - 2011
Mauritania 2007 - 2012
Niger 2006 - 2013
Sierra Leone 2008 - 2014
South Africa 2008 - 2013

[33] See Table A.2. for all the sequenced cases.

Zambia 2001/2 - 2008

Source: Authors' elaboration.

4.2. Discriminant analysis

The results obtained in the Cluster Analysis are statistically significant, yet they act as a black box. In order to have further understanding of the underlying reality, a linear discriminant analysis using the group number as response is proposed to estimate a model that classifies countries according to their features. This analysis offers a classification function that would allow estimating the membership group of countries not studied yet.

Variables used as predictors in the discriminant function were selected from variables rejected from the ANOVA test (Table 5) and, therefore, they show higher discriminant power among data.

Table 5. ANOVA test

	Wilks' Lambda	F	gl1	gl2	Sig.
Yearsofschooling	.978	.640	2	57	.531
Childschoolattendance	.992	.234	2	57	.792
Childmortality	**.825**	**6.053**	**2**	**57**	**.004**
Nutrition	.991	.259	2	57	.773
Electricity	.995	.152	2	57	.859
Improvedsanitation	**.915**	**2.659**	**2**	**57**	**.079**
Drinkingwater	.959	1.233	2	57	.299
Flooring	.976	.690	2	57	.506

Cookingfuel	**.830**	**5.829**	**2**	**57**	**.005**
Assetownership	.957	1.267	2	57	.289
educ_Gov_exp	.927	2.229	2	57	.117
Health_public	**.821**	**6.232**	**2**	**57**	**.004**
EducHealth	**.741**	**9.949**	**2**	**57**	**.000**
ODA_educ	**.420**	**39.319**	**2**	**57**	**.000**
ODA_health	**.352**	**52.563**	**2**	**57**	**.000**
ODA_energy	**.423**	**38.917**	**2**	**57**	**.000**
ODAelectri	**.437**	**36.665**	**2**	**57**	**.000**
ODAwater_sanit	**.566**	**21.852**	**2**	**57**	**.000**
ODA_other	**.554**	**22.981**	**2**	**57**	**.000**

Source: Authors' elaboration.

The structure matrix (Table 6) shows the low correlation between *Health_public* and *Improved_sanitation* with discriminant functions and thus, both variables are omitted in the estimation of the classification functions.

Table 6. Structure matrix

	Function	
	1	2
ODA_health	.507*	.063
ODA_educ	.438*	.135
ODA_energy	.434*	-.165
ODAelectri	.424*	-.072
ODAwater_sanit	.317*	.295
Health_public	**-.172***	**.119**
Cookingfuel	.013	.595*
ODA_other	.319	.372*
EducHealth	-.205	.287*
Childmortality	-.160	-.223*
Improvedsanitation	**-.109**	**.117***

Source: Authors' elaboration.

From the coefficients of the classification function (Table 7), Fisher's linear discriminant functions are obtained, which allow to estimate the membership group of a new country and thus we can identify its profile.

Table 7. Classification function coefficients

	Fisher discriminant lineal functions		
	I	II	III
X_1: Childmortality	-1.364	-1.839	-1.893
X2: Cookingfuel	-.645	1.467	1.052
X_3: EducHealth	1.553	1.373	1.521
X_4: ODA_educ	.041	.055	.055
X_5: ODA_health	.032	.112	.060
X_6: ODA_energy	.039	.212	.064
X_7: ODAelectri	-.054	.338	.014
X_8: ODAwater_sanit	-.016	-.030	.00034
X_9: ODA_other	-.022	-.035	-.014
(Constant)	-12.952	-36.050	-20.660

Source: Authors' elaboration.

The estimated model is validated by means of Leave One Out Cross Validation, obtaining a mean prediction accuracy of 88.3% (Table 8). This result is excellent as groups that were created using nonlinear nonconvex methods are being identified with a linear classifier.

Table 8. Confusion Matrix

		True class			Total
		1	2	3	
Predicted class	1	37	0	0	37
	2	1	11	1	13
	3	3	2	5	10
Sensitivity and Specificity	1	100%	0%	0%	100%
	2	7,7%	84,6	7,7	100%
	3	30%	20%	50%	100%

Source: Authors' elaboration.

The equations related to the Fisher discriminant lineal functions are:

$$F_{I,i} = -1.364X_{1,i} - 6.45X_{2,i} + 1.553X_{3,i} + 0.041X_{4,i} + 0.032X_{5,i} + 0.039X_{6,i} - 0.054X_{7,i} - 0.016X_{8,i} - 0.022X_{9,i} - 12.952$$

$$F_{II,i} = -1.839X_{1,i} + 1.467X_{2,i} + 1.373X_{3,i} + 0.055X_{4,i} + 0.112X_{5,i} + 0.212X_{6,i} + 0.338X_{7,i} - 0.030X_{8,i} - 0.035X_{9,i} - 36.050$$

$$F_{III,i} = -1.893X_{1,i} + 1.052X_{2,i} + 1.521X_{3,i} + 0.055X_{4,i} + 0.060X_{5,i} + 0.064X_{6,i} + 0.014X_{7,i} + 0.00034X_{8,i} - 0.014X_{9,i} - 20.660$$

Where:

$F_{g,i}$ discriminant score of individual i, in the group g= I, II, III

$X_{j,i}$ is the value of individual i in the observed variable X_j, j=1, 2, …, 9

New individuals (countries) will be classified in the group for which the classification function has a higher value, that is:

$$If\ F_{G,i} = \max_{g=I,II,III} F_{g,i}\quad then\ individual\ i\ belongs\ to\ group\ G.$$

4.3. Discussion and implications

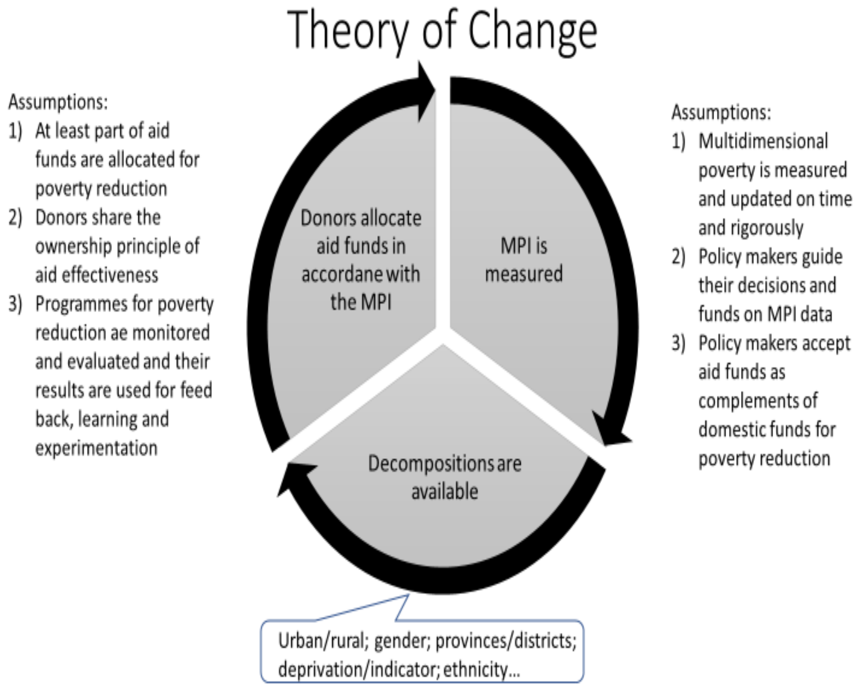
The applications of these groupings may be broad. For instance, policy makers of donor countries might plan and allocate their ODA resources taken into account the three clusters. It is remarkable that neither the income level (low, lower-middle or upper-middle income) nor the geographic criteria match exactly with the countries grouped in the three ODAs clusters. Indeed, it can be observed that in all three clusters there are Least Developing countries, Low-Income countries and Middle-Income countries. Similarly, all clusters feature Asian and Sub-Saharan countries.

Secondly, the clusters formed with the MPI indicators, show that a same country may be grouped in different clusters in different periods. For example, Senegal was grouped in the cluster number three in 2005-2010/12 and 2005-2012/14 but in the cluster number two for 2010/11-2012/14. Peru was classified in the third cluster for 2008-2013 but in the first one for 2005-2009. That means that there is no blueprint for poverty eradication. This can also be noticed by the greater amplitude (distances among countries) of cluster one. Countries grouped in the same cluster might compare the anti-poverty policies that each one has implemented and learn from each other.

Finally, these traits are also confirmed in our third step, when public expenditure in education and health are incorporated. Senegal in classified in cluster 3 for 2005-2012 but in the second one for 2010-2012/14. All clusters show countries for different continents and for different income levels.

Whatever the clustering results are, our main practical interest is to reinforce that ODA and MPI may be linked. Ownership has been identified as one of the main criteria for the effectiveness of foreign aid, at least since the OECD’s Paris Declaration in 2005. At the base of our normative approach to link ODA and MPI, lies a theory of change that can be seen in the Figure 6.

Figure 6. Theory of the change that underlies the relationship between ODA and MPI



Source: Authors' elaboration.

In short, we are assuming that, at least, some proportion of aid is really and directly oriented to multidimensional poverty reduction and that aid donors and their partners take the information provided by the MPI indicators as a starting and critical point for the anti-poverty policies, including the international development cooperation. The capacity of the MPI to disaggregate the deprivations by gender, ethnicity, subregion or districts, urban or rural and so on, can be a very useful input when donors and recipients' countries plan their ODA sectoral projects and programs. Aid resources might be allocated in line with the country needs and under each province, gender, vulnerable group or indicator of the MPI has been identified. Furthermore, this approach may be extended and applied to different forms and designs of MPI. For instance, there are a variety of

MPIs in Latin American countries (Santos and Villatoro 2018, 2020) or versions of the MPI for European or other countries[34].

To our knowledge, currently this is not the usual way to proceed in international development cooperation policy. Walking in this direction might accelerate the achievement of the SDG 1.

5. Conclusion

The goal of this paper is linking ODA and MPI changes. Data availability prevented a causal or complex econometric analysis such as regressions with dynamic panel data, nonetheless rigorous cluster analysis has been carried out to identify common patterns in MPI changes. It must be beard in mind that results are biased by the country sample and cases with available data and no causal inference should be inferred from the evidence show in the study. Notwithstanding, some interesting results have been got and they might be useful for policy makers.

There is a positive trend (convergence) between MPI changes and the initial level of the MPI. The higher the initial MPI is, the higher change in MPI happens. This should be taken into account when the progress in SDG 1 is assessed.

Regarding the changes in the ten indicators of the MPI, electricity has shown the highest correlations with the other MPI indicators. Although electricity was not the indicator that showed the greatest positive change in multidimensional poverty, it was positively correlated with nutrition, sanitation, fuel, assets, schooling and with the change of MPI, though their levels are 0.47 or lower. This may be taken into account by ODA donors because electricity was the sector that received the least sectorial ODA resources (on average, USD10.6 million that means near 1% of the average total net ODA considered in this paper). This claim may be reinforced with the positive correlations showed among ODA for electricity and the other considered sectorial ODA. On average, only 36% of the gross ODA was allocated to the sectors directly related to the MPI components.

Regarding education and health expenditures, it seems that their effect on changes in the MPI is low. We do not identify any statistically significant

[34] See the footnote 4 for some references.

correlation between these expenditures and MPI indicators or sectorial ODAs.

When a cluster analysis is considered, three heterogenous groups are identified under the three steps carried out. Neither geographical nor income level criteria explain the cluster compositions. We interpret this result as there is no single way to reduce multidimensional poverty using ODA flows. But donors (public and private) may consider our results as a guide for planning future ODA resources and for promoting evaluations that take the clusters show here as a base line. More concrete projects and programmes evaluations are needed if the causal effects of ODA resources on multidimensional poverty want to be identified. But a first step in this analysis should be reckoning that only a very low share of ODA flows have been allocated considering the information reported by the MPI indexes and indicators.

References

Alkire, S. and Foster, J. (2011a), “Counting and Multidimensional Poverty Measurement”, *Journal of Public Economics*, 95 (7-8), 476-487.

Alkire, S. and Foster, J. (2019), ‘The role of inequality in poverty measurement’, OPHI Working Paper 126, University of Oxford.

Alkire, S. and Foster, J. E. (2011b), “Understandings and misunderstandings of multidimensional poverty measurement”, *Journal of Economic Inequality*, 9(2), 289-314.

Alkire, S. and Kanagaratnam, U. (2018), ‘Multidimensional Poverty Index - Winter 2017-18: Brief methodological note and results’. OPHI MPI Methodological Notes No. 45, Oxford Poverty and Human Development Initiative, University of Oxford

Alkire, S. and Santos, M.E. (2014), “Measuring Acute Poverty in the developing World: Robusteness and Scope of the Multidimensional Poverty Index”, *World Development*, 59, 251-274.

Alkire, S., Apablaza, M., and Jung, E. (2014), “Multidimensional Poverty Measurement for EU-SILC Countries”, OPHI Research in Progress 36b.

Alkire, S., Conconi, A. and Seth, S. (2014), “Multidimensional Destitution: An Ordinal Counting Methodology for Constructing Linked Subsets of the Poor”, OPHI Research in Progress 42a, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., Conconi, A., Pinilla-Roncancio, M., and Vaz, A. (2019b), “How to Build a National Multidimensional Poverty Index (MPI): Using the MPI to inform the SDGs”. United Nations Development Programme (UNDP) and Oxford Poverty and Human Development Initiative (OPHI), University of Oxford, Oxford.

Alkire, S., Foster, J. E., Seth, S., Santos, M. E., Roche, J. M., and Ballon, P. (2015), *Multidimensional Poverty Measurement and Analysis*, Oxford: Oxford University Press.

Alkire, S., Jindra, Ch., Robles-Aguilar, G. and Vaz, A. (2017), “Multidimensional Poverty Reduction Among Countries in Sub-Saharan Africa”, *Forum for Social Economics*, 46(2), 178-191.

Alkire, S., Kanagaratnam, U. and Suppa, N. (2018), “The Global Multidimensional Poverty Index (MPI): 2018 revision”, OPHI MPI Methodological Notes 46, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., Kovesdi, F., Mitchell, C., Pinilla-Roncancio, M., and Scharlin-Pettee, S. (2019a), “Changes over time in the global Multidimensional Poverty Index: A ten-country study”, OPHI MPI Methodological Note 48, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., Roche, J. M. and Vaz, A. (2017), “Changes Over Time in Multidimensional Poverty: Methodology and Results for 34 countries”, *World Development*, 94, 232-249.

Argüeso, A.; Escudero, T.; Méndez, J.M. and Izquierdo, M.J. (2013), “Alternativas en la construcción de un indicador multidimensional de calidad de vida”, INE Documentos De Trabajo 01/2013.

D’Ambrosio, C., Deutsch, J. and Silber, J. (2011), “Multidimensional Approaches to Poverty Measurement: An Empirical Analysis of Poverty in Belgium, France, Germany, Italy and Spain, based on the European Panel”, *Applied Economics*, 43, 951-961.

Government of Chile (2015), Nueva Metodología de Medición de Pobreza por Ingresos y Multidimensional, Documentos Metodológicos 28, Santiago, 26 Enero.

Government of Costa Rica (2015) Índice de Pobreza Multidimensional (IPM). Metodología. INEC. San José. Octubre.

Government of El Salvador (2015), Medición Multidimensional de la Pobreza, El Salvador. San Salvador: Secretaría Técnica y de Planificación de la Presidencia y Ministerio de Economía, Dirección General de Estadística y Censos.

Government of Honduras (2016), Medición Multidimensional de la Pobreza (2016). Honduras. Tegucigalpa: Secretaría de Coordinación General de Gobierno y El Instituto Nacional de Estadística.

Government of Honduras (2017), Reducción de la pobreza multidimensional en la era de los ODS. http://www.scgg.gob.hn/ipm/ (Accessed on 17.10.2017)

Government of Panamá (2017), Índice de Pobreza Multidimensional de Panamá: Año 2017. Ministerio de Economía y Finanzas. Ministerio de Desarrollo Social. Instituto Nacional de Estadística y Censo.

Government of Dominican Republic (2017), IPM-RD. Índice de Pobreza Multidimensional de la República Dominicana. Vicepresidencia de la República Dominicana. Junio. http://www.siuben.gob.do/ipm/

Larrú, J.M. (2017), "Linking ODA to the MPI: A Proposal for Latin America", *Global Economy Journal*, 17(3), DOI: https://doi.org/10.1515/gej-2017-0041.

OPHI and UNDP (2019), *Global Multidimensional Poverty Index 2019. Illuminating inequalities*. Oxford Poverty and Human Development Initiative and United Nations Development Programme. Oxford.

Ravallion, M. (2011), "On Multidimensional Indices of Poverty", World Bank Policy Research Working Paper 5580.

Ravallion, M. (2012), "Mashup Indices of Development", *World Bank Research Observer*, 27(1), 1-32.

Rippin, N. (2016), "Multidimensional Poverty in Germany: A Capability Approach", *Forum for Social Economics,* 45(2-3), 230-255.

Santos, M.E. and Villatoro, P. (2018), "A Multidimensional Poverty Index for Latin America", *Review of Income and Wealth*, 64(1), 52-82.

Santos, M.E. and Villatoro, P. (2020), "The Importance of Reliability in the Multidimensional Poverty Index for Latin America (MPI-LA)", *The Journal of Development Studies*, 56(9), 1784-1789.

Suppa, N. (2016), "Comparing monetary and multidimensional poverty in Germany." OPHI Working Paper 103. University of Oxford.

United Nations (2015), *Transforming our World. The 2030 Agenda for Sustainable Development*. United Nations. New York. A/RES/70/1.

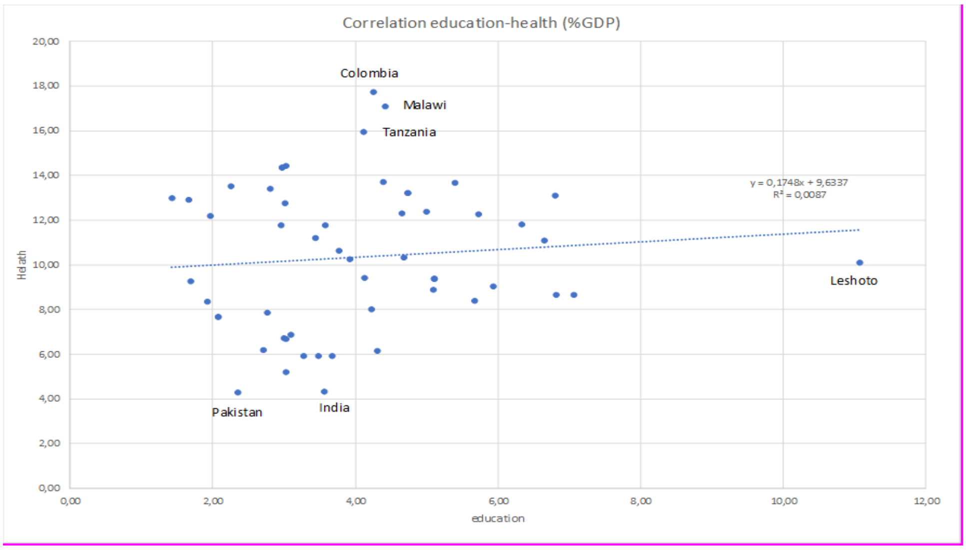
United Nations (2015b), *Addis Ababa Action Agenda of the Third International Conference on Financing Development*. United Nations. New York. Resolution 69/313 of 27 July.

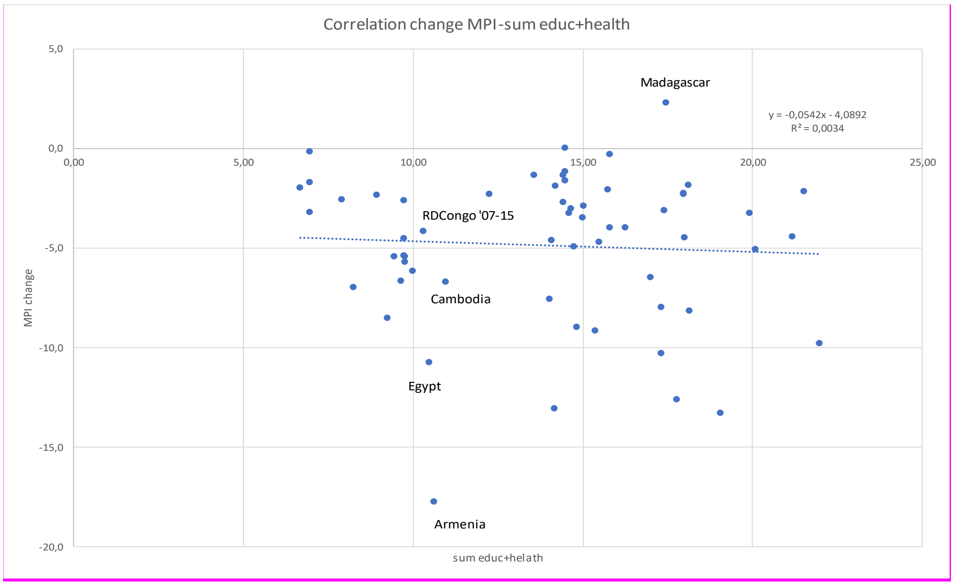
Wang, X., Feng, H., Xia, Q., and Alkire, S. (2016), "On the relationship between Income Poverty and Multidimensional Poverty in China." OPHI Working Paper 101, University of Oxford.

Whelan, Ch., Nolan, B. and Maitre, B. (2014), “Multidimensional Poverty Measurement in Europe: An Application of the Adjusted Headcount Approach”, *Journal of European Social Policy*, 24(2), 183-197.

ANNEXES

Figure A.1. Scatter plots of public expenditure in education and health and change in MPI

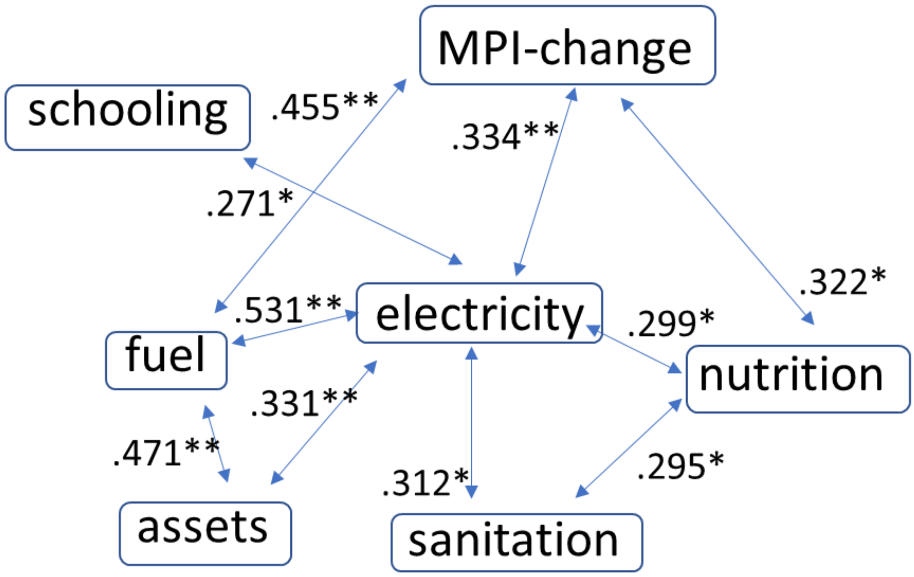




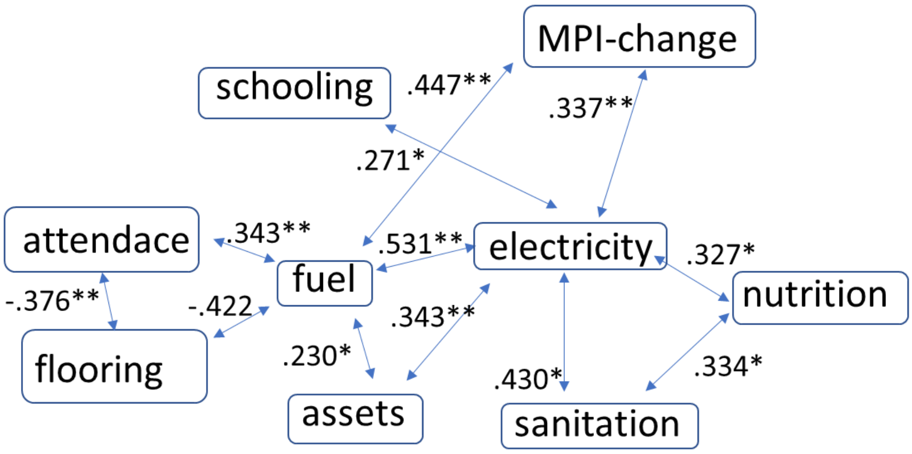
Source: Authors' elaboration.

Figure A.2. Sensitivity analysis for correlations between MPI components

Panel A. “Total sample” with imputed values for the missing values: N=60



Panel B. Restricted sample: when there were no missing values: N=42



Source: Authors' elaboration.

Figure A.3. Parameters after 100 iterations of Monte Carlo cross validation obtaining a median R^2 always below 0.25.

Note: The cross-validation was implemented with the caret package using train() with the train control train Control(method="LGOCV", number=100, p=0.8).
Source: Authors' elaboration.

Table A.1. Country classifications under each clusters steps.

Country	ODA	MPI	ALL
Armenia 2005 - 2011	1	1	1
Bangladesh 2004 - 2008	2	2	2
Bangladesh 2007 - 2012	2	2	2
Benin 2001 - 2007	1	3	1
Bolivia 2003 - 2009	3	3	1
Burkina Faso 2003 - 2011	3	3	1
Burundi 2005 - 2011	1	3	1
Cambodia 2005 - 2011	1	3	1
Cameroon 2004 - 2012	1	1	1
Central African Republic 2000 - 2011	1	3	1
Colombia 2005 - 2011	1	1	1
Comoros 2000 - 2013	1	3	1
Congo, Democratic Republic of the 2007 - 2013/15	2	3	2
Cote d'Ivoire 2005 - 2011/13	1	1	1
Dominican Republic 2002 - 2008	1	1	1
Egypt 2005 - 2009	3	1	3
Ethiopia 2000 - 2006	1	3	3
Ethiopia 2005 - 2012	2	3	2
Gabon 2000 - 2013	1	1	1
Gambia 2006 - 2014	1	3	1

Ghana 2003 - 2009	3	3	1
Guinea 2005 - 2013	1	3	1
Guyana 2005 - 2010	1	1	1
Haiti 2005/6 - 2013	1	3	1
India 1998/9 - 2005/7	3	1	3
Indonesia 2007 - 2013	2	1	2
Jordan 2007 - 2010	3	1	1
Kenya 2003 - 2008/10	3	1	3
Lesotho 2004 - 2010	1	1	1
Liberia 2007 - 2014	1	3	1
Madagascar 2004 - 2008/10	1	1	1
Malawi 2004 - 2011	1	3	1
Mali 2006 - 2012/14	3	3	1
Mauritania 2007 - 2012	1	3	1
Mozambique 2003 - 2012	3	3	3
Namibia 2000 - 2008	1	1	1
Nepal 2006 - 2012	1	2	1
Niger 2006 - 2013	1	3	1
Nigeria 2003 - 2008	1	1	3
Nigeria 2003 - 2013	2	1	3
Nigeria 2008 - 2014	2	1	2
Pakistan 2006/7 - 2012/14	2	1	2

Peru 2005 - 2009	1	1	1
Peru 2008 - 2013	3	1	3
Rwanda 2005 - 2011	1	2	3
Sao Tome and Principe 2000 - 2008/10	1	1	1
Senegal 2005 - 2010/12	3	1	3
Senegal 2005 - 2012/14	3	1	3
Senegal 2010/11 - 2012/14	3	2	2
Sierra Leone 2008 - 2014	1	3	1
South Africa 2008 - 2013	1	3	1
Tanzania 2008 - 2011	2	3	2
The Republic of the Congo 2005 - 2010	1	1	3
The Republic of the Congo 2005 - 2011/13	3	1	3
The Republic of the Congo 2009 - 2011/13	2	3	2
Togo 2010 - 2013/15	1	1	1
Uganda 2006 - 2012	3	1	3
Zambia 2001/2 - 2008	1	3	1
Zimbabwe 2006 - 2010/12	1	1	1
Zimbabwe 2010/11 - 2015	1	1	1

Source: Authors’ elaboration.

Table A.2. Sequencing the clusters.

1-1-1	2-1-2	3-1-1
Armenia 2005 - 2011	Indonesia 2007 - 2013	Jordan 2007 - 2010
Cameroon 2004 - 2012	Nigeria 2008 - 2014	
Colombia 2005 - 2011	Pakistan 2006/7 - 2012/14	3-1-3
Cote d'Ivoire 2005 - 2011/13		Egypt 2005 - 2009
Dominican Republic 2002 - 2008	2-1-3	India 1998/9 - 2005/7
Gabon 2000 - 2013	Nigeria 2003 - 2013	Kenya 2003 - 2008/10
Guyana 2005 - 2010		Peru 2008 - 2013
Lesotho 2004 - 2010	2-2-2	Senegal 2005 - 2010/12
Madagascar 2004 - 2008/10	Bangladesh 2004 - 2008	Senegal 2005 - 2012/14
Namibia 2000 - 2008	Bangladesh 2007 - 2012	The Republic of the Congo 2005 - 2011/13
Peru 2005 - 2009		Uganda 2006 - 2012
Sao Tome and Principe 2000 - 2008/10	2-3-2	
Togo 2010 - 2013/15	Congo, Democratic Republic of the 2007 - 2013/15	3-2-2
Zimbabwe 2006 - 2010/12	Ethiopia 2005 - 2012	Senegal 2010/11 - 2012/14
Zimbabwe 2010/11 - 2015	Tanzania 2008 - 2011	
	The Republic of the Congo 2009 - 2011/13	3-3-1
1-1-3		Bolivia 2003 - 2009
Nigeria 2003 - 2008		Burkina Faso 2003 - 2011
The Republic of the Congo 2005 - 2010		Ghana 2003 - 2009
		Mali 2006 - 2012/14
1-2-1		
Nepal 2006 - 2012		3-3-3
		Mozambique 2003 - 2012
1-2-3		
Rwanda 2005 - 2011		
1-3-1		
Benin 2001 - 2007		
Burundi 2005 - 2011		
Cambodia 2005 - 2011		
Central African Republic 2000 - 2011		
Comoros 2000 - 2013		
Gambia 2006 - 2014		
Guinea 2005 - 2013		
Haiti 2005/6 - 2013		
Liberia 2007 - 2014		
Malawi 2004 - 2011		
Mauritania 2007 - 2012		
Niger 2006 - 2013		
Sierra Leone 2008 - 2014		
South Africa 2008 - 2013		
Zambia 2001/2 - 2008		
1-3-3		
Ethiopia 2000 - 2006		

Note: the first number of the sequence means the ODA clusters; the second the MPIs indicators and the third when education and health expenditures are added.
Source: Authors' elaboration.