Oxford Poverty & Human Development Initiative (OPHI)
Oxford Department of International Development
Queen Elizabeth House (QEH), University of Oxford

OPHI WORKING PAPER NO. 105

Growth and Poverty Revisited from a Multidimensional Perspective

Maria Emma Santos*, Carlos Dabus** and Fernando Delbianco***

September 2016

Abstract
The actual impact of economic growth on poverty reduction is of fundamental importance to the development agenda, especially in view of the Sustainable Development Goals. So far, studies have focused on income poverty. This paper offers new empirical evidence on growth and poverty measured from a multidimensional perspective using the global Multidimensional Poverty Index. Results from a first difference estimator model suggest that while economic growth reduces multidimensional poverty, this impact is well below a one-to-one relationship. We also find that economic growth has a far bigger impact on reducing income poverty than on reducing multidimensional poverty. Results from an alternative cross-section model also support this result and additionally suggest that countries with higher levels of exports, a higher share of industry and services in their GDPs, and higher control of corruption have lower multidimensional poverty. All in all, the results highlight the need for countries to grow in order to reduce poverty, but they simultaneously suggest the limited power of economic growth *per se* to achieve grand reductions in poverty.

Keywords: multidimensional poverty, pro-poor growth, SDGs, growth elasticity of poverty

JEL classification: D31, I32, O15, O54

* Corresponding author: Maria Emma Santos. Instituto de Investigaciones Económicas y Sociales del Sur (IIES), Departamento de Economía, Universidad Nacional del Sur (UNS) – Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), San Andrés 800, Altos de Palihue, 8000 Bahía Blanca, Argentina. Oxford Poverty and Human Development Initiative, University of Oxford. msantos@uns.edu.ar; maria.santos@qeh.ox.ac.uk

** Instituto de Investigaciones Económicas y Sociales del Sur (IIES), Departamento de Economía, Universidad Nacional del Sur (UNS) – Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), San Andrés 800, Altos de Palihue, 8000 Bahía Blanca, Argentina.

*** Instituto de Investigaciones Económicas y Sociales del Sur (IIES), Departamento de Economía, Universidad Nacional del Sur (UNS) – Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), San Andrés 800, Altos de Palihue, 8000 Bahía Blanca, Argentina.

This study has been prepared within the OPHI theme on multidimensional measurement.

ISSN 2040-8188 ISBN 978-19-0719-491-8

Acknowledgements: Maria Emma Santos would like to thank ANPCyT-PICT 2015–2079 for research support.

Citation: Santos, M. E., Dabus, C., and Delbianco, F. (2016). "Growth and poverty revisited from a multidimensional perspective." *OPHI Working Paper* 105, University of Oxford.

The Oxford Poverty and Human Development Initiative (OPHI) is a research centre within the Oxford Department of International Development, Queen Elizabeth House, at the University of Oxford. Led by Sabina Alkire, OPHI aspires to build and advance a more systematic methodological and economic framework for reducing multidimensional poverty, grounded in people's experiences and values.

Oxford Poverty & Human Development Initiative (OPHI)
Oxford Department of International Development
Queen Elizabeth House (QEH), University of Oxford
3 Mansfield Road, Oxford OX1 3TB, UK
Tel. +44 (0)1865 271915 Fax +44 (0)1865 281801
ophi@qeh.ox.ac.uk http://www.ophi.org.uk

1. Introduction

The actual impact of economic growth on poverty reduction has been a matter of interest and study since it became evident that the 'trickle down' theory – in which the benefits of economic growth eventually reach the poor – was not being verified or, at least, the process was excessively slow. For example, the Cocoyoc Declaration (UNEP-UNCTAD 1975, p. 896) stated that "...We are still in a stage where the most important concern of development is the level of satisfaction of basic needs for the poorest sections in each society.... The primary purpose of economic growth should be to ensure the improvement of conditions for these groups". Similarly, Ahluwalia, Carter, and Chenery (1979, p.299) wrote: "Although the output of the world economy has expanded at an unprecedented rate in the past quarter century, the benefits of growth have only reached the world's poor to a very limited degree. (...) The failure lies in the distributional pattern of past growth, which has left the poorest groups largely outside the sphere of economic expansion and material improvements". Adelman and Morris (1973) and Chenery et al. (1974) have statements along the same lines.

Thus far, the relationship between economic growth and poverty has been empirically studied using income poverty. Most frequently, the dependent variable has been the change in some internationally comparable measure of income poverty such as the headcount ratio of people living with less than $1/day or some other member of the Foster-Greer-Thorbecke family of poverty measures (Foster, Greer, and Thorbecke 1984) or the Watts index (Watts 1969). This approach, called the **poverty measures approach** by Foster and Székely (2008), includes Fields (1989), Squire (1993), Ravallion (1995, 1997, 2001), Ravallion and Datt (2002), Bhalla (2002), Ravallion and Chen (1997, 2003, 2007), Adams (2004), and Kraay (2006).

The relationship has also been studied using what Foster and Székely (2008) call the **income standards approach** – a function that summarises the income distribution into a single "representative" level of income, focusing on the bottom of the distribution. This is the approach followed by Roemer and Gugerty (1997), Gallup et al. (1998), Dollar and Kraay (2000, 2002), who use the average income of the bottom quintile.[1]

However, Foster and Székely (2008) identify some weaknesses in both approaches. The poverty measures approach relies heavily on an internationally comparable poverty line that cannot be fully relevant for poorer *and* richer countries simultaneously. In turn, by using the average income of the

1 Earlier papers such as Adelman and Morris (1973), Ahluwalia (1976), and Ahluwalia et al. (1979) focused on the share of the lowest quintile.

poorest quintile, the income standard approach is also using – in practice – an arbitrary cutoff. Moreover, it is a subgroup-inconsistent measure, which is an inconvenient feature for policy purposes.[2] They propose using the general mean income, also known as Atkinson's equally distributed equivalent income. This is a subgroup-consistent income standard that can be used with a range of parameter values that assign alternative weights to lower incomes.[3]

For measuring economic growth, studies have most commonly used either growth in real GDP per capita data (from national accounts) or growth in the survey mean income or consumption (data from household surveys).[4] Typically, studies use an unbalanced panel of country-year observations and estimate a regression of the change in the poverty rate over the change in the income per capita variable, with variants across studies, and with new evidence as newer country data became available.[5] Similar estimations have been performed using state- or province-level data by Ravallion and Datt (2002) for India and by Ravallion and Chen (2003, 2004, and 2007) for China. In all cases an elasticity of poverty (or of the low income standard) to economic growth is obtained, indicating in what proportion poverty can be reduced (or low incomes increased) by a 1% average annual growth rate.

At the core of this literature is the idea of **pro-poor growth**, but the concept has been embedded with different meanings. In some papers it has been implicitly understood that economic growth is pro-poor if the elasticity of low incomes to growth is at or above unity (Roemer and Gugerty 1997; Gallup et al. 1998; Dollar and Kraay 2000, 2002), suggesting that the incomes of the poor rise, on average, equi- or more than proportionately with average incomes. However, when the incomes of the poor rise equiproportionately with average incomes, this implies that, in absolute terms, the rich still benefit much more from growth than the poor. "Given existing inequality, the income gains to the rich from distribution-neutral growth will of course be greater than the gains to the poor" (Ravallion 2001, p. 1806). In other papers, it has been understood that growth is pro-poor if growth reduces the poverty measure.

Other authors have developed more refined measures of pro-poor growth. Datt and Ravallion (1992), Kakwani and Pernia (2000), and Bhalla (2002) propose similar decompositions of the total change in

2 For example, it is possible that while the average income of the poorest 20% of the population decreases in every region, the average income of the poorest 20% in the country as a whole registers an increase; that is why the average income of the poorest 20% is a subgroup-inconsistent measure.

3 In fact, Foster and Székely show that the general means are the *only* subgroup-consistent income standards satisfying some basic compelling properties.

4 Ravallion (2001) and Adams (2004) offer insights and evidence on why these two measures can give different results.

5 This includes Fields (1989), Squire (1993), Ravallion (1995, 1997, 2001), Bhalla (2002), Adams (2004), Kraay (2006), and Ravallion and Chen (2007).

poverty into a **growth component** and a **redistribution component**. Growth is pro-poor whenever it has reduced poverty more than what it would have reduced poverty under distribution-neutral growth. Ravallion and Chen (2003) propose a growth-incidence curve that depicts the growth rate in per capita income for each quantile, with quantiles ranked by income. The rate of pro-poor growth is the mean growth rate for the poor.

What have been the empirical findings in terms of growth elasticity? Papers using the average income of the bottom quintile have generally found an elasticity of unity, as documented by Roemer and Gugerty (1997), Gallup et al. (1998), and Dollar and Kraay (2000, 2002). In contrast, using the equally distributed equivalent income, Foster and Székely (2008) find that as greater weight is given to lower incomes the elasticities drop dramatically, becoming insignificantly different from zero. Papers using the poverty measure have also found a wide range of elasticities ranging between -1.5 and -3 for studies that include several developing countries and use the extreme poverty headcount ratio. Lower estimates have also been found for varying poverty lines and specific areas (Ravallion and Chen 1997, Ravallion and Datt 2002). Interestingly, Bhalla (2002) argues that these elasticities are underestimated because the above estimations do not take into account that the estimated coefficient is a function of the poverty line.

Naturally, inequality has been the factor usually pointed to as mediating the impact of growth on poverty. There is cross-country evidence and evidence for India and China suggesting that higher initial income inequality entails a lower elasticity of poverty to average incomes (Ravallion 1997, Timmer 1997, World Bank 2000, Ravallion and Datt 2002, Ravallion and Chen 2007). At the same time, there is cross-country evidence on the lack of correlation between growth and changes in inequality (Ravallion 1995, Ravallion and Chen 1997, Ravallion 2001, Dollar and Kraay 2002, Kraay 2006, Ravallion 2001). However, as argued by Ravallion (2001), "no correlation does not mean no impact". First, there is sizeable error in the measurement of income inequality. Second, while average inequality may change little over time within countries, there are gainers and losers, people moving up and down the distribution. Additionally, varying initial levels of inequality and economic development can influence the effect of growth and other variables on the incomes of the poor.

Other variables have also been considered as influencing the impact of growth on poverty reduction, including inflation, government consumption, openness, level of financial development, rule of law, level of taxation, pattern of growth (urban vs. rural for example), and level of education, to mention a few. Evidence has been diverse, and we comment on this when discussing our results.

In any case, the available evidence of the link between poverty and growth is limited to the case of income poverty. Yet it is increasingly acknowledged that poverty is intrinsically multidimensional. This has been revealed by participatory studies (Narayan et al. 2000, UNDP 2013) and conceptually developed by frameworks such as the capability approach (Sen 1999, 2009), the human rights approach, or the basic needs approach, among others. The academic literature on poverty measurement has advanced on this front.[6] Moreover, the Millennium Development Goals (MDGs) as well as the just released Sustainable Development Goals (SDGs) also favour a multidimensional view of poverty. Some of the studies of economic growth and income poverty recognised the relevance of multidimensionality: "a proper evaluation would track a wide array of attainments and capabilities to determine how they are altered during the growth process" (Foster and Székely 2008, pp. 1143–1144); "broadly, pro-poor growth can be defined as one [such] that no person in society is deprived of the minimum basic capabilities" (Kakwani and Pernia 2000, p. 3).

When broadening the view beyond monetary indicators, evidence is somehow discouraging. In a study of the MDGs at their mid-point, Bourguignon et al. (2008, p. 4) found no correlation between growth and non-income MDGs such as reducing maternal mortality, improving children nutrition, and access to education. In the same spirit, Alkire et al. (2015) found very low correlations between extreme income poverty reduction and improvements in several non-income MDGs. Drèze and Sen (2013) insightfully expose the paradoxical case of India which, despite an outstanding recent growth performance (an average annual growth rate of 5.5% between 2000 and 2014), is really falling behind in fundamental living standard indicators such as female literacy, child mortality rate, access to improved sanitation, and proportion of underweight children.

This paper intends to contribute to the field with new empirical evidence on economic growth and poverty reduction, measuring it from a multidimensional perspective. As argued by Kakwani and Pernia, "it is hardly feasible" to "incorporate all the capabilities that enhance human well-being" in the measurement of pro-poor growth (2000, p. 5). Yet it is possible to synthesize at least a few key capabilities in a standalone poverty measure such as the global Multidimensional Poverty Index (MPI), which was developed by the Oxford Poverty and Human Development Initiative (OPHI) in collaboration with the United Nations Development Programme (Alkire and Santos 2010, 2014; UNDP 2010). The MPI has been reported in the UNDP Human Development Reports since 2010. The MPI follows the Alkire and Foster (2007, 2011) methodology of multidimensional poverty measurement. We understand that evidence in this paper may shed light on the link between the first and eighth SDGs, namely, ending poverty in all its forms and promoting inclusive growth.

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6 See for example Chakravarty, Mukherjee, and Ranade (1998), Tsui (2002), Bourguignon and Chakravarty (2003), Alkire and Foster (2007, 2011), Maasoumi and Lugo (2008), Chakravarty and D'Ambrosio (2013), Aaberge and Peluso (2012), Chakravarty and D'Ambrosio (2006), Bossert, Chakravarty, and D'Ambrosio (2013).

Foster (2014) proposes a general framework for evaluating the elasticity of poverty to growth, which includes the possibility of assessing multidimensional poverty using the MPI and its component sub-indices. This proposal is a non-parametric and descriptive approach, which permits computing country-level elasticities without assuming causality. It has been applied by Alkire and Seth (2015) to the case of India and by Ballon and Apablaza (2014) to the case of Indonesia. Here we explore a different approach that shares the motivation of Foster (2014) but intends to follow, in as much as current data permits, the pro-poor growth literature cited above, essentially doing a cross-country estimation of the elasticity of poverty to growth.

The paper is organised as follows. Section 2 describes the global Multidimensional Poverty Index and briefly reviews the income poverty measures, which are used in alternative estimates for comparison purposes. Section 3 presents the econometric approaches used. Section 4 describes the data. Section 5 discusses the results. Section 6 concludes. Additional information is contained in an Appendix.

2. Poverty Measures

2.1 The Global Multidimensional Poverty Index

The global MPI has the structure of Alkire and Foster's (2011) M_0 measure, also named the Adjusted Headcount Ratio. We briefly describe it, following Alkire and Foster et al. (2015).

Let $x_{ij} \in \mathbb{R}_+$ be the achievement of each person $i = 1, \dots, n$ in each indicator $j = 1, \dots, d$, and let z_j be the **deprivation cutoff** of indicator j. Deprivation of person i in indicator j is defined as $g_{ij}^0 = 1$ when $x_{ij} < z_j$ and $g_{ij}^0 = 0$ otherwise. Then, the deprivation of each person is weighted by the indicator's weight, given by w_j, such that $\sum_j w_j = 1$. From this, a deprivation score is computed for each person, defined as the weighted sum of deprivations $c_i = \sum_{j=1}^d w_j g_{ij}^0$. With this score, the poor are identified using a second cutoff, the **poverty cutoff**, denoted by k, which represents the proportion of minimum deprivation a person must experience in order to be identified as poor. In other words, someone is poor when $c_i \geq k$.

The deprivations of those not identified as poor are censored such that $g_{ij}^0(k) = g_{ij}^0$ when $c_i \geq k$ and $g_{ij}^0(k) = 0$ otherwise. The censored deprivation score is given by $c_i(k) = \sum_{j=1}^d w_j g_{ij}^0(k)$.

The M_0 measure is the product of two fundamental sub-indices: **poverty incidence**, the proportion of people who are multidimensionally poor, and **poverty intensity**, given by the average (weighted) deprivations among the poor. The proportion of poor people is given by

$$H_M = q_M / n, \qquad (1)$$

where q_M is the number of people identified as multidimensionally poor and n is the total population. Poverty intensity is given by

$$A = \sum_{i=1}^{n} c_i(k) / q_M. \qquad (2)$$

MPI, as M_0, is the product of these two sub-indices:

$$M_0 = H_M \times A = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{d} w_j g_{ij}^{0}(k). \qquad (3)$$

The M_0 measure has several convenient properties. First, by adjusting the incidence of multidimensional poverty by the intensity, M_0 satisfies **dimensional monotonicity**: if a poor person becomes deprived in an additional indicator, M_0 will increase (Alkire and Foster 2011). Second, M_0 can be decomposed into population subgroups, enabling the computation of the subgroups' percentage contribution to overall poverty. Additionally, after identifying the poor, M_0 can be **broken down by indicator**, enabling the computation of the contribution of deprivations in each indicator to overall poverty. Last, but not least, the M_0 measure is robust to the use of **ordinal variables**, as it dichotomizes individuals' achievements into 'deprived' and 'non-deprived'. This means that poverty values are not changed by changes in the variables' scales.

Table 1 presents the components of the global MPI, ten indicators that are organised into three dimensions – health, education and living standards – following the same dimensions and weights as the Human Development Index (HDI).[7] Most of them are directly related to the MDGs and, therefore, to the SDGs. Health and education indicators reflect achievements of all household members. Then, each person's deprivation score is constructed based on a weighted average of the deprivations they experience using a nested weight structure: equal weight across dimension and equal weight for each indicator within dimensions. People are identified as multidimensionally poor if their deprivation score meets or exceeds a 33.33% poverty cutoff. This cutoff captures the **acutely poor**, usually those who do not meet minimum internationally agreed standards in multiple indicators of basic functionings simultaneously. In practice, the cutoff implies that a person must be deprived in at least two (education or health) to six (living standard) indicators in order to be identified as multidimensionally poor. Alkire and Santos (2014) offer a range of robustness tests to the selection of this particular poverty cutoff and find the country rankings to be robust to changes in it, within a relevant interval (of 20% to 40%).

[7] For a more detailed description of the indicator definitions, see Alkire and Santos (2010, 2014).

Table 1: Dimensions, Indicators, Cutoffs and Weights of the MPI

Dimension	Indicator	Deprived if…	Relative Weight
Education	**Years of Schooling**	No household member has completed five years of schooling	16.7%
	Child School Attendance	Any school-aged child is not attending school in years 1 to 8	16.7%
Health	**Mortality**	Any child has died in the family	16.7%
	Nutrition	Any adult or child for whom there is nutritional information is malnourished*	16.7%
Living Standard	**Electricity**	The household has no electricity	5.6%
	Sanitation	The household's sanitation facility is not improved (according to MDG guidelines) or it is improved but shared with other households**	5.6%
	Water	The household does not have access to safe drinking water (according to MDG guidelines) or safe drinking water is more than a 30- minute walk from home, roundtrip.***	5.6%
	Floor	The household has dirt, sand, or dung floor.	5.6%
	Cooking Fuel	The household cooks with dung, wood, or coal.	5.6%
	Assets	The household does not own one of the following assets: radio, TV, telephone, bicycle, motorbike, or refrigerator and does not own a car or truck.	5.6%

Source: Alkire and Santos (2014).

*Adults are considered malnourished if their BMI is below 18.5. Children are considered malnourished if their z-score of weight-for-age is below minus two standard deviations from the median of the reference population. This was estimated following the algorithm provided by the WHO Child Growth Standards (WHO 2006). http://www.who.int/childgrowth/software/en/

**A household is considered to have access to improved sanitation if it has some type of flush toilet or latrine, or ventilated improved pit or composting toilet, provided that they are not shared.

***A household has access to safe drinking water if the water source is any of the following types: piped water, public tap, borehole or pump, protected well, protected spring or rainwater, and it is within a distance of 30 minutes' walk (roundtrip).

2.2 Income Poverty Measures

For comparison purposes we also estimate regression with the most commonly used income poverty measures as dependent variables. One of them is the income headcount ratio, also called income poverty incidence or income poverty rate. It is defined as

$$H_I = q_I/n, \quad (4)$$

where q_I is the number of people identified as income poor. In this paper we use the poverty rate of the \$1.25 PPP/day, which is the proportion of people living with less than \$1.25 PPP a day. This is an internationally comparable measure of extreme poverty. The extreme income poverty rate H_I is comparable to the acute multidimensional poverty rate H_M.

Another very often used measure is the income poverty gap, defined as

$$P_G = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{z-y_i}{z}\right), \quad (5)$$

where z is the income poverty line, in this case \$1.25 PPP/day, and y_i is the income of person $i = 1, \dots n$. Just like the MPI, the income poverty gap is also composed of two sub-indices: income poverty incidence and the income gap ratio. The income gap ratio is defined as

$$I_G = \frac{1}{q}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right). \quad (6)$$

In words, it is the average normalized income shortfall among the poor. It can be easily verified that

$$P_G = H_I * I_G. \quad (7)$$

The poverty gap ratio is somewhat comparable to the MPI (Alkire et al. 2015). While the first is multidimensional poverty incidence adjusted by poverty breadth or intensity, the second can be seen as income poverty incidence adjusted by the depth of poverty.

3. Econometric Models

To study the impact of economic growth on multidimensional poverty we use two different econometric approaches, which we describe in what follows.

3.1 First Difference Estimator Model

In the first place we follow Ravallion and Chen (1997) and Adams (2006) and use a first difference estimator (FDE) approach. Specifically, the link between poverty and mean GDP per capita can be stated as

$$logP_{it} = \alpha_i + \beta log\mu_{it}^{*} + \gamma_t + \varepsilon_{it}, \quad (8)$$

where P_{it} is the measure of poverty in country i (with $i = 1, \dots n$) at time t (with $t = 1, \dots, T$), α_i is a fixed effect reflecting time differences between countries in the distribution, β is the growth elasticity of poverty with respect to mean GDP per capita given by μ_{it}^{*}, γ_t is a trend rate of change over time t, and ε_{it} is a white-noise error term that includes errors in the poverty measure. In practice, one does not observe the true mean μ_{it}^{*}, but rather have an estimate given by

$$\log \mu_{it} = \log \mu_{it}^{*} + v_{it}, \quad (9)$$

where v_{it} is a time-varying error term that is assumed to be white noise. Replacing (9) with (8) and taking the first difference, the fixed effect term α_i is eliminated and one obtains

$$\Delta logP_{it} = \gamma + \beta\Delta log\mu_{it} + \Delta\varepsilon_{it} - \beta\Delta v_{it}. \qquad (10)$$

In Equation (10) the rate of poverty reduction is regressed on the rate of growth in mean GDP per capita and thus β can be directly interpreted as the growth elasticity of poverty with respect to the rate of growth in GDP per capita. This is the basic equation that is estimated by Ordinary Least Squares (OLS), corrected for heteroscedasticity. Note that, as described in Section 4, the data sources of the MPI estimates and of the GDP per capita and other considered explanatory variables are different; therefore, $Cov(\varepsilon_{it}, v_{it}) = 0$. Thus, the OLS estimates are consistent.

We estimate different versions of this model with alternative specifications of the dependent variable 'poverty' using the measures described in Section 2. We also estimate alternative specifications that include (the change in the log of) further independent or explanatory variables detailed below. The definition of the variables and data sources is detailed in Section 4.

3.2 A Cross-Section Estimator Model

Alternatively, we estimate a cross-section linear regression model with OLS given by

$$P_i = \varphi_0 + \varphi_1 X_{1i} + \varphi_2 X_{2i} + \cdots + \varphi_k X_{ki} + U_i, \qquad (11)$$

where P_i is poverty for country $i = 1, \ldots n$, and X_{ji}, with $j = 1, \ldots k$ are the independent or explanatory variables. As usual, φ_0 is the intercept, each φ_j is the parameter of variable j to be estimated, and U_i is the error term. As with the FDE approach, we estimate different versions of the model in Equation (11), with alternative specifications of the dependent variable 'poverty' and alternative of independent or explanatory variables, all of which is detailed in Section 4. All specifications are estimated with OLS corrected for heteroscedasticity with the Huber-White Sandwich estimator.

4. Data

The data used in this paper is of a secondary type and macro-level. Our focal explained variable is the MPI. We work with a total of 110 countries with MPI estimates for at least one point between 1999 and 2014, resulting in a total of 215 observations. All MPI estimates come from OPHI. The dataset is composed of a set of 107 MPI estimates for 50 countries, which have been strongly harmonized by OPHI for a study of changes in poverty over time. It also includes 108 estimates for another 60 countries that come from the several estimation rounds performed by OPHI between 2010 and 2015, during which MPI estimates were updated for all countries for which new datasets were available.[8] Of the 110 countries, 24 are in Europe and Central Asia (ECA), 10 are Arab States (AS), 19 are in Latin America and the Caribbean (LAC), 10 are in East Asia and the Pacific (EAP), 8 are in South Asia (SA), and 39 are in Sub-Saharan Africa (SSA).

Most observations for the MPI are computed by OPHI using data from the Demographic and Health Surveys (DHS) or from the Multiple Indicators Cluster Surveys (MICS). These surveys were selected because they contain information on health indicators fundamental to multidimensional poverty, such as nutrition and mortality, and because they are relatively well standardized across countries, enabling at least some good degree of comparability.[9] Yet for some countries for which none of these surveys was available, some other survey containing information on MPI indicators has been used. In particular, in 2010 the MPI for 19 countries was estimated using the World Health Survey (WHS) performed in 2003, as it was the only standardized survey including health indicators that was available for several countries that otherwise could not have been included in the study.[10] Also, for a few countries, namely Argentina, Brazil, China, Mexico, Morocco, and South Africa, a country-specific survey was used.[11]

Table A.1 in the Appendix lists the countries, years, and surveys used for the MPI data, as well as the MPI, H_M, and A estimates and the source of each estimate. Clearly, using different surveys affects comparability. Additionally, there are some country-year observations for which some of the MPI indicators are missing. Specifically, of the 215 country-year observations, 53 lack one indicator, 12 lack two, and three lack three indicators. This is also specified in Table A.1. Whenever there is some MPI indicator missing, the dimension's weight is equally distributed across the indicators that are present in the dimensions, thus receiving a higher weight (for details see Alkire and Santos 2014). However, in all cases and although the surveys do have baseline comparability, all the questions used to construct the MPI indicators were harmonized one-by-one to ensure the strongest comparability possible (Alkire and Santos 2014). Moreover, the estimates from the study of poverty over time are even further harmonized (see Alkire, Jindra, Robles, and Vaz 2016 and Annex 2 of Alkire, Roche, and Vaz 2014).

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8 Thus, the multidimensional poverty estimates used in this paper proceed from the over-time-harmonized MPI estimates reported in Table 6.1 (a,b,c) - Summer 2016 (Alkire, Jindra, Robles, and Vaz 2016 whose methodology is based on Alkire, Roche, and Vaz 2014); from Table 1.1 of 2011, 2013, 2014, and 2015 rounds of MPI estimates (all available at http://www.ophi.org.uk/multidimensional-poverty-index/mpi-resources/); as well as from the MPI 2010 round of estimates reported in Table 10 of Alkire and Santos (2014).

9 The main difference between the DHS and MICS affecting the MPI comparability is that nutritional information is collected for both children under five and women between 15–49 years of age in the DHS but only for children under five in the MICS.

10 The WHS was a one-time survey conducted in 2003. As other surveys became available for countries for which WHS was initially used, MPI was estimated using this newer data.

11 For details of cross-survey comparability in the early round of estimates, see Table II of Alkire and Santos (2014). For subsequent rounds, see the annual methodological notes http://www.ophi.org.uk/multidimensional-poverty-index/mpi-2015/mpi-methodology/.

All in all, 32 countries have one MPI estimate between 1999 and 2014, 53 countries have two estimates, 23 countries have three MPI observations, and two countries have four MPI observations. [12] Thus, we were able to form an unbalanced panel of 78 countries with two or more MPI observations over time for a total of 105 pairs of observations. The average distance between any two MPI observations is 5.2 years.

While the cross-country and over-time comparability issues of the MPI are acknowledged, it must be noted that they are not exclusive to multidimensional poverty measures. Analogous, if not more problematic, comparability issues have been acknowledged in studies of growth and income poverty, including the estimate of the PPP exchange rate; the fact that while some surveys collect information on consumption, others collect information on incomes; differing survey designs; and variation in the relative importance of consumption of nonmarket goods (see for example, Ravallion 1995 and Ravallion and Chen 1997).

For comparative purposes, we estimate both the first difference and the cross-section models (Equations 10 and 11, correspondingly) for four alternative poverty measures: the MPI; the headcount ratio of multidimensional poverty (one of the MPI components); the income poverty gap at $1.25 a day (PPP), which is comparable to the MPI; and the income headcount ratio at $1.25 a day (PPP), which is comparable to the headcount ratio of multidimensional poverty.

Data on income poverty proceeds from the World Development Indicators (WDI). For the FDE approach model, from the set of countries of the MPI panel, we were able to form a panel of 56 countries and 119 income poverty observations, replicating – as much as possible– the countries and years of the MPI observations. A total of 50 countries have two income poverty observations, five countries have three, and one country has four. Table A.2 lists the countries, years, and income poverty estimates of this panel. For each country, the year of the income poverty observation is within four years of an MPI observation and on average it is 0.95 years from an MPI observation (76% of the countries have income poverty observations for the same year of the MPI observation). The average time between every two observations of income poverty is 5.2 years, which is the same as in the MPI case – the result of our attempt to replicate the panel as much as possible. For robustness analysis, we also formed an alternative panel from the total of 110 countries with MPI data – but which does not replicate the MPI

12 Out of the 53 countries with two MPI estimates, such estimates over time have been strongly harmonized for 30 of them. Out of the 23 countries with three MPI estimates, seven of them have the three MPI observations strongly harmonized, and eleven have two of the three observations strongly harmonized. The two countries with four MPI estimates over time have only two of those estimates strongly harmonized. When we say that the estimates have been strongly harmonized we mean that they come from the study of changes in poverty over time (Alkire, Jindra, Robles and Vaz 2016).

panel. Rather we selected the first and last observation of income poverty. In this way we formed a panel of 82 countries with two income poverty observations between 1980 and 2014. In this case, the average distance between the two income poverty observations is 9.3 years.

In terms of explanatory variables, clearly, the growth rate is the one of main interest. Yet, building on previous literature, we also consider other additional explanatory variables, namely, trade (as a percent of the GDP), inequality, the value added by the different economic sectors (agriculture, industry, services, and a particular sub-group of industry which is manufacturing), and a governance indicator that measures the control of corruption. All explanatory variables, except for the Control of Corruption Index, were obtained from the WDI. The GDP per capita information reported by the WDI comes from the national accounts system of each country.[13] The Control of Corruption Index, designed and computed by Kaufmann, Kraay, and Mastruzzi (2010), was obtained from the Worldwide Governance Indicators Database.[14] This index reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as the "capture" of the state by elites and private interests. It ranges from -2.5 (weak control of corruption) to 2.5 (strong control of corruption). We were not able to include the Control of Corruption Index in the FDE estimations due to an insufficient number of observations over time for the set of considered countries.

In the case of the FDE model, for the explanatory variables, we take the change in the mean value of each of them over the five years previous to the poverty measure observation. For example, in the case of Bolivia, there are MPI observations for the year 2003 and for the year 2008. Thus the data considered in Equation (10) for this country is the difference in the log of MPI in 2008 and the log of MPI in 2003 against the difference in the log of the mean GDP per capita between 2003 and 2007 (the five years prior to 2007) and the log of the mean GDP per capita between 1998 and 2002 (the five years prior to 2003). The same applies to other considered explanatory variables.

In the case of the cross-section model the dependent variable (MPI, H_M, P_G, and H_I, alternatively) is defined as the mean of the observed poverty estimates between 2000 and 2014.[15] As explained above, given MPI data availability, for some countries the mean over time of the MPI (and H_M) is taken over four observed values, for others over three observed values, for others over two, and for others it simply refers to one observation. Then, each country's mean poverty measure is regressed against the mean

13 http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators#

14 http://info.worldbank.org/governance/wgi/index.aspx#home

15 The only exception is India, which has one MPI estimate for 1999. We also take this estimate to compute the mean MPI of India.

value – taken between 1980 and 2014 – of the different explanatory variables, which are detailed below.[16] Using the mean poverty estimates – for countries for which this is possible – is more informative than a single specific value for understanding the link between growth – a long-term process – and poverty. One particular observation might be influenced by a particular recent episode of either outstanding expansion or recession. The mean smooths potentially extreme values. Additionally, by using the mean we also alleviate data problems that might influence one particular estimate, such as unavailability of a particular indicator in the case of the MPI.

Table A.3 in the Appendix details the definition of each of the explanatory variables used. Table 2 below presents the summary statistics of the variables used. For simplicity, we present the mean of the poverty measures between 2000 and 2014 and for the explanatory variables, the mean of each variable taken between 1980 and 2014, as used in the cross-section regressions. Note however that the explanatory variables in the FDE regressions are the mean over the five years previous to the poverty measure observation. Table 3 reports the matrix correlation coefficient. Additionally, in Figure 1, we present a set of scatterplots between the mean MPI of each country and the mean value of some explanatory variables, adjusted by a local polynomial regression. This regression adjusts the data around a mean and standard deviation at different points of interest of the independent variable, using data from the neighbourhood around such points and making no assumption about the functional form. Thus, one can obtain different functions adjusting different parts of the data, including linear, quadratic, or cubic functions.

The figure suggests that not controlling for anything the (mean) MPI seems to have a negative and linear association with the (mean) economic growth rate, although this association is not so strong. This is also evidenced by a correlation coefficient of -0.31 (Table 2). The relationship depicted in the scatterplot between MPI and inequality seems to be non-linear, with an inverted-U pattern, which is consistent with the low correlation coefficient observed in Table 2 (0.14). The MPI and the imports level (as a percentage of GDP) also appear to have an inverted-U pattern at lower levels of imports, but the decreasing part of the inverted-U is longer, and thus the correlation coefficient is -0.30. In turn, the MPI and the exports level (as a percentage of GDP) have a negative relation and close to linearity throughout the whole data range, except for certain points. The correlation coefficient between these two variables is -0.46. The MPI is strongly positively associated with the value added of agriculture (as a percentage of GDP) and also with a linear relation throughout, except for two outlier values. In fact, the correlation coefficient between these two variables is the highest in absolute value, 0.70.

16 In order to compare the regression coefficients when using other poverty measures as the dependent variable, we express the MPI values in percentage points.

Table 2: Descriptive Statistics of Used Variables

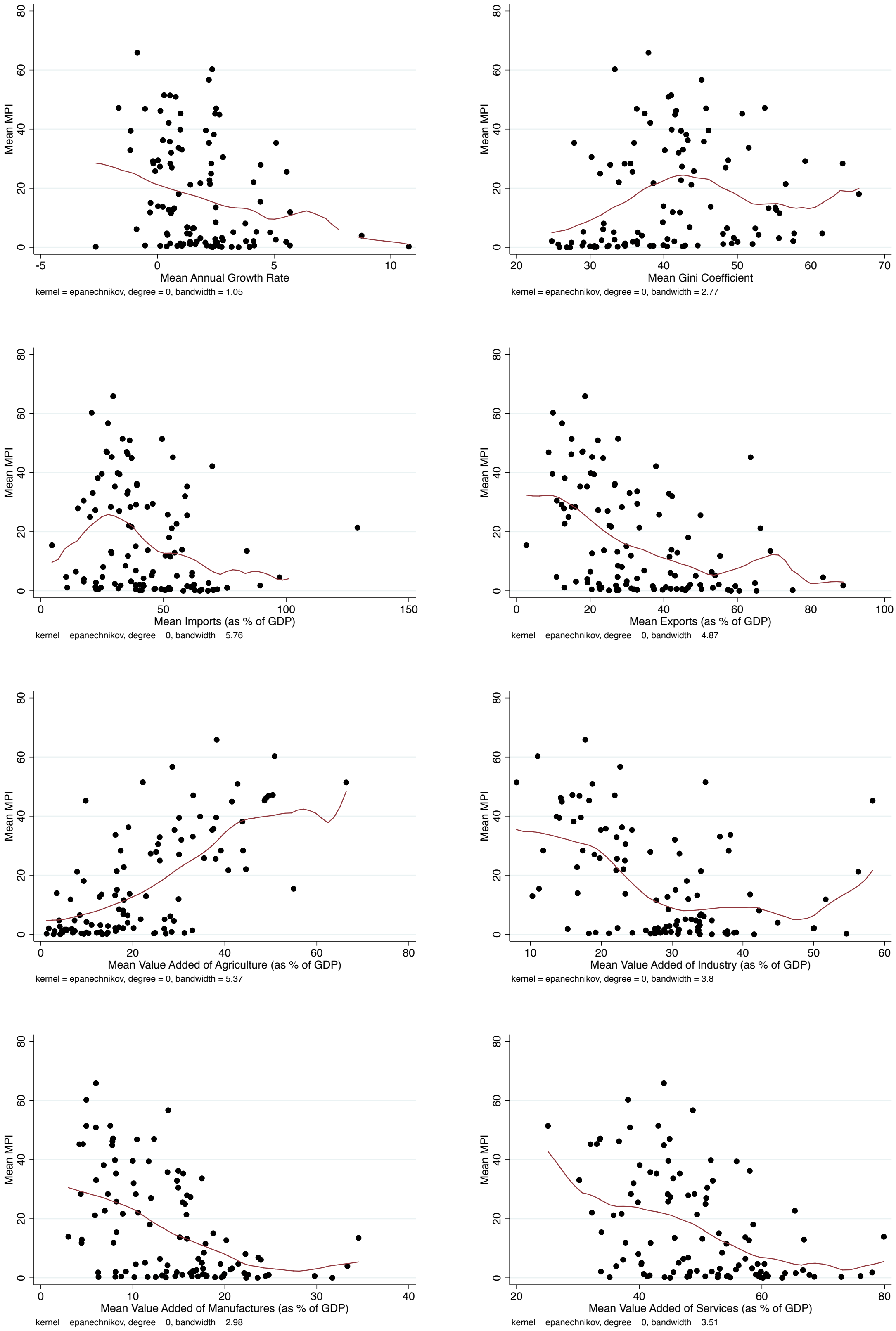
Variable	N Obs	Mean	Std. Dev.	Min	Max
Alternative P_i (explained) variables					
Mean MPI (2000–2014)	110	17.3	17.8	0.0	65.9
Mean Multidimensional Headcount Ratio (2000–2014)	110	31.9	29.6	0.0	91.8
Mean Income Poverty Gap ($PPP1.25/day) (2000–2014)	95	9.6	11.2	0.0	43.4
Mean Income Headcount Ratio ($PPP1.25/day) (2000–2014)	95	25.1	24.2	0.0	83.8
X_{ji} (explanatory) variables					
Mean Growth Rate (1980–2014)	109	1.9	2.0	-2.6	10.8
Mean Gini Coefficient (1980–2014)	104	41.1	9.3	24.8	66.5
Mean Trade (as % GDP) (1980–2014)	109	76.2	34.2	7.2	182.5
Mean Imports (as % GDP) (1980–2014)	109	42.9	19.6	4.5	129.1
Mean Exports (as % GDP) (1980–2014)	109	33.4	17.4	2.7	88.8
Mean Value Added of Agriculture (as % GDP) (1980–2014)	105	22.0	14.1	1.3	66.4
Mean Value Added of Industry (as % GDP) (1980–2014)	105	28.5	10.3	8.0	58.3
Mean Value Added of Manufacturing (as % GDP) (1980–2014)	105	14.2	6.6	3.0	34.5
Mean Value Added of Services (as % GDP) (1980–2014)	105	49.5	11.0	25.1	79.9
Mean Control of Corruption (1980–2014)	109	-0.5	0.5	-1.7	1.0

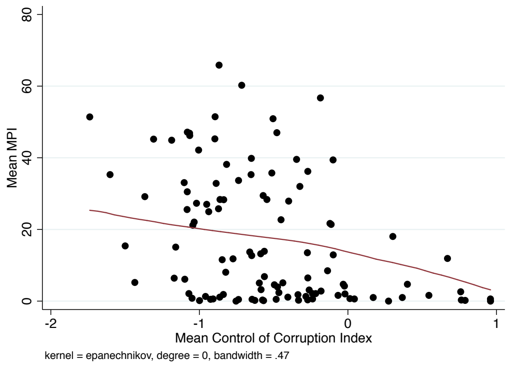
Table 3: Correlation Coefficients among Variables

Variable	MPI	Growth	Gini	Trade	Imports	Exports	VA Ag.	VA Ind.	VA Manuf.	VA Ss.
Growth	-0.31									
Gini	0.14	-0.34								
Trade	-0.41	0.19	-0.06							
Imports	-0.30	0.20	-0.04	0.94						
Exports	-0.46	0.14	-0.06	0.91	0.71					
VA Agric.	0.70	-0.17	-0.03	-0.40	-0.25	-0.51				
VA Industry	-0.44	0.14	-0.04	0.25	0.07	0.43	-0.59			
VA Manuf.	-0.52	0.21	-0.11	0.11	0.05	0.16	-0.44	0.39		
VA Services	-0.46	0.08	0.07	0.27	0.24	0.23	-0.69	-0.17	0.17	
Control of Corruption	-0.40	0.20	0.05	0.24	0.21	0.23	-0.49	0.03	0.25	0.58

The association between MPI and the value added by industry is a bit more complex, exhibiting a negative association for most of the data points, although it is not linear; the association becomes positive but only for some outlier values. The correlation coefficient is -0.44. In turn, the association between MPI and the value added by a sub-sector of industry – the manufacturing sector – is much clearer, with a more consistent negative relation throughout the data points and close to linearity; the correlation coefficient is -0.52. The MPI and the value added by the services sector are also negatively associated with a non-linear convex shape. The correlation coefficient between the MPI and services is -0.47. Finally, the MPI is negatively and linearly associated with the Control of Corruption Index, with a correlation coefficient of -0.41.

Figure 1: Scatterplots of MPI and Explanatory Variables Adjusted with a Local Polynomial Regression





5. Results

5.1 First Difference Estimator Model

Table 4 presents the first difference estimator results of the change in the MPI considering six different specifications (numbered sequentially at the top of each column of the table), with different combinations of explanatory variables. Results of the first specification suggest that, without considering or controlling for anything else, a 1% increase in the growth rate leads – on average – to a 0.56% reduction in the MPI and this is significant at the 10% level. When we include other explanatory variables, namely, trade and sectorial composition of the GDP, we find that growth remains as a significant determinant (even increasing in significance in some specifications) and the estimated elasticity of multidimensional poverty to growth does not change substantially, whereas none of the other considered variables appear to be significant. It is interesting to note that when inequality is included, the growth elasticity more than doubles (it increases to 1.2) and becomes more significant (at 5%). This suggests that if inequality did not change, the impact of economic growth on reducing poverty would be much stronger than when growth simultaneously produces changes in inequality (presumably increasing it). Thus, along the lines of Datt and Ravallion (1992) and Kakwani and Pernia (2000), on average, growth does not seem to be pro-poor, as poverty is reduced less than what it would be reduced under distribution-neutral growth.

Table 5 presents the first difference estimator results of the change in the multidimensional headcount ratio H_M, considering the same six different specifications presented in Table 4. As described in Section 2, H_M is a sub-index of the MPI. The key difference between H_M and the MPI is the intensity component. Results are quite similar to those of the MPI. The main difference is that the growth elasticity of multidimensional poverty as measured by the Head Count Ratio (H_M), rather than by the Adjusted Headcount Ratio (MPI), is higher in absolute value, 0.73, and has higher level of significance (5%), suggesting that it may be more difficult for economic growth to reduce poverty among the poorest poor. The same result emerges when including the inequality variable; that is, we find a higher growth elasticity and significance when inequality is controlled for. Both with MPI and H_M regressions, the overall goodness of fit is quite low, suggesting that – unfortunately – most of the change in multidimensional poverty remains unexplained.

Table 4: First Difference Estimator

Dependent Variable: Change in the Multidimensional Poverty Index (MPI)

	SPECIFICATION					
	1	**2**	**3**	**4**	**5**	**6**
Growth of GDPpc	-0.56*	-1.20**	-0.56*	-0.57*	-0.55*	-0.72**
Gini		-0.10				
Trade (%GDP)			-0.02			0.04
Exports (%GDP)				0.08		
Imports (%GDP)				-0.10		
VA Industry (%GDP)					-0.54	
VA Services (%GDP)					-0.56	
VA Manufacturing (%GDP)						-0.25
R2	0.03	0.12	0.03	0.04	0.06	0.06
N	100	65	100	100	96	94

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table 5: First Difference Estimator
Dependent Variable: Change in the Multidimensional Poverty Incidence (H_M)

	SPECIFICATION					
	1	**2**	**3**	**4**	**5**	**6**
Growth of GDPpc	-0.73**	-1.41***	-0.73**	-0.74**	-0.71**	-0.84**
Gini		0.43				
Trade (%GDP)			0.11			-0.08
Exports (%GDP)				0.03		
Imports (%GDP)				-0.13		
VA Industry (%GDP)					-0.46	
VA Services (%GDP)					-0.61	
VA Manufacturing (%GDP)						-0.16
R2	0.05	0.14	0.06	0.06	0.07	0.07
N	102	67	102	102	98	96

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Multidimensional vs. Income Poverty with the FDE Model

A natural question is whether growth has a different impact on multidimensional poverty than on income poverty. To address this, we have estimated the same six specifications for two international measures of income poverty introduced in Section 2.2, replicating the countries and years of the MPI panel as much as possible. These are the income poverty incidence or headcount ratio H_I of people who live on less than $1.25 (PPP) a day and the poverty gap measure P_G – also using the $1.25 (PPP) a day poverty line. Regression results using P_G are reported in Table 6, which can be compared to those obtained using the MPI in Table 4. Regression results using H_I $\boldsymbol{H_I}$ are reported in Table 7, which can be compared to those obtained using H_M $\boldsymbol{H_M}$ in Table 5.

Table 6: First Difference Estimator
Dependent Variable: Change in Income Poverty Gap (P_G)

	SPECIFICATION					
	1	2	3	4	5	6
Growth of GDPpc	-2.78**	-3.68***	-2.57***	-2.94***	-2.60***	-3.03***
Gini		0.55				
Trade (%GDP)			-0.09			0.07
Exports (%GDP)				-1.42***		
Imports (%GDP)				0.96**		
VA Industry (%GDP)					-0.05	
VA Services (%GDP)					-1.53	
VA Manufacturing (%GDP)						-0.28
R2	0.27	0.36	0.27	0.37	0.32	0.29
N	59	38	59	59	58	58

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table 7: First Difference Estimator
Dependent Variable: Change in Income Poverty Incidence (H_I)

	SPECIFICATION					
	1	2	3	4	5	6
Growth of GDPpc	-2.36***	-3.27***	-2.28***	-2.40***	-2.18***	-2.51***
Gini		1.27				
Trade (%GDP)			-0.31			-0.19
Exports (%GDP)				0.63		
Imports (%GDP)				-1.15		
VA Industry (%GDP)					-0.25	
VA Services (%GDP)					-1.54*	
VA Manufacturing (%GDP)						0.08
R2	0.23	0.32	0.24	0.29	0.27	0.24
N	61	40	61	61	60	60

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Looking at these tables and comparing results one can note three things. First, economic growth seems to be more effective at reducing income poverty than reducing multidimensional poverty. The estimated average elasticity of the income poverty gap to economic growth (-2.78) is much higher – and with higher significance – than that of the MPI; similarly, the estimated growth elasticity of the income headcount ratio is much higher than that of the multidimensional headcount ratio.[17] Also, as with multidimensional poverty, the other included variables are, in general, non-significant, except for exports

[17] It is also worth noting that the estimated growth elasticity of income poverty (in the different considered specifications) is within the range found by previous studies.

and imports in the case of the income poverty gap. When the same models are estimated with the alternative income panel (not necessarily replicating the MPI panel), results are similar in terms of significance, but the estimated elasticities are lower, although they are still higher than those of multidimensional poverty.

5.2 Cross-Section Estimator Model

Tables 8–11 present the estimation results of the cross-section model using four alternative dependent variables – the mean of observed poverty values between 2000 and 2014 of the MPI, H_M, P_G, and H_I – and nine different specifications numbered sequentially at the top of each column of the table, with different combinations of explanatory variables. Looking at the tables, one can extract the following results.

Economic growth is significantly associated with a reduction in multidimensional poverty, measured either by MPI (Table 8) or H_M (Table 9). Without including any other explanatory variable, a mean growth rate one percentage point higher is associated with a 2.6 percentage points lower average MPI, and with 4.4 percentage points lower multidimensional headcount ratio. Note, however, that the reported coefficients are not elasticities. These are computed and reported in Table 12 below and indicate – in line with the FDE results – that the impact of economic growth on poverty reduction is actually modest. As additional explanatory variables are included, the growth coefficient remains significant but the coefficient decreases.

Comparing incidence with incidence adjusted by intensity (i.e. comparing Table 8 with Table 9), one notices that while the results are the same in terms of significance of the variables, the estimated coefficients of all variables are between 1.6 and 3.4 times higher when multidimensional poverty incidence is the dependent variable than when the dependent variable is the MPI. This would suggest, in line with the FDE results, that economic growth and the other explanatory variables may have a bigger impact on poverty incidence than on poverty incidence adjusted by intensity. However, this outcome does not hold when we obtain the implied elasticity values, which are discussed below.

In terms of the other included variables, except for the case of inequality, variables that are not significant in the FDE model are significant in the cross-section one. This offers complementary information that may be interpreted as the 'country profile' that is associated with lower multidimensional poverty. We comment on each variable in what follows.

Table 8: Cross-section OLS Estimates
Dependent Variable: Multidimensional Poverty Index (MPI)

	SPECIFICATION								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Growth of GDPpc	-2.59***	-2.78***	-2.23***	-2.40***	-1.81***	-1.22**	-1.99***	-2.05***	-1.78***
Gini		0.073							
Trade (%GDP)			-0.177***			-0.170***	-0.13***		
Exports (%GDP)				-0.56***				-0.35***	
Imports (%GDP)				0.169*					
VA Industry (%GDP)					-0.86***				-0.85***
VA Services (%GDP)					-0.83***				-0.80***
VA Manufacturing (%GDP)						-1.22***			
Control of Corruption							-9.86***	-8.81***	-1.02
R2	0.09	0.11	0.20	0.28	0.52	0.40	0.29	0.33	0.52
N	109	104	109	109	105	105	109	109	105

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table 9: Cross-section OLS Estimates
Dependent Variable: Multidimensional Poverty Incidence (H_M)

	SPECIFICATION								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Growth of GDPpc	-4.32***	-4.44***	-3.72***	-4.02***	-2.97***	-2.02**	-3.32***	-3.41***	-2.93***
Gini		0.25							
Trade (%GDP)			-0.29***			-0.27***	-0.21***		
Exports (%GDP)				-0.97***				-0.57***	
Imports (%GDP)				0.32**					
VA Industry (%GDP)					-1.43***				-1.40***
VA Services (%GDP)					-1.37***				-1.30***
VA Manufacturing (%GDP)						-2.02***			
Control of Corruption							-17.14***	-15.53**	-2.45
R2	0.09	0.11	0.20	0.29	0.52	0.39	0.29	0.33	0.52
N	109	109	109	105	105	105	109	109	105

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Inequality

In line with the FDE results, when income inequality is included, although this variable is not significant, the coefficient of growth increases, both in the case of MPI (Table 8) and H_M (Table 9), suggesting that holding the income distribution constant, economic growth would have a higher poverty-reducing impact. It is also worth noting that the fact that we find no significant impact of inequality does not mean that inequality is not associated with multidimensional poverty. As mentioned in the introduction, there are issues with measurement error and opposing effects at the country-level being cancelled out. In fact, the scatterplot between MPI and Gini in Figure 1 suggests that there is a non-linear relationship between these two variables.

Trade Openness

In particular, in Specification 3 we include the average growth rate and average trade measured with imports plus exports as a percentage of GDP, and in Specification 4 we discriminate between exports and imports. Results suggest that more trade is significantly associated with less poverty, and this does not reduce the significance of the growth variable, although the coefficient is slightly reduced. Moreover, we find exports to be the variable with a significant negative association with MPI and H_M, whereas imports have a positive significant association. That is, countries that export more and import less are on average less multidimensionally poor. These results differ from previous evidence that suggests that greater openness does not significantly affect either the incomes of the poor (Dollar and Kraay 2002, Foster and Székely 2008[18]) or the income poverty headcount ratio (Kraay 2006, Ravallion and Chen 2007), at least not directly, although trade may impact poverty indirectly given that openness is often found as a significant growth determinant. Our evidence suggests that an export-led growth strategy seems to be favourable to pro-poor economic growth.

Sectorial Composition of GDP

In Specification 5 we explore the impact of the types of growth in terms of the sectorial composition of the GDP. We find that the mean value added by industry (as a percentage of GDP) as well as the mean value added by services (also as a percentage of GDP) are significantly and negatively associated with the average MPI and H_M. Besides, while the growth coefficient is reduced, it remains significant.[19]

In Specification 6 we include growth, trade, and the value added of the manufacturing sector, which is a subgroup of industry that excludes mining, construction, electricity, water, and gas. The three variables are significant. It is worth noting that (a) the trade coefficient remains similar to that of Specification 3 (when it is included only alongside growth) both in the case of the MPI (Table 8) and in the case of the

18 Foster and Székely (2007) find an impact significant at 10% (t value of 1.6) only when using the arithmetic mean income but not significant when using means that give higher weight to lower incomes.

19 We also estimated specifications considering the value added of each sector separately in turn, alongside growth, and found similar results to the case in which they are included together. The value added of agriculture has a positive and significant association with multidimensional poverty.

H_M (Table 9); (b) the growth coefficient is reduced (to -1.25 in the case of the MPI and to -2.07 in the case of H_M), suggesting that part of growth's association with poverty is through its sectorial composition; and (c) the coefficient of the value added by manufacturing is 1.4 times that of industry (both in the case of the MPI and in the case of H_M), which should indicate that this sub-sector may have a stronger association with poverty than industry as a whole. This result is intuitively acceptable, as manufacturing tends to be more labour-intensive than industry in general.[20]

These results are along the same lines as Kraay (2006) who finds that countries with a higher relative productivity in agriculture are more likely to experience poverty-increasing changes in relative incomes. However, there is different evidence for two important cases: India and China. Using data spanning over forty years, Ravallion and Datt (1996) found that in India output growth in the primary and tertiary sectors reduced poverty whereas growth in the secondary sector did not have an impact. Also in the case of India, Ravallion and Datt (2002) found that farm yield growth reduced poverty over the period 1960–94, whereas non-farm growth had a bigger impact on poverty reduction in states with better initial conditions in terms of farm yields, female literacy rates, infant mortality, urban–rural disparities in consumption levels, and landlessness. Similarly, for the case of China during the period 1980–2001, Ravallion and Chen (2007) found that growth in the primary sector had a far higher impact (about four times higher) than growth in the secondary and tertiary sectors.

Results from the India and China studies are not directly comparable with this cross-country evidence, as the kind of data and methods differ substantially. However, it is sensible to read them as complementary. While the case studies of the pattern of growth of India and China over time suggest that growth in the agricultural sector may have a stronger poverty reducing effect than growth in the industrial sector, cross-country evidence suggests that, in the long run, fostering industrialization can help to reduce poverty. Thus, a strategy that aims to increase the contribution of industry to growth while sustaining agricultural growth can maximize the potential of growth to reduce poverty. In fact, for many developing countries, agro-industrial-oriented growth is becoming a promising path for development (IICA 2004; Mucavele 2009; Guanziroli 2007, 2012).

Governance

Specifications 7 to 9 incorporate a governance indicator, which is the mean between 1980 and 2014 of the annual value of the control of corruption indicator. The higher the value of this index, the higher control there is over corruption. This variable could not be included in the FDE models because of an

20 When the value added by the manufacturing sector was included only alongside growth, the coefficient was very similar (1.26) and equally significant.

insufficient number of observations over time for the countries of the panel. It is worth noting that Dollar and Kraay (2002) included a related indicator, the rule of law (from Kaufmann et al. 1999), and found it to have a positive but insignificant association with the incomes of the poorest quintile – although they also found it to be a significant determinant of growth.

In Specification 7 we include the control of corruption indicator alongside economic growth and trade, and in Specification 8 we also add exports. Unlike Dollar and Kraay (2002), we find that the control of corruption indicator is significantly and negatively associated with poverty. The intuitive idea is that countries where corruption is better controlled tend to have lower multidimensional poverty, either as measured by MPI (Table 8) or H_M (Table 9). The estimated coefficient is actually the highest of the three. The growth coefficient is slightly reduced when compared to Specification 3 and remains significant. The trade and export coefficients in the corresponding specifications are reduced by a somewhat larger amount but also remain significant.

However, when the control of corruption coefficient is included alongside the GDP sectorial composition indicators, it is no longer significant. Moreover, the growth, industry, and services variables' coefficients remain virtually unchanged as compared to Specification 5, in which the control of corruption indicator is not included. Looking at Table 3, one notices that the (mean of the) control of corruption indicator has a correlation of 0.58 with the (mean of the) value added by the services sector, as a proportion of the GDP, which explains why this indicator is no longer significant when included alongside the services variable. While we cannot infer causality from this, it sounds reasonable that countries that have been able to achieve higher levels of control of corruption have also been able to increase their value added from the services sector, which includes government, financial, transport, professional, education, health care, and real estate services. Moreover, these are also countries that tend to have lower levels of multidimensional poverty.

Overall Goodness of Fit

In terms of the overall goodness of fit, Specifications 5 and 9 exhibit the highest R^2, which is 0.53. Specification 5 includes growth and the value added by industry and services, and Specification 9 additionally includes control of corruption. However, this last variable is not significant, and it does not change the coefficients of industry and services. This is followed by Specification 6 with an R^2 of 0.40, including growth, trade, and the value added by manufacturing. These R^2 values are similar to those obtained in previous literature. However, they suggest that much of multidimensional poverty remains unexplained.

Multidimensional vs. Income Poverty with the Cross-Section Model

Comparing one more time multidimensional poverty with income, Tables 10 and 11 report the estimation results of the nine different model specifications with the income poverty measures P_G, and H_I as the dependent variables, correspondingly. Table 10 can be compared with Table 8, and Table 11 with Table 9. Results are similar to those of multidimensional poverty, namely, countries that export more, have a higher share of industry and services in the GDP, and higher control of corruption have lower income poverty. Two things are worth noting though. First, income inequality as measured by the (average) Gini coefficient, which is not significantly (linearly) associated with the multidimensional poverty measures, H_M is significantly and positively associated with the income poverty measures. The intuition is that income inequality is expected to be more closely related to income poverty than to multidimensional poverty, which comprises many non-monetary dimensions. Second, the magnitudes of the estimated coefficients are slightly higher for the multidimensional poverty measures than for the income poverty measures, yet the implied elasticity values are the other way around, as discussed below.

Table 10: Cross-section OLS Estimates
Dependent Variable: Income Poverty Gap (P_G)

	SPECIFICATION								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Growth of GDPpc	-2.02***	-1.57**	-1.88***	-1.86***	-1.26***	-1.25***	-1.61***	-1.49***	-1.33***
Gini		0.28**							
Trade (%GDP)			-0.045			-0.043	-0.037		
Exports (%GDP)				-0.33***				-0.17***	
Imports (%GDP)				0.195***					
VA Industry (%GDP)					-0.413***				-0.418***
VA Services (%GDP)					-0.444***				-0.478***
VA Manufacturing (%GDP)						-0.53***			
Control of Corruption							-4.81**	-4.63**	1.42
R2	0.13	0.18	0.15	0.26	0.40	0.25	0.19	0.24	0.40
N	95	95	95	95	91	91	95	95	95

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table 11: Cross-section OLS Estimates
Dependent Variable: Income Poverty Incidence (H_I)

	SPECIFICATION								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Growth of GDPpc	-4.3***	-3.51***	-3.82***	-3.78***	-2.48**	-2.42**	-3.14***	-2.90***	-2.55**
Gini		-0.496**							
Trade (%GDP)			-0.145*			-0.138*	-0.124		
Exports (%GDP)				-0.757***				-0.44***	
Imports (%GDP)				0.365**					
VA Industry (%GDP)					-1.09***				-1.09***
VA Services (%GDP)					-1.15***				-1.19***
VA Manufacturing (%GDP)						-1.33***			
Control of Corruption							-12.42***	-12.19***	1.62
R2	0.13	0.16	0.17	0.27	0.50	0.29	0.22	0.28	0.50
N	95	95	95	95	91	91	95	95	95

N 95 95 95 95 91 91 95 95 95

*** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Elasticity of Poverty to Economic Growth

In the cross-section regression, we have assumed a linear model; thus, by definition, the elasticity of poverty to growth can obtained as

$$\eta^P_{g\,i} = \hat{\beta}_1 \frac{g_i}{P_i}, \quad (12)$$

where $\eta^P_{g\,i}$ is the elasticity of poverty – for which we use alternative specifications – to economic growth of country i, $\hat{\beta}_1$ is the estimated coefficient of the economic growth indicator, g_i is the (average) growth rate between 1980 and 2014, and P_i is the (average) poverty value between 2000 and 2014. By definition, this ranges from very high (tending to infinite) to very low (tending to zero) in absolute values.[21]

Clearly, the elasticity obtained in this way is different from the one obtained from the FDE model. When computing the poverty-to-growth elasticity from the cross-section estimation results, we are implicitly assuming that the average over-time effect for a country equals the average cross-country

21 There are even some positive elasticity values for countries that have had (average) negative growth rates.

effect, which is admittedly a strong assumption. However, this exercise may be understood as a robustness analysis of the results obtained from the FDE model.

Table 12 presents the average elasticity estimate for each of the four considered poverty measures within the 3rd quintile of the corresponding poverty indicator. The 3rd quintile of the poverty measure distribution includes the mean and median values, except for the case of the income poverty gap, in which case it includes the median but not the mean, which is included in the 4th quintile. We also present the average estimated elasticity for the countries in the 2nd, 3rd, and 4th quintiles of the distribution of the corresponding poverty indicator. To obtain these elasticity estimates we have used the $\hat{\beta}_1$ estimated coefficient obtained in Specification 1 in each case. Thus, we take these elasticity values as an 'upper bound', given that the growth coefficients decrease when other explanatory variables are included.

Comparing the elasticity values in Table 12 with those in Tables 5 to 7, it is worth noting that the implied elasticity value of MPI to economic growth for the third quintile of the MPI distribution, -0.60, is quite similar to that obtained from the FDE model, -0.57. However, the other elasticity values obtained from the cross-section for H_M, P_G, and H_I differ from those obtained from FDE. Yet two important conceptual results hold across the two kinds of econometric models. First, the association of economic growth with multidimensional poverty seems to be – at most – quite moderate, with a poverty to growth elasticity below unity, either for MPI or H_M. Specifically, a 1% increase in the average economic growth rate is associated – on average – with a 0.57 to 0.60% reduction in the MPI. This suggests that poverty reduction does not move *pari passu* with economic growth but only to a lesser extent. This elasticity is just above unity only when computing the average elasticity for the 2nd to 4th quintiles of MPI in the cross-section and when including inequality in FDE.

Second, economic growth is more strongly associated with income poverty reduction than with multidimensional poverty reduction, as was already mentioned in the FDE results. This is also evidenced from the cross-sectional estimates comparing both the average elasticities of MPI vs. P_G ($|-0.9|>|-0.6|$ and $|-2.82|>|-1.21|$), and H_M vs. H_I ($|-0.53|>|-0.38|$ and $|-1.831|>|-0.84|$).

As a third comment, while the elasticities obtained in the FDE model suggest that economic growth has a bigger reducing impact on multidimensional poverty incidence than on multidimensional poverty incidence adjusted by intensity, the elasticity estimates obtained from the cross-section models suggest the opposite ($|-0.6|>|-0.38|$ and $|-1.21|>|-0.84|$). Thus, this conclusion is not robust throughout the two econometric models.

Table 12: Average Implied Elasticity Values of Different Poverty Measures to Growth from Cross-Section Estimations

	3rd Quintile of the Corresponding Poverty Indicator*	**2nd to 4th Quintile of the Corresponding Poverty Indicator**
Average Elasticity of MPI to Growth	-0.60	-1.21
Average Elasticity of P_G to Growth	-0.90	-2.82
Average Elasticity of H_M to Growth	-0.38	-0.84
Average Elasticity of H_I to Growth	-0.53	-1.31

Note: In the case of MPI, H_M, and H_I, the third quintile of the corresponding poverty indicator includes in each case the mean and median value of the poverty indicator. In the case of P_G, the third quintile includes the median but not the mean; the mean is included in the 4th quintile. All elasticity values were estimated using Equation (12), and the $\hat{\beta}_1$ estimated coefficients of Specification 1 in each case are reported in Table 8–11 correspondingly.

Other Estimated Models

It is worth noting that we have also performed two other sets of estimations. First, given that all the poverty measures used a range between 0 and 100, we estimated the same nine specifications of the cross-section using a Tobit model. Results do not vary in terms of sign and significance. Second, we estimated a set of OLS cross-section regressions in which, rather than using the mean values, we take each estimate of the MPI for each country and year as a different observation. For the explanatory variables, we take the mean value of each of them over the five years previous to the MPI observation, as done in the FDE model. Results are essentially the same as the ones described above in terms of the sign and significance of each variable. The estimated coefficients are smaller.

6. Concluding Remarks

In this paper we have asked whether economic growth contributes to the reduction of multidimensional poverty as measured by the global Multidimensional Poverty Index, as well as one of its components, the multidimensional headcount ratio. We have estimated a first difference estimator model for 78 developing countries and complemented these results by estimating a cross-section OLS model. In all cases we considered alternative specifications of the set of explanatory variables (aside from economic growth) and estimated each regression for income poverty measures for comparability purposes.

We find two main results that are robust to the econometric model used. First, while economic growth seems to contribute to a reduction in multidimensional poverty, its impact is, at best, quite moderate, with an elasticity well below unity. This holds both for the multidimensional poverty incidence (H_M) and adjusted incidence (MPI). Specifically, the FDE model suggests that a 1% increase in the economic growth rate leads to a 0.57% reduction in the MPI and a 0.73% reduction in the H_M, whereas the cross-section models suggest that countries with an average growth rate 1% higher have a 0.60% lower MPI and a 0.38% lower H_M. The second main result is that economic growth has a bigger and more significant impact on income poverty than on multidimensional poverty. In other words, growth does not seem to be particularly pro-poor when poverty is measured from a multidimensional perspective.

From the cross-section regressions, we also find that countries that export more, with a higher share of industry in their GDPs, especially manufacturing, and with a higher share of services in their GDPs have lower average multidimensional poverty. Additionally, countries with a higher control of corruption also exhibit lower poverty.

The FDE model also suggests that it is easier for economic growth to reduce multidimensional poverty incidence than incidence adjusted by poverty intensity, which would suggest that it is more difficult for the poorest poor to benefit from economic growth than for those closer to the poverty threshold, which is an intuitive result. Yet this is not verified in terms of the elasticity values obtained from the cross-section regressions.

In sum, "promoting pro-poor growth requires a strategy that is deliberately biased in favour of the poor so that the poor benefit proportionally more than the rich" (Kakwani and Pernia, 2000, p. 3). The evidence here suggests that so far economic growth has been quite timid in reaching the multidimensionally poor. Thus, the eighth Sustainable Development Goal – inclusive growth – poses a great challenge ahead. As the MPI continues to be estimated forward (as new data is released) and backwards (using older datasets), further studies will be possible. A lot more needs to be explored in terms of the growth pathways and patterns that are favourable to multidimensional poverty reduction.

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