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Revisiting Cross-Country Poverty Convergence in the Developing World with a Special Focus on Sub-Saharan Africa

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ABSTRACT

Revisiting Cross-Country Poverty Convergence in the Developing World with a Special Focus on Sub-Saharan Africa

The literature on poverty convergence is sparse and much of the empirical evidence relies on Ravallion (2012) who found a lack of poverty convergence across some ninety Less Developed Countries (LDCs) during 1977-2007. This paper revisits cross-country poverty convergence using data from the same sources but an extended period, i.e. 1977-2014. We find that while poverty convergence remains absent across LDCs during 1981-2014, it is explained by initial poverty nullifying the effectiveness of growth in reducing poverty; whereas an adverse direct effect of initial poverty on growth – which is recognized as the main impediment to cross-country poverty convergence during 1977-2007 – is not found. In SSA, in contrast, we find strong cross-country poverty convergence during both periods examined, as an adverse direct poverty effect is not found, and the indirect poverty effect is not large enough to cancel the mean convergence effect.

JEL Classification: O10, O55

Keywords: cross-country poverty convergence, growth, poverty, Sub-Saharan Africa

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I. Introduction

With some 1.6 billion people, or 23 percent of the world's 7.1 billion population, still living at less than $2 per person per day in 2005 Purchasing Power Parity (PPP) terms, reducing poverty remains one of today's most important challenges for humanity (de Janvry and Sadoulet 2016: 82). And as growth is the main means through which poverty reduction is pursued, understanding connections between growth and poverty reduction is critical.

One might expect to see *cross-country poverty convergence*, whereby initially poorer countries would experience faster reduction in poverty than countries starting out richer; because after all, both the notion of convergence in mean --- as predicted in the neoclassical growth model (Slow 1956; Swan 1956) --- and that of the advantage of growth have found support in a vast literature[1], though some studies have expressed skepticism[2].

[1] Convergence in mean ---whereby countries starting out with lower per capita income would subsequently grow faster than those starting out richer --- is found across some one hundred developing countries during 1968-1985/90 (Barro 1991 and 1996; Mankiw *et al.* 1992) as well as 1977-2007 (Ravallion 2012, Table 1) and 1981-2014 (current study). Still based on data from the World Bank, de Janvry and Sadoulet (2016, Table 2.1) suggested that the developing world experienced selective convergence in mean during 1980-2013, with countries in East Asia and the Pacific and South Asia growing faster than industrialized ones while those in the rest of the developing world, particularly Sub-Saharan Africa (SSA), grew more slowly. They also noted that since around 2000, all developing regions, especially SSA, started to catch up. The notion of *advantage of growth,* whereby countries enjoying faster economic growth tend to experience faster reduction in poverty, is also empirically supported (Dollar and Kraay 2002; Dollar, Kleinberg, and Kray 2016).

[2] Prichett (1997), for example, argued that income gap between the world's rich and poor economies widened between the late 18th and the mid-20th century. Rodrik (2011, 2014) recognized that many developing Asian countries enjoyed faster growth since the late 1970s and there has been an economic take-off in Africa and Latin America since the mid-1990s, but noted that the average productivity gap between advanced and developing economies remained as wide in 2008 as it was in 1950.

In a seminal paper on growth–poverty relationship based on cross-sectional data from some 90 developing countries surveyed during 1977–2007, however, Ravallion (2012) documented a *lack* of cross-country poverty convergence, whereby countries starting out with higher poverty incidences did *not* subsequently experience faster poverty reduction than those starting out with lower poverty incidences. He then demonstrated that this is explained by (i) a *direct poverty effect*, whereby for a given initial mean income or consumption expenditure, countries with higher initial poverty incidences grew subsequently more slowly, with or without considering other initial conditions including initial inequality; and (ii) an *indirect poverty effect*, whereby for a given growth in mean, countries with higher initial poverty incidence subsequently experienced a lower reduction in poverty. Together, the two poverty effects neutralized the convergence in mean and the advantage of growth and led to an absence of cross-country poverty convergence in the developing world during 1977-2007. Ravallion (2012) is recognized as the first, and so far the only (to the best of our knowledge), to provide cross-country empirical evidence on poverty convergence. It also provides the first empirical evidence of a direct negative link between initial growth --- as distinct from initial inequality as identified in previous literature --- and subsequent growth, though an earlier conceptual discussion is seen in Perry *et al*. (2006) and Lopez and Servén (2009) provided a quantitative investigation based on semi-simulation data[3].

[3] Lopez and Servén (2009) found quantitative evidence using an empirical model similar to that in Ravallion (2012), but simulation/non-empirical poverty data constructed using per capita income data --- which is more available than poverty data --- following a lognormal approximation approach that dates back to Gibrat (1931).

In this paper, we revisit cross-country poverty convergence among developing or Less Developed Countries (LDCs) using data from the same sources but an extended period of 1977-2014. In particular, we give a special focus on countries in Sub-Saharan Africa (SSA), where both poverty and inequality are found to be falling rapidly since the mid-1990s (Pinkovskiy and Sala-i-Martin 2014), and the growth-poverty dynamics is found quite different from that in the LDCs as a group (Fosu 2015; Thorbecke and Ouyang 2017).

Our empirical model is based on that in Ravallion (2012), which consists of a set of equations standard within the class of Barro's growth regressions motivated by the Solow-Swan model. We present the model in Section II, where we also discuss why it is suitable for this analysis despite concern that it does not identify the effect of inequality, which, however, is proved to be linked to poverty reduction and growth in mean by an analytical identity[4].

[4] In particular, we consider Fosu (2015, footnote 7)'s concern that "What factors actually constitute initial poverty in such a structural model [of Ravallion's (2012)] has yet to be identified. [While a potential alternative] the Bourguignon (2003) model is based on an `identity' specification". As we shall explain in Section II, this should not be a concern as poverty convergence, as distinct from poverty reduction, is only affected by *cross-country average* change in inequality, which is close to zero during the periods studied.

To cover years between 1977 and 2014, we use two data sets in this analysis: the Ravallion (2012) data set[5] --- which we shall refer to as the RDS hereinafter --- sourced from the December 2008 version of the World Development Indicators (WDI) and covering 97 LDCs surveyed during 1977-2007; and an extended data set --- which we shall refer to as the EDS hereinafter --- that we construct using the August 2016 version of the WDI[6] to cover 114 LDCs surveyed during 1981-2014. The regression sample sizes vary by regression and tend to be smaller than 94 and 117; but the extension of the EDS over the RDS remains at around 20 countries for the LDC samples and nine for the SSA sub-samples (see Appendix A for a list of these countries). We present summary statistics and discuss other data issues, including the choice of poverty measures and welfare data type, in Section III.

[5] We thank Ravallion (2012) for sharing with us his data.

[6] All data in the two data sets are sourced from the WDI, except data on price index of investment goods, which we obtain, following Ravallion (2012), from the Penn World Tables (PWT) version 6.2. This index is used to control for initial degree of market distortions.

We analyze the data following three regression procedures: (i) a simple Ordinary Least Square (OLS) procedure; (ii) a Method of Moments (MM) procedure introduced by Yohai (1987) to correct for potential outliers that may bias OLS estimates in this study, a concern raised by Cuaresma *et al.* (2016) in replicating the Ravallion (2012) results[7]; and (iii) a cross-sectional Generalized Method of Moments (GMM) estimation which controls for endogeneity like a regular Instrument Variable (IV) estimator but improves its efficiency in the presence of heterskedasticity of unknown form (Baum *et al*. 2003). Details of these regression procedures also appear in Section III.

From our analysis, we have come to the following findings. In the developing world as a whole, cross-country poverty convergence remains absent during 1981-2014. However, it largely results from a strong mean convergence effect cancelled by a strong indirect poverty effect; whereas an adverse direct poverty effect --- which Ravallion (2012) recognized as the main impediment to poverty convergence across LDCs during 1977-2007 --- becomes marginal once initial conditions other than initial poverty headcount ratio are controlled for. Opposite to what is found in the whole developing world, we find significant and robust cross-country poverty convergence in SSA during both 1977-2017 and 1981-2014. It is explained by a mean convergence effect stronger than that found across LDCs dominating a significant indirect poverty effect that is less sizable than its LDC counterpart; while again, a significant direct poverty effect is not found, whether or not initial conditions other than initial poverty incidence is controlled for.

[7] In their replication using the RDS, Cuaresma *et al.* (2016) found poverty convergence significant at the 5% level if as few as four outliers in the RDS were removed from the analysis or accounted for through a dummy variable.

Since initial poverty is found to hinder cross-country poverty convergence mainly through weakening the effectiveness of growth in reducing poverty, an important implication of our findings is that effective poverty reduction relies on not just growth, but also the inclusiveness of growth. To this end, government policies conscientiously designed to help lagging regions can be crucial. Indeed, anti-poverty policies, which many SSA countries are committed to since the beginning of the new millennium, are likely to explain why we find cross-country poverty convergence in the region; though testing this hypothesis goes beyond the scope of this paper and would require additional data.

The rest of this paper is organized as follows. In Section II we present and discuss the empirical model. In Section III we describe our data and discuss our choice of regression approaches. In Section IV we report and interpret our empirical results. Section V concludes.

II. Empirical Model and Limitations

The empirical model we use in this analysis is from Ravallion (2012) and consists of several regression equations standard within the class of Barro regressions motivated by the Solow-Swan model, which, despite some skepticism[8], remains the most widely used econometric framework in the convergence literature.

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[8] Quah (1993), for example, argued that a negative initial condition coefficient in the Barro regression does not necessarily suggest convergence, as it will always be non- positive by the Cauchy-Schwarz inequality. Others who challenged the conventional growth econometrics include Durlauf and Quah (1999), Durlauf (2000), Temple (2000), Durlauf *et al.* (2005). More recently, Eberhardt and Teal (2013) suggested that the assumptions of aggregation and technology homogeneity in conventional convergence regression are inappropriate and responsible for “many of the puzzling elements in aggregate cross-country empirics”.

For this analysis, we recognize three key regression equations. The first is Equation (1) below for the identification of poverty convergence:

(1) $$g_i(H_{it}) = \alpha_i + \beta_i \ln H_{it-\tau} + \varepsilon_{it} \ .$$

In this equation, the annual average rate of poverty reduction for country i between year t and year $(t-\tau)$ --- which approximately equals the annualized change in log headcount ratio $g_i(H_{it}) \equiv (\ln H_{it} - \ln H_{it-\tau})/\tau$ --- is regressed on its initial headcount ratio --- also in natural logarithm ($\ln H_{it-\tau}$). If the regression returns a negative and statistically significant estimate of β, then we have evidence for a strong unconditional poverty convergence at the rate of β --- meaning that if $\ln H_{it-\tau}$ drops by one percent, the poverty reduction rate would increase (or decrease in absolute term) by β percentage points. Adding additional controls would yield a conditional poverty convergence rate.

Here we note Equation (1) implicitly assumes unconditional mean convergence and a log-linear relationship between poverty and mean income or consumption at any time, which is recognized by many as a strong assumption but remains standard in the literature. Specifically, Equation (1) can be derived from

(2) $$g_i(\mu_{it}) = \alpha_i^* + \beta_i^* \ln \mu_{it-\tau} + \epsilon_{it}^* \ , \text{ and}$$

(3) $$\ln H_{it} = \delta_i + \eta_i \ln \mu_{it} + v_{it}$$

, where $g_i(\mu_{it}) \equiv (\ln\mu_{it} - \ln\mu_{it-\tau})/\tau$ approximately equals the annual average rate of growth in mean income or consumption for country i between year t and year $(t-\tau)$; H_{it} is country i's poverty headcount ratio at year t; $\mu_{it-\tau}$ and μ_{it} are, respectively, country i's level of mean income or consumption at the beginning and end of the growth spell defined between the two years. Parameters in Equation (1) are related to parameters in Equations (2) and (3): $\alpha_i = \alpha_i^*\eta_i - \beta_i^*\delta_i$, $\beta_i = \beta_i^*$, and $\varepsilon_{it} = \varepsilon_{it}^*\eta_i + v_{it} - (1+\beta_i^*)v_{it-1}$. We view these as assumptions but not key equations in this study, and we shall not separately report their estimates.

The second key equation in this analysis, is an augmented version of Equation (3), which we present below as Equation (4):

(4) $$g_i(\mu_{it}) = \alpha + \beta ln\mu_{it-\tau} + \gamma lnH_{it-\tau} + \varepsilon_{it} \text{ .}$$

Equation (4) is used to identify two contributing effects of poverty convergence. A significantly negative estimate of β would suggest a strong mean convergence effect (conditioning upon initial poverty level), whereby low level of initial mean welfare is related to faster subsequent growth in mean. A significantly negative estimate of γ from regressing Equation (4), on the other hand, would be interpreted as suggesting a strong direct poverty effect, whereby high level of initial poverty directly retards subsequent growth in mean welfare (upon controlling for the growth effect of initial mean).

The third key equation in this research is Equation (5) below for the identification of the poverty elasticity effect:

(5) $$g_i(H_{it}) = \eta(1 - H_{it-\tau})g_i(\mu_{it}) + v_{it}$$

, where η measures the elasticity of poverty reduction ($g_i(H_{it})$) in response to growth in mean ($g_i(\mu_{it})$) adjusted to initial poverty level ($H_{it-\tau}$)[9]. A significantly negative η suggests that for a given level of initial mean income or consumption expenditure, a given rate of growth in mean is less effective in reducing poverty in countries starting out with higher levels of initial poverty.

After one identifies poverty convergence and its three contributing effects, it is also useful if we can see their relative sizes and hence contributions to poverty convergence or the lack of it. To this end, we need Equation (6) which is derived by inserting Equation (4) into Equation (5) and taking partial derivative with respect to log initial poverty ($lnH_{it-\tau}$):

$$(6)\quad \frac{\partial g_i(H_{it})}{\partial lnH_{it-\tau}} = \eta\beta(1-H_{it-\tau})\left(\frac{\partial lnH_{it-\tau}}{\partial ln\mu_{it-\tau}}\right)^{-1} + \eta\gamma(1-H_{it-\tau}) + [-\eta g_i(\mu_{it})H_{it-\tau}].$$

(Mean convergence effect) (Direct effect of poverty) (Poverty elasticity effect)

[9] To prove that η, rather than the standard elasticity obtained from regressing change in poverty against growth in mean, is the relevant elasticity, one needs to run an encompassing test: $g_i(H_{it}) = \delta_0 + \delta_1 lnH_{it-\tau} + \eta_0 g(\mu_{it}) + \eta_1 H_{it-\tau} \cdot g(\mu_{it}) + v_{it}$ and show that δ_1 is not significantly different from zero (no sign of conditional convergence) and $\eta_0 + \eta_1 = 0$ is easily accepted (Ravallion 2012: 518). Data in this study passes this test comfortably.

The three terms in Equation (6) capture, respectively, the mean convergence effect, the direct poverty effect, and the poverty elasticity effect. While Equation (6) is a neat summary of results from previous equations, we should note that it is *not* a regression equation, but rather a computational equation whose key parameters (β, γ, η) come from regression Equations (4) and (5). Therefore, we use Equation (6) to identify the relative magnitude of the three effects, but it is the regression results from Equations (4) and (5) that determine whether they are statistically significant. Another thing to note here, is that the signs and sizes of the three terms in Equation (6) are empirically determined and do not have to always fully account for the actual change in poverty when different data points and parameter estimates are examined; though we expect the sum to largely match the empirical poverty convergence rate from regression Equation (1) if the model includes all major factors contributing to poverty convergence. If the computed and empirical rates are very different, it may suggest that poverty convergence or lack of it is driven by factors not included in the model specifications, such as policy orientations; though testing this hypothesis goes beyond the scope of this paper.

A main advantage of the empirical model presented above, is that it allows researchers to see how convergence in mean could be eroded by high initial poverty through direct and indirect channels to eventually yield no convergence in poverty despite the advantage of growth as discussed in Section I. One concern about the model, is that it seems to have left out the effect of inequality, which, as Fosu (2015, footnote 7) noted, is linked to poverty reduction and growth in mean income by an analytical *identity* (Bourguignon 2003) and supported by a number of empirical studies (Datt and Ravallion 1992; Kakwani 1993; Bourguignon 2003; Fosu 2008, 2009, 2011). We carefully considered this concern, and have come to realize that it should not be one. Examination of the identity relationship suggests that the only way inequality affects the poverty convergence rate ($\frac{\partial g_i(H_{it})}{\partial lnH_{it-\tau}}$)[10] --- as distinct from the pace of poverty reduction ($g_i(H_{it})$) --- is through change in inequality and its interaction with initial poverty. Therefore, when the *cross-country average* Gini index remains unchanged in the studied period --- as is the case in both the RDS and the EDS --- then we would not, on average, see an inequality effect[11]. Our exploration here therefore suggests that for the purpose of this analysis, the Ravallion (2012) model is suitable.

[10] Running the RDS and the EDS through the identity model, we find that higher initial Gini and improving income distribution are both related to lower pace of poverty reduction ($g_i(H_{it})$).

[11] That said, we do notice that *country-specific* change in Gini varies greatly by country in both data sets. We measure the annual average proportional change in Gini index, namely $g_i(GINI_{it}) \equiv (\ln GINI_{it} - \ln GINI_{it-\tau})/\tau$. In the RDS, this variable ranges between -0.04 (Uzbekistan) and 0.08 (Bosnia and Herzegovina) with a sample average of .0016 and a sample standard deviation of .020 (sample size is 97). In the EDS, it varies between -0.05 (Uzbekistan) and 0.04 (Macedonia) with a sample average of -.0030 and a sample standard deviation of .013 (sample size is 107).

III. Data and Regression Procedures

As mentioned in Section I, we use two cross-country data sets, i.e. the RDS (1977-2007) the EDS (1981-2014), to study cross-country poverty convergence in the whole developing world and in SSA alone during 1977-2014. In this section we describe these two data sets (III.1) and discuss our choice of estimation approaches (III.2).

III.1 Data Description

Each observation unit/country in the RDS and the EDS is characterized by one growth spell that is defined by the first and last year this particular country is surveyed during the studied period. As reported in Table 1 below, the cross-country average growth span is respectively 12.9 and 17.1 years in the RDS and the EDS. Table 1 also reports, by sample, *cross-country average* poverty headcount ratios and per capita income or consumption expenditure from first and last surveys; annual average proportionate changes in poverty and per capita welfare; and a number of other initial conditions, including the Gini coefficient, per capita consumption expenditure from national accounts, gross primary school enrollment rate, life expectancy at birth, relative price index of investment goods (as a measure of market distortions), and three measures of the middle class: (i) the welfare share of the middle three quintiles; (ii) the share of people living between $2 and $13 a day in 2005 terms, also known as the share of middle class population by developing-country standard; and (iii) the share of people living above $13 a day, or the share of middle class population by western standard. All initial condition data are from the first or the earliest available survey year.

Among the several poverty measures available in the data sets, we focus on poverty headcount ratio, which we measure against two international poverty lines: the extreme poverty line of 1.25 international dollar per person per day in 2005 Purchasing Power Parity (PPP) terms, or equivalently, $1.9 in 2011PPP terms[12]; and the poverty line of $2 in 2005PPP terms or $3.2 in 2011PPP terms. We also face a choice of mean welfare data type, as for a given survey year, countries can have either per capita consumption expenditure data or per capita income data or both. As mean consumption expenditure is generally believed to be a better measure of welfare compared to mean income, we shall report analysis results based on countries with consumption data; which reduces the analysis sample size of the RDS to 73 and that of the EDS to 94[13].

As one can see in Table 1, the RDS and the EDS are largely similar, though developing countries as a whole (LDCs) on average seem to have experienced faster growth in mean and reduction in poverty during the extended period of 1981-2014.

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[12] In October 2015, World Bank updated to a richer set of poverty lines in 2011PPP terms, where $1.9 per person per day is the median poverty line for 33 low income or poorest countries, $3.2 for 32 lower middle-income countries, $5.5 for 42 upper middle income countries, and $21.7 for 29 high income countries (Ferreira and Sanchez 2017). We constructed the EDS to include headcount ratios measured against $1.9, $3.2, and $21.7 per person per day; which largely correspond to $1.25, $2, and $13 in 2005PPP terms, respectively. Income and consumption survey data in the EDS are also measured in 2011PPP terms, as opposed to 2005PPP terms in the RDS.

[13] Analysis results based on all countries (hence mixed mean data type) actually gives quite similar results and are available upon request.

Table 1: Cross-country Averages, by Region and Period

	Variables	Full sample (all LDCs)				SSA sub-sample			
		EDS		RDS		EDS		RDS	
		N	Mean	N	Mean	N	Mean	N	Mean
1	Growth span (years)	114	17.14	97	12.88	37	15.90	28	12.49
2	per capita income or consumption, first survey	114	193.32	97	167.69	37	94.95	28	52.81
3	per capita income or consumption, last survey	114	274.05	97	167.02	37	117.41	28	61.00
4	Annual average growth in mean welfare	114	0.02	97	0.01	37	0.02	28	0.02
5	Poverty headcount ratio (%)	114	47.85	97	43.6	37	74.54	28	78.22
6	Poverty headcount ratio (%)	114	32.99	97	38.3	37	65.66	28	72.53
7	Annual average rate of reduction in poverty	109	-0.04	89	-0.02	37	-0.01	28	-0.01
8	Extreme poverty headcount ratio (%), first survey	114	31.84	97	29.68	37	57.59	28	62.08
9	Extreme poverty headcount ratio, last survey	114	18.94	97	23.1	37	43.48	28	51.76
10	Annual average rate of reduction in extreme poverty	103	-0.05	82	-0.03	37	-0.02	28	-0.02
11	Gini index, first survey	107	42.27	97	41.48	35	46.77	28	47.78
12	Gini index, last survey	112	40.23	97	41.35	37	44.18	28	44.01
13	Annual average rate of change in Gini	107	0.00	97	0.00	35	0.00	28	-0.01
	Other initial conditions:								
14	Gross primary school enrollment (%)	112	94.66	95	92.42	37	79.71	28	75.18
15	Life expectancy at birth (years)	114	62.03	97	61.66	37	52.88	28	50.66
16	Relative price index of investment from PWT6.2	105	70.97	93	79.7	34	93.86	28	108.58
17	Share of income in the middle three quintiles (%)	114	45.3	97	46.07	37	42.34	28	42.09
18	per capita expenditure from national account	98	280.83	90	177.78	31	141.23	28	60.93

Notes: Welfare in the RDS is measured in 2005 Purchasing Power Parity (PPP) terms; and is measured in 2011PPP terms in the EDS. Poverty in the RDS is measured against the international poverty lines of $2 and $1.25 per person per day in 2005PPP terms. Poverty in the EDS is measured against $3.2 and $1.9 in 2011 PPP terms.

Since a special focus of this paper is on SSA, we also report in Table 1 summary statistics from the SSA sub-samples of the RDS and the EDS. Compared to LDCs, SSA countries as a whole experienced about the same growth in mean, less poverty reduction, and more reduction in inequality. Before analyzing and reporting on poverty convergence in the SSA region, however, we need to address two valid concerns. First, are the SSA sub-samples representative of the region? And second, is there sufficient sample variance within them to capture the true relationship? Although it would be preferable to have access to even larger SSA samples, we feel that the present samples are relatively representative of the geographical and economic diversity of the subcontinent. As one can see in Appendix A, of the 47 less developed countries in SSA[14], our SSA sub-samples have covered, respectively, 28 during 1977-2007 and 37 during 1981-2014. We recognize that the SSA subsamples of the RDS and the EDS may not be ideal to capture poverty convergence due to lack of sufficient variance in the initial level of poverty. However, whether this translates into a standard deviation of the OLS estimator that is too large to be useful also depends on the size of the error variance and the correlation among the independent variables. For statistical inference, what matters is how big the estimator is in relation to its standard error (Wooldridge 2009: 97-99). As we shall see in Section IV.2, our SSA estimators have sufficiently large t-statistics after correcting for heterskedasticity; which lends us confidence in our SSA results. Technical grounds aside, there are important factors that make the SSA subsamples appealing to the subject of poverty convergence. Most of the SSA countries covered in the sample have experimented with policy reforms, often transiting from state-led to market-led economic systems. Also, the commitment of the international community to tackle extreme poverty in these countries may have added to the momentum for policy orientation in favor of poverty reduction, particularly in low-income countries where the influence of the donor community has a much stronger effect on public policy.

III.2 Choice of Regression Approaches

To analyze the data, we run them through the empirical model represented in Section II following three regression procedures. The first is the simple Ordinary Least Squares (OLS) approach, where the estimator minimizes the sum of squared residuals.

Next, we consider an MM estimator proposed by Yohai (1987) to correct for potential bias due to outliers. In their replication of Ravallion (2012) results, Cuaresma *et al.* (2016) found poverty convergence significant at the 5% level if as few as four outliers in the RDS were removed from the analysis or accounted for through a dummy variable[15]. Upon careful consideration of this concern, we come to realize that to properly correct for outliers, including an outlier dummy in a standard OLS regression is not the best way; as OLS estimator minimizes the sum of squared residuals, while squaring inevitably award excessive importance to outliers which have larger residuals. A better estimator needs to be one that uses a loss function which can mitigate the excessive weight given to outliers. Among the several classes of outlier-robust estimators proposed to correct for outliers in linear regressions, as demonstrated cogently in Verardi and Croux (2009), the MM-estimators introduced by Yohai (1987) are preferred as (i)

[14] According to the World Bank country classification, there are 48 countries in the SSA region, of which 47 are developing countries (with the only exception being Seychelles).

[15] Cuaresma *et al.* (2016) also found that poverty convergence would be significant at the 1% level if, in addition to the four above mentioned, another seven outliers were also removed. All these outliers happened to be transition economies from Central and Easter Europe. Their findings are found robust to the choice of poverty line.

they have a high breakdown point of 50% and therefore are robust to outliers of all types[16]; and (ii) they are highly efficient when errors follow a normal/Gaussian distribution.

But still, we are concerned about endogeneity due to measurement error. Following Ravallion (2012), we address this concern by estimating a cross-sectional Generalized Method of Moments (GMM) estimator, which controls for endogeneity like a regular Instrument Variable (IV) estimator, but improves its efficiency in the presence of heterskedasticity of unknown form (Baum *et al.* 2003). Noticing that a subset of some 70 countries in the RDS and some 90 countries in the EDS are surveyed three times[17], we use information from the extra one survey as instrument in the GMM estimation. Specifically, for poverty convergence rate, we regress the poverty reduction rate from the latter two surveys on an inter-temporal initial poverty from averaging poverty in the former two surveys, which is then instrumented by poverty level from the first survey and the number of years between the first two surveys.

As we shall report in section IV, all three procedure give consistent estimates suggesting a lack of poverty convergence across LDCs but strong poverty convergence across countries in SSA.

[16] A breakdown point of 50% means 50% of the incorrect observations an estimator can handle. An estimator that are not corrected for outliers has a breakdown point of 0. A breakdown point cannot exceed 50% because if more than half of the observations are contaminated, it is not possible to distinguish between the underlying distribution and the contaminating distribution.

[17] We construct the 3-wave EDS from the original WDI data, where most countries are surveyed more than twice. We decide the middle survey would be the median survey if the country is surveyed odd number of times; and the survey immediately before the median year if the country is surveyed even number of times. We obtain the 3-wave RDS from Ravallion (2012).

Before moving to the results section, it may be worth noting that our analysis in this paper is largely cross-sectional. Though cross-sectional analysis has become less popular compared to panel analysis in recent years, we find it appropriate in this study. Indeed, the main appeal of panel analysis is that it could address endogeneity due to existence of unobservable but time-invariant heterogeneity across observation units, namely fixed effects, through differencing. In this study, however, differencing could introduce new source of endogeneity while removing fixed effects, as we have lagged independent variable, which would become related to the error term after differencing[18]. Specifically, suppose we would like to estimate poverty convergence rate β in Equation (1) $g(H_{it}) = \alpha_i + \beta_i \ln H_{it-1} + \varepsilon_{it}$, where ε_{it} can be viewed as consisting of two parts: a fixed effect part a_i and an idiosyncratic part v_{it}. First differencing would give (7) $g(H_{i,t}) - g(H_{i,t-1}) = \alpha_i + \beta_i(\ln H_{it-1} - \ln H_{it-2}) + (v_{it} - v_{it-1})$. One immediately notices in Equation (7) that while fixed effect a_i is removed, the regressor now becomes correlated with the error term through v_{it-1}.

Cross-sectional analysis is also appropriate in this study as our focus here is *cross-countr*y poverty convergence which explores whether, during a given period of time and on average, countries starting out with higher poverty incidences experience faster reduction in poverty than those starting out richer. In this case, exploring information on the time-series

[18] Citing a simulation study by Hauk and Wacziarg (2009), Ravallion (2012: 517) suggested that fixed effects (FE) regression is not suitable for convergence analysis as it tends to “heavily underestimate the effects of initial conditions on subsequent growth in mean”, hencing making FE estimates “not useful for detecting true relationships” and “hard to [be] take[n] seriously”. However we find this less relevant in determining whether differencing is a suitable approach in this analysis, as OLS regression of the EDS also gives a negligible effect of initial poverty on subsequent growth.

dimension is not indispensable. Considering panel data of course would reveal new information on the time-series dimension. Specifically, panel data would allow us to investigate whether countries tend to experience faster reduction in poverty as their own initial poverty incidences drop *over time*. We refer to this type of poverty convergence as *within-country* poverty convergence, and recognize it as different from cross-country poverty convergence, and have explored it, in a separate paper (Ouyang *et al.* 2018), using four panel data sets and a *panel* Generalized Method of Moments approach which allows us to address both fixed effects and other idiosyncratic disturbances (Arellano and Bond 1991; Arellano and Bover 1995; Cameron and Trivedi 2005; Roodman 2009).

IV. Cross-Country Poverty Convergence in the Developing World and in SSA

Have Less Developed Countries (LDCs) as a whole experienced any poverty convergence during 1977-2014; and why? What about their members from Sub-Saharan Africa (SSA), where the poverty-growth dynamics is found to be different from the rest of the developing world? In this section we present our analysis results based on empirical model, data, and econometric approaches described in the previous sections.

IV.1. Poverty convergence across less developed countries (LDCs)

Table 2 below reports poverty convergence rates from estimating Equation (1) in Section II. In this table we see all three estimates (OLS, MM, and GMM) suggest a lack of cross-country poverty convergence among LDCs during the two periods studied, regardless of the choice of poverty line and inclusion of controls[19].

Table 2: Poverty Convergence across LDCs, by Data Set and Poverty Line

RDS (1977-2007)	Conditional	Unconditional		
	OLS	OLS	MM	GMM
$2/day in 2005PPP terms				
Initial poverty headcount ratio ($\ln H_{it-\tau}$)	0.004	0.021	.004	0.028*
	[0.241]	[1.872]	[1.415]	[2.226]
Initial relative price index of investment	0.036**			
	[2.736]			
N	64	68	68	68
R^2 or F	0.228	.097		4.811
$1.25/day in 2005PPP terms				
Initial poverty headcount ratio ($\ln H_{it-\tau}$)	-0.019	0.005	0.017*	.0243
	[-0.806]	[0.328]	[2.631]	[1.191]
Initial relative price index of investment	0.035*			
	[2.182]			
N	59	62	62	66
R^2 or F	0.240	0.006		1.375
EDS (1981-2014)	Conditional	Unconditional		
	OLS	OLS	MM	GMM
$3.2/day in 2011PPP terms				
Initial poverty headcount ratio ($\ln H_{it-\tau}$)	-0.016	0.004	0.008	-0.006
	[-1.066]	[0.406]	[0.424]	[-0.576]
Initial life expectancy at birth	-0.160*			
	[-2.284]			
N	68	90	90	90
R^2 or F	0.211	.006		0.325

[19] For the sake of conciseness, Table 2 reports only statistically significant OLS estimates from Equation (1) with controls including gross primary school enrollment rate, life expectancy at birth, relative price index of investment goods (as a measure of market distortions), and per capita consumption expenditure from national accounts.

$1.9/day in 2011PPP terms				
Initial poverty headcount ratio ($\ln H_{it-\tau}$)	-0.011	0.003	0.015	0.001
	[-0.915]	[.454]	[1.049]	[0.163]
Initial relative price index of investment	0.0421**			
	[2.848]			
N	64	85	85	87
R^2 or F	0.2259	.004		0.026

Notes: This table reports empirical poverty convergence rate (β_i) in Equation (1): $g_i(H_{it}) = \alpha_i + \beta_i \ln H_{it-\tau} + \varepsilon_{it}$, with and without controlling for other initial conditions including log initial Gini coefficient, log initial primary enrollment, log initial life expectancy, log initial price index of investment goods. For sake of conciseness we only report statistically significant OLS estimates from Equation (1) with controls. T-ratios are corrected for heteroskedasticity and reported in brackets. F-statistics are reported for cross-sectional GMM estimates. Wherever applicable, critical values for small sample sizes are used to determine the significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To see what explains the lack of poverty convergence in LDCs, we then estimate Equations (4) and (5) as specified in Section II, which explore the interrelationships among the rates of mean growth and poverty reduction and their initial values. We report our results in Tables 3 and 4 below. For the sake of conciseness, we shall report only OLS estimates in the rest of this paper, unless otherwise specified.

Table 3: Regressions of Mean Consumption Growth and Poverty Reduction on Initial Mean and Initial Poverty by Data Set and Poverty Line, among all LDCs as a group

	RDS (1977-2007)			
	Eq(4)		**Eq(4) with controls**	
	Z=\$1.25	Z=\$2	Z=\$1.25	Z=\$2
Log initial mean ($\hat{\beta}$)	-0.044***	-0.044***	-0.051***	-0.050***
	[-11.02]	[-12.89]	[-11.31]	[-11.56]
Log initial poverty ($\hat{\gamma}$)	-0.015***	-0.025***	-0.015*	-0.028***
	[-4.41]	[-7.82]	[-2.67]	[-5.47]
Log initial relative price index of investment goods			-0.017**	-0.017**
			[-2.82]	[-2.98]
N	64	69	64	69
R2	.380	.384	.552	.557
	EDS (1981-2014)			

	Eq(4)		Eq(4) with controls	
	Z=$1.25	Z=$2	Z=$1.25	Z=$2
Log initial mean ($\hat{\beta}$)	-0.040***	-0.031**	-0.049*	-0.050**
	[-3.805]	[-3.090]	[-2.49]	[-2.76]
Log initial poverty ($\hat{\gamma}$)	-0.011***	-0.0102*	-0.007	-0.011
	[-3.409]	[-2.194]	[-1.22]	[-1.73]
Log initial relative price index of investment goods			-0.011	-0.010
			[-1.76]	[-1.69]
N	92	93	65	82
R^2	.241	.184	.440	.435

Notes: This table reports $\hat{\beta}$ and $\hat{\gamma}$ from Equation (4) $g_i(\mu_{it}) = \alpha + \beta ln\mu_{it-\tau} + \gamma lnH_{it-\tau} + \varepsilon_{it}$, with and without controlling for other initial conditions including log initial Gini coefficient, log initial primary enrollment, log initial life expectancy, log initial price index of investment goods. T-ratios are in brackets and corrected for heteroskedasticity. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Estimates in Table 3 above suggest two things. First, for a given initial poverty level, countries starting out with lower levels of initial mean consumption subsequently enjoyed a faster growth in mean ($\hat{\beta}$); and this is robust to the inclusion of other initial conditions and to the choice of poverty line and time period. Second, controlling for initial mean consumption level, initial poverty directly retards subsequent growth in mean ($\hat{\gamma}$); this, however, is not robust to the inclusion of controls in the EDS which covers some 20 more LDCs and seven more years than the RDS. In another word, the direct effect of initial poverty on subsequent growth in mean, which Ravallion (2012) identified as a main impediment to poverty convergence during 1977-2007, is not robust when we examine a larger sample covering longer time period.

Estimates reported in Table 4 below, on the other hand, suggest that for both periods examined, mean consumption growth -adjusted to initial level of poverty is less effective in reducing poverty in countries with higher initial poverty incidence ($\hat{\eta}$); and this holds for both periods examined[20].

Together, estimates in Tables 3 and 4 suggest that for LDCs during 1977-2007, the lack of cross-country poverty convergence results from mean convergence effect canceled by the combination of two adverse poverty effects; and all three effects are statistically significant and robust. This is nothing new but only confirms what Ravallion (2012) reported, though our sample size is slightly smaller as we focus on countries with mean consumption expenditure data. The new observation we make in this paper, is that the lack of poverty convergence across LDCs during the extended period of 1981-2014, however, is only explained by an adverse poverty elasticity effect large enough to wipe out the mean convergence effect; while a direct effect of initial poverty on subsequent growth in mean, plays little role. That is, a direct effect of initial poverty on subsequent growth in mean, which Ravallion (2012) recognized as a key to the lack of cross-country poverty convergence in the developing world during 1977-2007, may only be transitory.

Table 4: Poverty-adjusted Mean Consumption Growth Effectiveness for Poverty Reduction by Data Set and Poverty, among all LDCs as a group

	RDS (1977-2007)	
	Z=$1.25	**Z=$2**
Poverty-adjusted growth in mean	-2.70***	-2.651***
$(1 - H_{it-\tau})g_i(\mu_{it})$	[-6.61]	[-6.44]
N	68	62
R^2 or χ^2	.686	.526
	EDS (1981-2014)	
	Z=$1.25	**Z=$2**
Poverty-adjusted growth in mean	-3.30***	-3.209***

[20] We also note these growth elasticity estimates are quite similar to those obtained from estimating the Identity Model (Thorbecke and Ouyang 2017) using panel data.

$(1-H_{it-\tau})g_i(\mu_{it})$	[-7.49]	[-6.50]
N	85	90
R^2 or χ^2	.477	.511

Notes: This table reports $\hat{\eta}$ from Equation (5): $g_i(H_{it}) = \eta(1-H_{it-\tau})g_i(\mu_{it}) + v_{it}$. T-ratios are in brackets and corrected for heteroskedasticity. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

With estimates from Tables 3 and 4, along with sample averages of initial poverty level and mean consumption growth rate, and the standard elasticity obtained from regressing poverty reduction rate against growth in mean (namely, $\frac{\partial lnH_{it-\tau}}{\partial ln\mu_{it-\tau}}$, as opposed to $\hat{\eta}$ which is the poverty-adjusted growth elasticity of poverty reduction), we are able to compute the sizes of the three contributing effects and hence see their relative contribution to poverty convergence. We refer to this exercise as decomposition of poverty convergence and report the full results in Table 5 below, where we note that the poverty elasticity remains robust during both periods examined, and has become larger in magnitude during the extended period, i.e. 1981-2014.

Table 5: Decomposing Poverty Convergence in LDCs, by Data Set and Poverty Line

RDS (1977–2007)	**z=$1.25**	**z=$2**	**EDS (1981–2014)**	**z=$1.25**	**z=$2**
Mean convergence effect	-.060 *	-.053 *	Mean convergence	-.059 *	-.049 *
Direct effect of poverty	.020 *	.032 *	Direct effect of poverty	.024	.018
Indirect effect of poverty	.019 *	.025 *	Indirect effect of	.028 *	.039 *
Sum of the three effects	-.024	.004	Sum of the three effects	-.007	.008
Empirical poverty convergence rate	.005 [0.33]	.021 [1.87]	Empirical poverty convergence rate	.003 [0.45]	.004 [0.41]
N	62	68	N	85	90
R^2	.006	.097	R^2	.004	.006

Notes: The table reports the three contributing effects to poverty convergence in Equation (6): $\frac{\partial g_i(H_{it})}{\partial lnH_{it-\tau}} = \eta\beta(1-H_{it-\tau})\left(\frac{\partial lnH_{it-\tau}}{\partial ln\mu_{it-\tau}}\right)^{-1} + \eta\gamma(1-H_{it-\tau}) + [-\eta g_i(\mu_{it})H_{it-\tau}]$; where β, γ, and η are from Tables 3 and 4. Effects are robust and denoted by an asterisks (*) if β, γ, and η in computing them are robust. The sum of the three effects give the predicted poverty convergence rates which may or may not exactly match the empirical rates from estimating Equation (1):

$g_i(H_{it}) = \alpha_i^* + \beta_i^* \ln H_{it-\tau} + \epsilon_{it}^*$ as reported in Table 2.

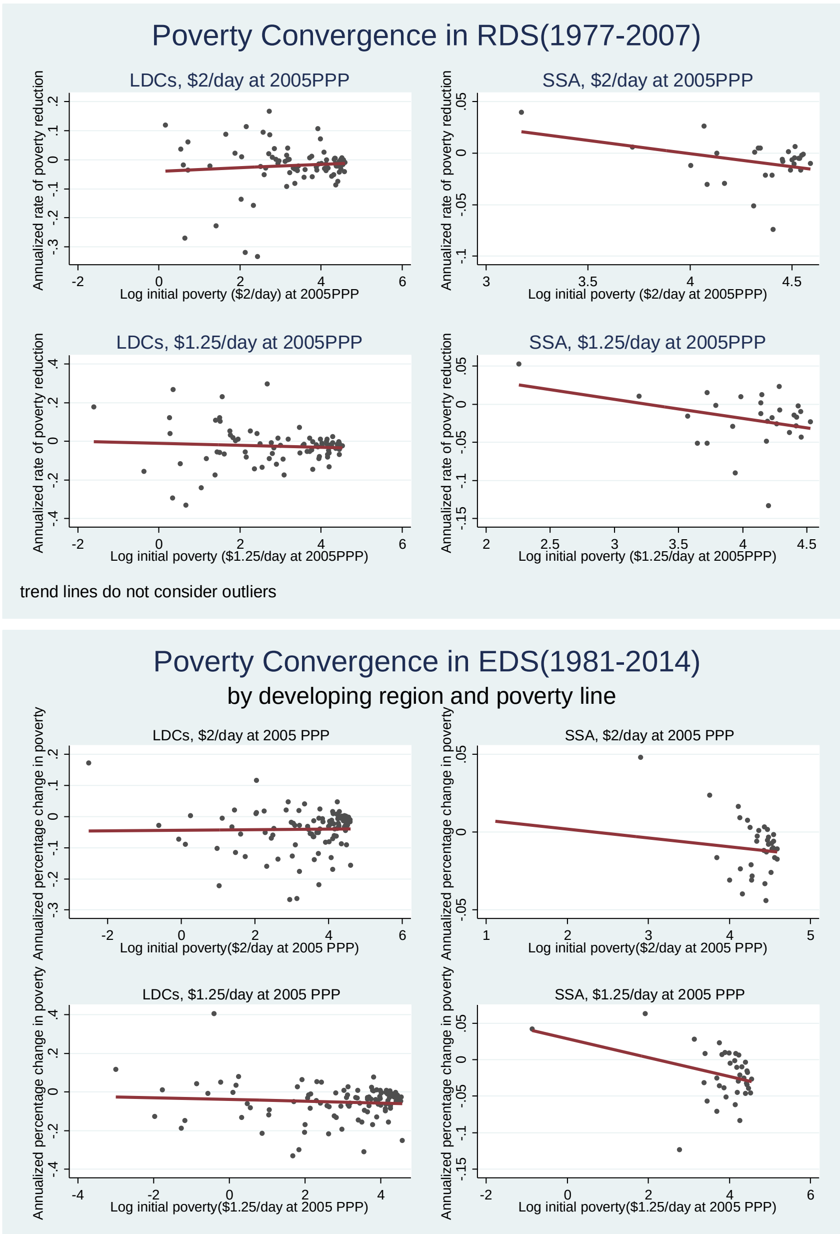
To summarize this section (IV.1): between the late 1970s and the early 2010s, LDCs as a whole experienced little cross-country poverty convergence despite strong convergence in mean. An adverse poverty elasticity effect offsetting the mean convergence effect explains the lack of poverty convergence across LDCs throughout the entire period examine (1977-2014); while a direct poverty effect only plays a role during a sub-period, i.e. 1977-2007.

IV.2. Poverty convergence across countries in Sub-Saharan Africa (SSA)

Despite having experienced a resurgence since the beginning of the new millennium (Thorbecke and Ouyang 2016), countries in Sub-Saharan Africa (SSA) remain the poorest among all developing countries. In 2013, their average headcount ratio was still as high as 66% and 41%, respectively, for poverty measured against \$1.9 and \$3.2 (in 2011 PPP terms); as opposed to 29% and 11% for LDCs in the same year (PovcalNet regional aggregation). Have countries in SSA experienced poverty convergence among themselves during the past decades? And how has initial poverty affected the pace of poverty convergence in SSA?

We start our investigation by plotting the annual average rate of poverty reduction ($g_i(H_{it})$) against the initial poverty level ($\ln H_{it-\tau}$) using SSA data the RDS and the EDS. Figure 1 below shows that the poverty convergence trend in SSA is different from that in LDCs during both periods examined. LDCs starting out poorer (greater values on the horizontal axis) do not seem to experience faster reduction in poverty (more negative values on the vertical axis). There even seems to exist a positive relationship between initial poverty and its annual rate of change, i.e. poverty divergence, across LDCs when poverty is measured against the higher poverty line, which is more relevant for most developing countries today. Among SSA countries, in contrast, those with higher initial poverty levels experienced faster pace of poverty reduction. This is more obvious for poverty measured against the lower poverty line ($1.25 in 2005PPP terms or equivalently $1.9 in 2011PPP terms), which is arguably more relevant for SSA countries. What is also worth noting here, is that SSA countries in the EDS (1981-2014) started out at about the same level of initial poverty, but ended experiencing quite different poverty reduction rates. This is likely because some SSA countries are more committed to anti-poverty policies while some are less committed; hence implying the crucial role of government policies in reducing the adverse poverty effect on subsequent growth in mean and poverty reduction.

Figure 1: Poverty Convergence by Data Set/Time Period, Poverty Line, and Region



Next we estimate poverty convergence rate from Equation (1) as specified in Section II. As reported in Table 6 below, SSA experienced significant cross-country poverty convergence during the three decades examined, and the convergence is robust to the choice of poverty lines and inclusion of controls.

Table 6: Poverty Convergence across countries in SSA, by Data Set and Poverty Line

RDS (1977-2007)	Conditional	Unconditional		
	OLS	**OLS**	**MM**	**GMM**
$2/day in 2005PPP terms				
Initial poverty headcount ratio	-0.041***	-0.025*	-0.030**	-0.017*
	[-4.400]	[-2.374]	[-3.532]	[-2.267]
Initial life expectancy at birth	-0.095**			
	[-3.267]			
N	28	28	28	17
R^2 or F	0.432	0.134		4.533
$1.25/day in 2005PPP terms				
Initial poverty headcount ratio	-0.037***	-0.025*	-0.031**	-0.028*
	[-4.422]	[-2.386]	[-7.434]	[-2.208]
Initial life expectancy at birth	-0.125*			
	[-2.356]			
N	28	28	28	17
R^2 or F	0.364	0.113		4.300
EDS (1981-2014)	**Conditional**	**Unconditional**		
	OLS	**OLS**	**MM**	**GMM**
$3.2/day in 2011PPP terms				
Initial poverty headcount ratio	-0.039**	-0.006	-0.038***	-0.017
	[-3.496]	[-0.871]	[-12.01]	[-0.854]
Initial life expectancy at birth	-0.079*			
	[-2.22]			
Initial per capita consumption expenditure from national account	-0.013*			
	[-2.418]			
N	28	37	37	23
R^2 or F	0.490	0.031		0.666
$1.9/day in 2011 PPP terms				
Initial poverty headcount ratio	-0.034*	-0.013*	-0.034***	-0.024
	[-2.37]	[-2.361]	[-9.072]	[-1.220]
	*no * control*			
N	28	37	37	23
R^2 or F	0.408	0.1223		1.358

Notes: This table reports empirical poverty convergence rate (β_i) in Equation (1): $g_i(H_{it}) = \alpha_i + \beta_i \ln H_{it-\tau} + \varepsilon_{it}$, with and without controlling for other initial conditions including log initial Gini coefficient, log initial primary enrollment, log initial life expectancy, log initial price index of investment goods. For sake of conciseness we only report statistically significant OLS estimates from Equation (1) with controls. T-ratios are corrected for heteroskedasticity and reported in brackets. F-statistics are reported for cross-sectional GMM estimates. Wherever applicable, critical values for small sample sizes are used to determine the significance level: $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$. Outliers identified in MM regressions are Carbo Verde and

Mauritius for poverty measured against both poverty lines.

How do growth in mean consumption expenditure and distributions of initial mean and initial poverty contribute to the strong poverty convergence across SSA countries reported in Table 6 above? As shown in Table 7 below, SSA countries experienced significant convergence in mean consumption expenditure but little direct poverty effect during both periods examined, whether or not other initial conditions are controlled for.

Table 7: Regressions of Growth in Mean on Initial Poverty and Initial Mean by Data Set/ Time Period and Poverty Line, SSA sub-samples

	RDS (1977-2007)			
	Eq(4) without controls		**Eq(4) with controls**	
	Z=$1.25	Z=$2	Z=$1.25	Z=$2
Log initial mean ($\hat{\beta}$)	-0.025	-0.029	-0.049*	-0.044*
	[-1.45]	[-1.79]	[-2.35]	[-2.31]
Log initial poverty ($\hat{\gamma}$)	0.004	-0.004	-0.012	-0.007
	[0.23]	[-0.14]	[-0.55]	[-0.26]
Log initial life expectancy			.124*	.125*
			[2.62]	[2.53]
N	28	28	28	28
R2	.171	.171	.474	.471
	EDS (1981-2014)			
	Eq(4) without controls		**Eq(4) with controls**	
	Z=$1.25	Z=$2	Z=$1.25	Z=$2
Log initial mean ($\hat{\beta}$)	-.038**	-.0379**	-.0312	-.033
	[-3.28]	[-3.51]	[-0.55]	[-0.51]
Log initial poverty ($\hat{\gamma}$)	-0.009	-0.014	0.063	0.074
	[-1.62]	[-1.82]	[0.97]	[0.85]
Share of middle class population by western standard			.0084**	.0095*
			[3.10]	[2.83]
N	37	37	26	26
R^2	.344	.347	.742	.735

Notes: This table reports $\hat{\beta}$ and $\hat{\gamma}$ from Equation (4) $g_i(\mu_{it}) = \alpha + \beta ln\mu_{it-\tau} + \gamma lnH_{it-\tau} + \varepsilon_{it}$, without and with controlling for other initial conditions including log initial Gini coefficient, log initial primary enrollment, log initial life expectancy, log initial price index of investment goods, and three measures of middle class (see section III for definition of middle class). We report only the significant controls. Cross-sectional regressions follow a simple Ordinary Least Square (OLS) procedure; and panel regressions a Fixed-Effects (FE) procedure because Hansen and Sargan test statistics suggest PGMM results are weakened by instruments and not robust. T-ratios are in brackets and corrected for hetero-skedasticity. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

On the other hand, as shown in Table 8 below, initial poverty indirectly hinders poverty convergence by making growth less effective in reducing poverty during both periods examined, regardless of the choice of poverty line. And since the size of the poverty elasticity effect turns out to be much smaller than that of the mean convergence effect, which we report in Table 9 after Table 8, SSA ended up experiencing strong poverty convergence.

Table 8: Poverty-adjusted Mean Consumption Growth Effectiveness for Poverty Reduction by Data Set/Time Period and Poverty Line, SSA sub-samples

	RDS (1977-2007)	
	Z=$1.25	**Z=$2**
Poverty-adjusted growth in mean	-2.291***	-2.269***
$(1 - H_{it-\tau})g_i(\mu_{it})$	[-6.26]	[-6.57]
N	28	28
R^2 or χ^2	.803	.826
	EDS (1981-2014)	
	Z=$1.25	**Z=$2**
Poverty-adjusted growth in mean	-2.092***	-1.970***
$(1 - H_{it-\tau})g_i(\mu_{it})$	[-8.63]	[-9.33]
N	37	37
R^2 or χ^2	.596	.761

Notes: This table reports $\hat{\eta}$ from Equation (5): $g_i(H_{it}) = \eta(1 - H_{it-\tau})g_i(\mu_{it}) + v_{it}$. T-ratios are in brackets and corrected for heteroskedasticity. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: Decomposing Poverty Convergence by Data Set and Poverty Line, SSA samples

RDS (1977–2007)	z=$1.25	z=$2	EDS (1981–2014)	z=$1.25	z=$2
Mean convergence effect	-.027 *	-.031 *	Mean convergence effect	-.047 *	-.109 *
Direct effect of poverty	-.003	.002	Direct effect of poverty	.008	.024
Indirect effect of poverty	.029 *	.036 *	Indirect effect of poverty	.025 *	.047 *
Sum of the three effects	-.001	.007	Sum of the three effects	-.014	-.037
Empirical poverty	-.025*	-.025*	Empirical poverty	-.013*	-.038***
convergence rate	[-2.39]	[-2.37]	convergence rate	[-2.36]	[-12.05]
N	28	28	N	37	37
R^2	.113	.134	R^2	.122	-

Notes: The table reports the three contributing effects to poverty convergence in Equation (6): $\frac{\partial g_i(H_{it})}{\partial lnH_{it-\tau}} = \eta\beta(1 - H_{it-\tau})\left(\frac{\partial lnH_{it-\tau}}{\partial ln\mu_{it-\tau}}\right)^{-1} + \eta\gamma(1 - H_{it-\tau}) + [-\eta g_i(\mu_{it})H_{it-\tau}]$; where β, γ, and η are from Tables 7 and 8. Effects are robust and denoted by an asterisks (*) if β, γ, and η in computing them are statistically significant and robust to inclusion of controls. The sums of these three effects give the predicted poverty convergence rates which may or may not exactly match the empirical rates from estimating Equation (1): $g_i(H_{it}) = \alpha_i^* + \beta_i^* \ln H_{it-\tau} + \epsilon_{it}^*$ as reported in Table 6.

Taken together, analysis in Section IV.2 suggests that during the three decades examined, SSA experienced significant and robust cross-country poverty convergence explained by a strong mean convergence effect weakened by an adverse indirect effect of initial poverty, while a direct poverty effect is not found.

V. Conclusion

In this paper, we explore cross-country poverty convergence in the developing world during 1977-2014 with a special focus on SSA.

Much of the empirical evidence crrently relies on Ravallion (2012), who documented a lack of cross-country poverty convergence in the developing world during 1977-2007 because high initial poverty cancels the convergence in mean and the advantage of growth not only through indirectly weakening the effectiveness of growth in reducing poverty, but also through directly impeding growth --- which is not documented in previous literature.

Our study adds to the small but important literature. First, we find that while cross-country poverty convergence remains missing in the developing world during the extended period of 1981-2014, it is explained by initial poverty wiping off the mean convergence effect, whereas a robust direct link between high initial poverty and low subsequent growth is not found. Second, we present the first --- to the best of our knowledge --- empirical evidence on cross-country poverty convergence in SSA during both 1977-2017 and 1981-2014. The convergence is explained by a strong mean convergence effect and an indirect poverty effect which, though equally significant, is much less sizable. Our finding for the existence of strong poverty convergence in SSA is consistent with past research which finds that the region has experienced faster growth in per capita income, reduction in poverty, and improvement in inequality after the mid-1990s (Pinkovskyi and Sala-i-Martin 2014; Fosu 2015); and that poverty reduction in SSA has become more responsive to income growth and improvement in inequality in recent years (Thorbecke and Ouyang 2017).

An important implication of our findings is that effective poverty reduction relies on not just growth, but growth that is inclusive; because initial poverty is found to impede the pace of poverty reduction mainly through weakening the effectiveness of growth in reducing poverty. For inclusive growth, government policies conscientiously designed to help lagging regions may be crucial, as the strong poverty convergence we find across SSA countries could well be related to anti-poverty government policies that many of these countries are committed to since the beginning of the new millennium; though testing this hypothesis would require additional data and goes beyond the scope of this paper.