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ABSTRACT

Do Developing Countries Enjoy Faster Poverty Reduction as Their Initial Poverty Incidences Decline over Time? A Dynamic Panel Analysis

Empirical evidence in the sparse literature on poverty convergence currently relies on cross-sectional analysis, where Less Developed Countries (LDCs) starting out poorer are found to have enjoyed no faster subsequent poverty reduction during the past three decades than those starting out richer, as initial poverty retards growth and makes it less effective in reducing poverty. Applying a dynamic panel approach to four panel data sets including two covering some 90 LDCs from 1977-2014 and two covering, respectively, 42 Ethiopian and 33 Rwandan regions during 1995-2010 and 2000-2010; this study finds that LDCs as well as Ethiopian and Rwanda regions do enjoy faster subsequent poverty reduction within themselves as their initial poverty incidences decline over time. Our analysis also finds initial poverty as having little direct effect on growth in LDCs, except in SSA where higher initial poverty is associated with faster growth.

JEL Classification: O10, O40, I32

Keywords: within-country poverty convergence, growth, poverty, less developed countries, Sub-Saharan Africa

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I. Introduction

By 2014, up to 23 percent of the world's population, or 1.6 billion individuals, still live at less than $2 per day(in 2005 Purchasing Power Parity terms (de Janvry and Sadoulet 2016: 82). As growth remains the most important means through which poverty reduction is attained, it is crucial that we understand the links between growth and poverty reduction.

One very important yet much less studied inquiry in this regard, is how the pace of poverty reduction is linked to initial poverty level, or the issue of poverty convergence.One might expect the existence of poverty convergence, as countries starting out poorer are widely documented to have enjoyed faster growth in mean than those starting richer (for example, Barro 1991, 1996; Mankiw et al. 1992; and more recently de Janvry and Sadoulet 2016); and growth is found to be good to the poor 2016 (Dollar and Kraay 2002; Dollar, Kleinberg, and Kray 2016).

Empirical evidence currently available, however, suggests the opposite. Using cross-country data from some ninety Less Developed Countries (LDCs) during 1977-2007, Ravallion (2012) found LDCs with higher initial poverty incidences did not, on average, enjoy faster poverty reduction; even though they did enjoy faster growth in mean. This finding is largely confirmed in a recent exercise of ours using cross-sectional data from the same sources but an extended period (i.e. 1981-2014); though we do find cross-country poverty convergence if analysis is limited to countries in Sub-Saharan

Africa (SSA)[1].

Cross-sectional analysis is useful to the extent that it allows a comparison of time-average poverty reduction rates across countries and hence sheds light on whether there is a catch-up effect in poverty reduction favoring countries starting out poorer over those starting out relatively richer. But leaving out information from the time-series dimension means that cross-sectional analysis cannot satisfactorily answer a perhaps more relevant inquiry from the viewpoint of individual developing countries, which is: *do countries enjoy faster subsequent poverty reduction within themselves as their initial poverty incidences decline over time?*

This study makes an attempt to understand poverty convergence in this sense ---- which we shall refer to as *within-country poverty convergence*, as distinct from *cross-country poverty convergence* documented in previous literature ---- in the hope that it would contribute to a more comprehensive understanding of the link between growth and poverty reduction in the developing world; and potentially provide extra incentives for policy makers to design and implement pro-poor policies.

The empirical model we use in this analysis, which we take from Ravallion (2012), consists of a set of equations standard within the class of Barro's growth

[1] Using Ravallion (2012)'s empirical model and a cross-sectional data set constructed from the August 2016 version of the World Development Indicators (WDI) database, we find that poverty convergence remains absent across LDCs during 1981-2014; though it is mainly explained by initial poverty canceling the effectiveness of growth in reducing poverty, whreas an adverse direct effect of initial poverty on growth --- which Ravallion (2012) recognized as the main impediment to cross-country poverty convergence during 1977-2007 --- is not found. For details see Ouyang *et al.* (2018).

regressions that together allows one to estimate a poverty convergence rate and decompose it into three contributing effects, including (i) a mean convergence effect, whereby, for a given initial poverty, lower initial mean income or consumption expenditure contributes to faster growth in mean; (ii) a direct poverty effect, whereby higher initial poverty directly hinders subsequent growth in mean at a given initial mean; and (iii) an indirect poverty effect, whereby higher initial poverty weakens the effectiveness of growth in reducing poverty reduction.

We use in total four panel data sets in this analysis, including (i) two from the World Bank covering some one hundred LDCs surveyed on average five and nine times during 1977-2007 and 1981-2014, respectively; and (ii) two from the African Development Bank covering, respectively, 42 Ethiopian regions each surveyed four times during 1995-2010 and 33 Rwanda regions each surveyed three times during 2000-2010.

We run these data through the empirical model following four panel regression procedures: (i) a system Generalized Method of Moments (SYSGMM) estimator; (ii) a difference GMM estimator with forward orthogonal deviations transformation (FODGMM); (iii) a standard pooled ordinary least square (POLS) estimator; and (iv) a standard fixed effects (FE) estimator. The two GMM estimators are variants of the dynamic panel estimator proposed in Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998). Following earlier works of Anderson and Hsiao (1981) and Holtz-Eakin, Newey and Rosen (1988), the Arellano-Bond estimator provides consistent and efficient estimates in situations with, among others, fixed effects but meanwhile right-hand variables that are correlated with past and possibly current realization of the error, in which case standard FE regression could give rise to Nickell's

(1981) dynamic panel bias (Roodman 2009). The POLS and FE regressions, for their part, are performed to provide references values between which consistent estimates should fall.

Our analysis suggests there exists significant poverty convergence within LDCs during 1977-2014 as a result of strong mean convergence effect only partly weakened by indirect poverty effect, which is highly significant but less sizable. A direct link between initial poverty and growth, for its part, is not found in LDCs as whole; and found to be significantly *positive* in SSA countries during the three decades examined. At the interregional level, similarly, we find initially poorer Ethiopian and Rwandan regions to have experienced faster poverty reduction during 1995-2010 and 2000-2010, respectively; as a strong mean convergence effect, combined with a significantly *positive* direct poverty effect, dominates a significant but less sizable indirect poverty effect.

We organize the rest of the paper follows. Section II describes the empirical model and our choice of econometric methods. Section III describes the data. Section IV reports empirical results and discussions. Section V concludes.

II. Empirical Model and Empirical Methods

II.1. Empirical Model

Though we depart from cross-sectional analysis, we find the empirical model developed by Ravallion (2012) suitable for panel analysis. Consisting of a number of regression equations standard within the class of Barro regressions motivated by the Solow-Swan model when augmented to allow initial distribution to affect the growth rate[2], the model allows the identification and decomposition of poverty convergence.

The first equation in the model is for the identification of mean convergence.

(1) $$g_i(\mu_{it}) = \alpha_i^* + \beta_i^* ln\mu_{it-\tau} + \epsilon_{it}^*$$

, where $\mu_{it-\tau}$ and μ_{it} are, respectively, country i's level of mean income or consumption at years t and year $(t-\tau)$; and $g_i(\mu_{it}) \equiv (\ln\mu_{it} - \ln\mu_{it-\tau})/\tau$ approximately equals the annual average rate of growth in mean for country i during the growth spell defined by the two years. Coefficient β is the mean convergence rate. If it is estimated to be significantly negative, then we have evidence for unconditional mean convergence at the rate of β --- meaning that if $ln\mu_{it-\tau}$ drops by one percent, the growth in mean would increase by β percentage points.

Next, assuming a log-linear relationship between poverty and mean income or consumption at any time as specified in Equation (2) below[3], we would obtain Equation (3) which will be used to test for poverty convergence.

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

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

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[2] Barro equations have been widely used in the convergence literature, though using time-average growth rates to study convergence over time does receive some skepticism. 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".

[3] Equation (2) is recognized by many as a strong assumption but remains standard in the literature.

In Equation (1), $H_{it-\tau}$ and H_{it} are, respectively, country i's poverty headcount ratio at years $(t-\tau)$ and t; and $g_i(H_{it}) \equiv (\ln H_{it} - \ln H_{it-\tau})/\tau$ is its annual average rate of poverty reduction during the period defined by $(t-\tau)$ and t. Coefficient β is of main interest in this study. If the regression returns a negative and statistically significant estimate of β, then we have evidence for 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. Through Equation (2), parameters in Equations (1) and (3) are related: $\alpha_i = \alpha_i^* \eta_i - \beta_i^* \delta_i$, $\beta_i = \beta_i^*$ and $\varepsilon_{it} = \varepsilon_{it}^* \eta_i + v_{it} - (1+\beta_i^*) v_{it-1}$. Here $\beta_i = \beta_i^*$ suggests that if there is no other forces at play, poverty convergence should not only accompany convergence in mean, but also happen at theoretically the same rate.

To explore how initial poverty and potentially other initial conditions affect growth, Ravallion (2012) augmented Equation (1) into Equation (4):

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

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 initial level of 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 initial poverty directly retards subsequent growth in mean welfare (upon controlling for the growth effect of initial mean). Likewise, we have evidence for a positive direct effect of initial poverty on subsequent growth if we obtain a significantly positive estimate of γ --- as is the case in SSA at country level and Ethiopia at interregional level as reported in Section IV.

The next equation, namely Equation (5) below, is for the identification of the indirect poverty effect:

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

The parameter η in this equation measures the growth effectiveness in reducing poverty, with growth adjusted to initial poverty level $(H_{it-\tau})$[4]. A significantly negative η would suggest an adverse indirect poverty effect on poverty convergence, meaning that a given growth in mean would be made less effective in reducing poverty if there is a higher initial poverty incidence.

The above equations allow one to identify whether there exists poverty convergence; and in which directions it is affected by convergence in mean and initial poverty. But what are the relative sizes of the three effects to the existence or absence of poverty convergence? To see this, 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) $$\frac{\partial g_i(H_{it})}{\partial lnH_{it-\tau}} = \eta\beta(1 - H_{it-\tau})\left(\frac{\partial lnH_{it-\tau}}{\partial ln\mu_{it-\tau}}\right)^{-1} + \eta\gamma(1 - H_{it-\tau}) + [-\eta g_i(\mu_{it})H_{it-\tau}].$$

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

[4] 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 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; but testing this hypothesis would go beyond the scope of this paper.

A main advantage of this empirical model, as mentioned above, is that it provides a neat framework allowing researchers to identify and then decompose poverty convergence into its main contributing factors. A potential 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). Ravallion (2012) suggested that inequality is irrelevant to the extent that only its change matters for poverty convergence, whereas the *cross-country average* Gini index in his data remains almost unchanged (at around 42). While this justifies the exclusion of inequality in the model, we note that changes in Gini could vary greatly by country leading to varying *country-specific* effect on poverty convergence.

II.2. Econometric Methods

A standard panel regression procedure is the Fixed Effects (FE) procedure whose main appeal is that it removes, through demeaning transformation, fixed effects, which is the part of error that is specific to individual groups, likely correlated with the regressor(s), but invariant over time.

In this analysis where regressions involve lagged regressor(s), however, standard FE regression may bring the so-called dynamic panel bias (Nickell 1981) as the demeaning process subtracting the mean value of the lagged regressor would create a correlation between the demeaned regressor and the error term. Specifically, suppose we would like to estimate poverty convergence rate β in Equation (3) $g(H_{it}) = \alpha_i + \beta_i \ln H_{it-1} + \varepsilon_{it}$, 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}.

Fortunately, we can address this concern by following the dynamic panel procedure known as the Arellano-Bond estimator (ABE), which is proposed and/or popularized by Arellano and Bond (1991) following earlier work of Anderson and Hsiao

(1981) and Holtz-Eakin, Newey and Rosen (1988). In obtaining an ABE, a demeaning transformation would be used to remove the fixed effect; and then the regressor in difference would be instrumented by its second, third, and potentially all available lags, either in the forms of lagged difference or lagged levels.

Specifically, if a first difference equation is estimated, instruments will be lagged levels, and the estimator is commonly referred to as difference GMM, as the ABE estimator is essentially a panel Generalized Method of Moments (GMM) estimator. One disadvantage of the first difference equation, however, is that it magnifies gaps in unbalanced panels. This motivates an alternative demeaning transformation: the forward orthogonal deviations (FOD) transformation, proposed by Arellano and Bover (1995). In contrast to first-difference transformation which subtracts the previous value from the current value, the FOD transformation subtracts the average of all available future observations from the current value, and hence computable for all periods except the last one, even in the presence of gaps in the panel.

Another potential weakness in the ABE estimator, as recognized in Arellano and Bover (1995) and Blundell and Bond (1998), is that the lagged levels are often poor instruments for differenced variables, especially if the lagged regressor is a random walk (Roodman 2009; Baum 2003). This motivates estimating two equations: a difference equation instrumented with lagged levels, and a level equation instrumented with lagged differences. This expanded estimator is known as system GMM as it estimates a system of (two) equations.

In this analysis, we estimate both system GMM (SYSGMM) and difference GMM with FOD transformation (FODGMM) using xtabond2 developed by Roodman

(2009). As these GMM estimators are instrument variables methods, we also report over-identification test statistics, including the Sargan (1958) test statistic and the Hansen (1982)'s J test statistic. We shall report p-values for both statistics, as the two each has its own advantage and disadvantage: the Hansen J test statistic is robust to the presence of heterskedasticity but tends to be weakened by large number of instruments; the Sargan test statistic, in contrast, is not robust to the presence of heterskedasticity but is also less weakened by large number of instruments. Roodman (2009: 99) cited Ruud (2000: 515) that there is little literature on how many instruments is "too many", and advised that instrument counts should not exceed the number of observations as "a minimally arbitrary rule of thumb". As we report in Section IV, the numbers of instruments we use in this analysis are all well below the corresponding numbers of observations; and all the Hansen/Sargan test statistics we obtain in this analysis have large p-values, leading to no rejection to the null that says the instruments are jointly exogenous/valid.

Another important diagnostic test to perform in running dynamic GMM regressions is the test for autocorrelation among the residuals. Following command default, we test for first- and second-order autocorrelation among residuals (AR(1) and AR(2)); and use lags from three and more periods earlier as instruments if AR(2) test statistic has large p-values.

Besides SYSGMM and FODGMM estimators, we also estimate the pooled OLS (POLS) and the standard FE estimators, as while the two estimators themselves tend to be inconsistent, their values provide to be useful reference: as the lagged regressor is positively correlated with the error in the POLS regression while negatively correlated with the error in the FE regression, consistent estimates should lie between the POLS and FE estimates[5].

III. Data Description

As mentioned in Section I, our four panel data sets include two at country level and two at interregional level. We shall describe them separately in Sections III.1 and III.2 below.

III.1 Country-level Panel Data

We obtain our first country-level panel data set, which we shall refer to as "The 1981-2014 Panel", from the August 2016 version of the World Bank Indicators (last accessed in February 2017). It contains 1,055 observations representing 114 developing countries each surveyed at least two and on average nine times during 1981-2014. Among the 1,055 observations, 627 representing 94 developing countries surveyed at least twice and on average seven times have per capita consumption expenditure data, and they constitute our 1981-2014 analysis sample, as consumption expenditure is commonly viewed as better welfare measures than income.

[5] Citing a simulation study by Hauk and Wacziarg (2009), Ravallion (2012: 517) suggested that FE regression is not ideal for convergence analysis as it tends to "heavily underestimate the effects of initial conditions on subsequent growth in mean" and hence "not useful for detecting true relationships" and "hard to [be] take[n] seriously". However we find this a less relevant point in determining whether FE should be performed in this analysis. As we report in Section IV, FE does identify initial mean, and in one case initial poverty, as mattering significantly for growth.

Our second country-level data set, which we shall refer to as "The 1977-2007 Panel", is from Fosu (2015:44) who "derived [the data] from the POVCALNET data of the World Bank"[6]. It contains 517 observations representing 97 developing countries surveyed at least twice and on average five times during 1977-2007. There is no information in this data set on the type of welfare indicator each country has --- it can be either consumption or income per person. However we do not expect this to largely bias our results, as regressions using all countries and using only countries with data on mean consumption growth give quite similar results in the 1981-2014 Panel. See Appendix for a list of countries in the 1981-2014 and 1977-2007 Panel.

Among the several poverty measures available in the data sets, this analysis focus on the poverty headcount ratio measured against the international poverty line of \$2 per person per day in 2005 Purchasing Power Parity (PPP) terms, or equivalently, \$3.2 in 2011PPP terms[7].

Since a special focus of this paper is on SSA, we note that the 1977-2007 Panel contains 94 observations representing 28 SSA countries surveyed on average 3.4 times during 1980-2006 with an average growth spell of 5.3 years; and the 1981-2014 panel contains 101 observations representing 37 SSA countries surveyed on average 3.7 times

[6] We thank Fosu (2015) for sharing with us his data.

[7] 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). These new poverty lines largely correspond to \$1.25, \$2, and \$13 in 2005PPP terms, respectively. Income and consumption survey data in the 1981-2014 Panel are also measured in 2011PPP terms, as opposed to 2005PPP terms in the 1977-2007 Panel.

during 1985-2014 with an average growth spell of 5.2 years. All SSA observations in our four country-level data sets have mean consumption data from surveys.

Before analyzing and reporting on these SSA sub-samples, we need to address two valid concerns: First, are the SSA subsamples 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 the Appendix, of the 47 less developed countries in SSA[8], our SSA subsamples have covered, respectively, 28 during 1977-2007 and 37 during 1981-2014. We recognize that the SSA subsamples may be less ideal to capture poverty convergence due to lack of sufficient variance. However, whether this translates into a standard deviation that is too large to be useful also depends on the size of the error variance and the correlation among the independent variables. That our SSA estimates from multiple panel regression procedures actually have sufficiently large t-statistics 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

[8] 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).

much stronger effect on public policy.

Table 1 below reports summary statistics of main variables in the two country-level panels described above. We note that all LDCs as a group experienced, on average, much faster growth in mean and reduction in poverty during 1981-2014 that they did during 1977-2007. Developing countries in SSA, in contrast, experienced, over time and on average, a slight decline in mean growth rate and a significant increase in poverty reduction rate, which is consistent with what is documented in Pinkovskyi and Sala-i-Martin (2014) and Fosu (2015), and hints that the growth-poverty dynamics in SSA is different from LDCs as a whole. It is also interesting to note that as LDCs' initial poverty incidences decline over time from 44 percent during 1977-2007 to 33 percent during 1981-2014, their average annual poverty reduction rate increased from about 2 percent to close to 10 percent; which itself hints that there could be a negative association between initial poverty incidence and poverty reduction rate.

Table 1: Descriptive Statistics on Country-Level Panel Data

	The 1977-2007 Panel			The 1981-2014 Panel		
Variable	**Obs**	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
LDCs						
Annual average poverty reduction rate	392	-0.017	0.202	523	-0.097	0.366
Initial poverty headcount ratio	415	43.596	32.093	533	33.159	30.463
Annual average mean growth rate	415	0.017	0.091	533	0.026	0.082
Initial mean consumption expenditure	415	172.95	122.45	533	232.72	154.84
SSA						
Annual average poverty reduction rate	66	-0.002	0.040	101	-0.005	0.051
Initial poverty headcount ratio	66	81.139	15.530	101	70.532	19.949
Annual average mean growth rate	66	0.016	0.087	101	0.012	0.046
Initial mean consumption expenditure	66	51.92	31.60	101	101.90	63.45

Note: Mean consumption expenditure is measured in 2005 and 2011 Purchasing Power Parity terms during 1977-2007 and 1981-2014, respectively.

III.2 Ethiopian and Rwandan Panel Data

To test poverty convergence at micro level, we use two panel data sets based on household-level unit record from Ethiopia and Rwanda. Specifically, the data for Ethiopia covers the period 1996–2011 in four waves in a space of 5 years and consists of the history of 79,099 households. As shown in Table 2 below, Ethiopia households experienced a steady rise in per capita consumption expenditure during this recent period. This has led the national headcount ratio to decline at an annual rate of 2.3 percent in the 15 years covered by the data. In our subsequent regression analysis, we focus specifically on spatial trends in annual per capita consumption growth and poverty in 42 regions of the country over 15 years, as a function of initial conditions. The data are representative of the specified regions.

Table 2: Descriptive Statistics on Ethiopian Household Budget Surveys 1996–2011

Variable	N	Mean	Std. Dev.	Min	Max
-> year = 1995/96					
Headcount ratio	12342	0.46	0.50	0.00	1.00
Mean consumption	12342	1311	964	184	49335
Gini coefficient	12342	0.26	0.03	0.22	0.34
-> year = 2000					
Headcount ratio	17332	0.44	0.50	0.00	1.00
Mean consumption	17332	1327	891	196	51925
Gini coefficient	17332	0.27	0.04	0.21	0.40
-> year = 2005					
Headcount ratio	21595	0.39	0.49	0.00	1.00
Mean consumption	21595	1541	2266	161	155948
Gini coefficient	21595	0.27	0.05	0.22	0.57
-> year = 2011					
Headcount ratio	27830	0.30	0.46	0.00	1.00
Mean consumption	27830	1825	1532	202	133286

Notes: Per capita consumption in Ethiopian Birr 1996 prices (1 USD~=6.50).

The data for Rwanda are presented in similar fashion in Table 3 below for the period of 2000–2010. The data set consists of a sample of 27,626 households, which is representative at the level of 33 districts. As can be seen from the data, Rwanda also managed to reduce poverty through growth, even when inequality was slightly increasing. Both of these countries undertook reforms and significant public sector investment to promote growth and reduce poverty.

Table 3: Descriptive Statistics on Rwandan Household Budget Surveys 2000–2010

Variable	N	Mean	Std. Dev.	Min	Max
-> year = 2000					
Headcount ratio	6420	0.56	0.5	0	1
Mean consumption	6420	91375	164540	3661	5831642
Gini coefficient	6420	0.4	0.08	0.28	0.57
-> year = 2005					
Headcount ratio	6900	0.53	0.5	0	1
Mean consumption	6900	104923	229999	3429	9761221
Gini coefficient	6900	0.46	0.1	0.26	0.74
-> year = 2010					
Headcount ratio	14306	0.45	0.5	0	1
Mean consumption	14306	120778	274102	7097	12300000
Gini coefficient	14306	0.43	0.07	0.32	0.63

Notes: Per capita consumption in Rwandan Franc 2000 prices (1 USD~=500).

IV. Empirical Results

Have LDCs in the past three decades experienced faster subsequent reduction in poverty as their initial poverty incidences declined over time? And what could explain the presence or absence of within-country poverty convergence among them? What about LDCs from Sub-Saharan Africa (SSA), where poverty is found to be reducing rapidly in recent years and the poverty-growth dynamics is found to be different from the rest of the developing world? In this section we present empirical results from analyzing all LDCs as a group, SSA countries alone, and Ethiopian and Rwandan regions in three separate sub-sections.

IV.1 Less Developed Countries (LDCs)

As shown in Table 4 below, when information from the time-series dimension is considered, LDCs as a group actually did experience poverty convergence during both periods examined, as greater poverty reduction rate (more negative value) is significantly associated with higher initial poverty incidence. This finding is robust to the choice of regression procedures; and as expected, the system GMM estimate lies between the POLS estimate that is biased downward (as the dependent variable takes negative value) and the FE estimate that is biased upward.

Other than χ^2 for overall fit, we also report p-values for diagnostic tests in dynamic GMM regressions. Large p-values for second-order autocorrelation tests (AR(2)) leads to reject of the null of no serial correlation, and we use lags from three or more periods earlier as instruments. The numbers of instruments are all well below their corresponding numbers of observations, suggesting we can be less concerned about the Sargan and Hansen test statistics being weakened by too many instruments. Lastly, the large p-values for Sargan and Hansen test statistics lead to no rejection of the null which says the instruments are jointly valid/exogenous[9].

[9] Roodman (2009) on the one hand suggests that one should view Hansen p-values smaller than 0.1 or greater than 0.25 as "potential sign for trouble"; but on the other hand notes that the Sargan/Hansen test statistics "should not be relied upon too faithfully". This insight is confirmed in this exercise, where we notice that Hansen p-values between 0.1 and 0.25 are few and tend to be associated with coefficient estimates that are well outside the range defined by POLS and FE estimates, which Roodman (2009) suggests as having suffered from large loss of efficiency.

Table 4: Poverty Convergence in LDCs, by Data Set

	POLS	FE	SysGMM	FODGMM
LDCs, 1981-2014				
natural log of initial poverty	0.013	-0.158***	-0.086*	-0.189***
	[0.999]	[-3.479]	[-2.415]	[-3.636]
N	523	523		523
R^2	0.069	0.1470		
for GMM estimates				
χ^2			223.23	581.78
AR(2) p-value			0.158	0.181
Sargan p-value			1.000	0.562
Hansen p-value			1.000	0.000
Number of instruments			210	194
LDCs, 1977-2007				
natural log of initial poverty	-0.051**	-0.259***	-0.170***	-0.299***
	[-3.295]	[-7.520]	[-4.314]	[-11.476]
N	392	392	392	392
R^2	0.179	0.544		
for GMM estimates				
χ^2			6.90E+04	214.44
AR(2) p-value			0.514	0.406
Sargan p-value			0.998	0.992
Hansen p-value			1.000	1.000
Number of instruments			78	100

Notes: This table reports empirical poverty convergence rates from estimating Equation (3): $g_i(H_{it}) = \alpha_i + \beta_i \ln H_{it-\tau} + \varepsilon_{it}$. T-ratios are corrected for heteroskedasticity and reported in brackets. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To see what explains the strong poverty convergence found within LDCs, we then estimate Equations (1), (4), and (5) as specified in Section II, which explore mean convergence and the interrelationships among the growth in mean, poverty reduction, and their initial levels. We report our results in Tables 5 and 6 below. To save space, we shall not report diagnostic statistics for GMM estimates in our tables, unless otherwise specified. Also we shall only report FE and SYSGMM estimates in Table 6 for parsimony. All results not reported are available upon request.

Table 5 suggests LDCs experienced significant and robust unconditional convergence during both periods studied. Table 6, for its part, suggests three 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 ($\hat{\beta}$). Second, controlling for initial mean consumption level, initial poverty directly retards subsequent growth in mean ($\hat{\gamma}$). Finally, 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[10].

Table 5: Mean Convergence in LDCs, by Data Set

	POLS	FE	Sys GMM	FOD GMM
LDCs, 1981-2014				
natural log of initial poverty	0.013	-0.158***	-0.086*	-0.189***
	[0.999]	[-3.479]	[-2.415]	[-3.636]
N	523	523	523	523
R^2 or χ^2	0.069	0.1470	223.23	581.78
LDCs, 1977-2007				
natural log of initial poverty	-0.051**	-0.259***	-0.170***	-0.299***
	[-3.295]	[-7.520]	[-4.314]	[-11.476]
N	392	392	392	392
R^2 or χ^2	0.179	0.544	6.90E+04	214.44

Notes: This table reports empirical mean convergence rates from estimating Equation (1): $g_i(\mu_{it}) = \alpha_i + \beta_i \ln\mu_{it-\tau} + \varepsilon_{it}$. T-ratios are corrected for heteroskedasticity and reported in brackets. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[10] We also note these growth elasticity estimates are quite similar to those obtained from estimating the Identity Model using panel data sets (Fosu 2015; Thorbecke and Ouyang 2017).

Table 6: Direct and Indirect Poverty Effects in LDCs, by Data Set

	Direct Poverty Effect		Indirect Poverty Effect	
	FE	**sysGMM**	**FE**	**sysGMM**
LDCs, 1981-2014				
natural log of initial mean ($\hat{\beta}$)	-0.151^{***}	-0.061^{*}		
	[-4.513]	[-2.414]		
natural log of initial poverty ($\hat{\gamma}$)	0.002	-0.007		
	[0.198]	[-1.025]		
poverty-adjusted growth ($\hat{\eta}$)			-3.309^{***}	-3.279^{***}
			[-9.463]	[-5.434]
N	528	528	523	523
R^2 or χ^2	0.219	431.185	0.311	316.534
LDCs, 1977-2007				
natural log of initial mean ($\hat{\beta}$)	-0.257^{***}	-0.237^{***}		
	[-7.391]	[-3.888]		
natural log of initial poverty ($\hat{\gamma}$)	0.005	-0.021		
	[0.238]	[-1.590]		
poverty-adjusted growth ($\hat{\eta}$)			-2.823^{***}	-2.807^{***}
			[-9.261]	[-6.661]
N	396	396	392	392
R^2 or χ^2	0.509	398.140	0.719	480.391

Notes: This table reports $\hat{\beta}$ and $\hat{\gamma}$ from Equation (4) $g_i(\mu_{it}) = \alpha + \beta ln\mu_{it-\tau} + \gamma lnH_{it-\tau} + \varepsilon_{it}$; and $\hat{\eta}$ 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: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

With estimates from Tables 5 and 6, 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 results in Table 7 below. Here we note that overall, the sum of the three effects matches the empirical poverty convergence rate reasonably well, suggesting that they are important contributing factors for poverty convergence found in LDCs during the examined period.

Table 7: Poverty Decomposition in LDCs, by Data Set

	LDCs, 1981-2014		**LDCs, 1977-2007**	
Regression procedure decomposition is based on	FE	system GMM	FE	system GMM
Mean Convergence Effect	-0.145*	-0.068*	-0.241***	-0.212***
Direct Poverty Effect	-0.004	0.015	-0.007	0.032
Indirect Poverty Effect	0.029***	0.028***	0.021***	0.021***
Sum of the above three	-0.120	-0.025	-0.228	-0.159***
Empirical poverty convergence rate	-0.158***	-0.086*	-0.259***	-0.170***
	[-3.479]	[-2.415]	[-7.520]	[-4.314]
N	523	523	392	392
R^2 or χ^2	0.147	223.23	0.512	6.90E+04

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 5 and 6. Effects are statistically significant and denoted by an asterisks (*) if β, γ, and η in computing them are statistically significant. The sum of the three effects give the predicted poverty convergence rates as reported in Table 4.

To summarize this section (IV.1): between the late 1970s and the early 2010s, LDCs experienced strong poverty convergence within themselves, whereby poverty reduction accelerates as countries' initial poverty incidences decline over time. The convergence is explained by a strong mean convergence effect that is only partly cancelled by a significant but less sizable indirect poverty effect. A direct poverty effect is not observed.

IV.2 Sub-Saharan African Countries (SSA)

Although countries in SSA have experienced, on average, rapid reduction in poverty, improvement in inequality, and quantum growth (Pinkovskyi and Sala-i-Martin 2014; Fosu 2015; Thorbecke and Ouyang 2016); they remain the poorest among all developing countries. By 2013, their average headcount ratio was 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 why?

As shown in tables below, developing countries in SSA also experienced significant poverty convergence during the periods examined (Table 8). What contribute to this, is not just strong mean convergence (Table 9) more sizable than the indirect poverty effect, but also a significantly positive direct poverty effect (Table 10), whereby high initial poverty is related to faster growth in mean. As summarized in Table 11, this positive direct poverty effect explains about 15 percent of the empirical poverty convergence rate observed in SSA during 1977-2007.

Table 8: Poverty Convergence in SSA, by Data Set

	POLS	FE	Sys GMM	FOD GMM
SSA, 1981-2014				
natural log of initial poverty	-0.009	-0.147***	-0.114***	-0.114***
	[-0.926]	[-4.367]	[-4.662]	[-4.662]
N	101	101	101	101
R^2 or χ^2	0.708	0.912	5.90E+04	5.90E+04
SSA, 1977-2007				
natural log of initial poverty	-0.072*	-0.321***	-0.101***	-0.072
	[-2.098]	[-9.466]	[-3.654]	[-1.581]
N	66	66	66	66
R^2	0.521	0.826	5.10E+05	1.70E+06

Note: The sysGMM and FODGMM estimates differ only slightly in the number of instruments used and Sargan test statistics (not reported and available upon request).

Table 9: Mean Convergence in SSA, by Data Set

	POLS	FE	Sys GMM	FOD GMM
SSA, 1981-2014				
natural log of initial mean	-0.021*	-0.130***	-0.072***	-0.075**
	[-2.540]	[-6.192]	[-2.713]	[-2.697]
N	101	101	101	101
R^2 or χ^2	0.529	0.734	2.90E+08	3.10E+08
SSA, 1977-2007				
natural log of initial mean	-0.091*	-0.355***	-0.069*	-0.074
	[-2.266]	[-12.445]	[-2.337]	[-1.625]
N	66	66	66	66
R^2 or χ^2	0.370	0.878	7.00E+05	3.50E+06

Table 10: Direct and Indirect Poverty Effects in SSA, by Data Set

	Direct Poverty Effect		**Indirect Poverty Effect**	
	FE	**sysGMM**	**FE**	**sysGMM**
SSA, 1981-2014				
natural log of initial mean ($\hat{\beta}$)	-0.109***	-0.108*		
	[-4.031]	[-3.237]		
natural log of initial poverty ($\hat{\gamma}$)	0.048	-0.011		
	[1.526]	[-0.390]		
poverty-adjusted growth ($\hat{\eta}$)			-1.365***	-1.164***
			[-17.625]	[-14.760]
N	101	101	101	101
R^2 or χ^2	0.74	641.777	0.944	3.50E+03
SSA, 1977-2007				
natural log of initial mean ($\hat{\beta}$)	-0.349***	-0.041***		
	[-7.101]	[-10.509]		
natural log of initial poverty ($\hat{\gamma}$)	0.018	*0.042****		
	[0.158]	*[7.604]*		
poverty-adjusted growth ($\hat{\eta}$)			-1.349***	-1.929***
			[-9.906]	[-5.397]
N	66	66	66	66
R^2	0.879	57.815	0.856	354.437

Table 11: Poverty Decomposition in SSA, by Data Set

	SSA, 1981-2014		**SSA, 1977-2007**	
Regression procedure this decomposition is based on	FE	system GMM	FE	system GMM
Mean Convergence Effect	-0.091***	-0.076*	-0.296***	-0.071***
Direct Poverty Effect	-0.020	0.004	-0.005	*-0.016****
Indirect Poverty Effect	0.011***	0.009***	0.017***	0.025***
Sum of the above three	-0.100	-0.062	-0.284	-0.062
Empirical poverty convergence rate	-0.147***	-0.114*	-0.321***	-0.101***
	[-4.367]	[-4.662]	[-9.466]	[-3.654]
N	101	101	66	66
R^2 or χ^2	0.922	5.40E+04	0.828	5.10E+05

IV.2 Ethiopian and Rwandan Regions

What happens when the above findings are tested with micro-level data from different regions within individual LDCs? To answer this question, we rely on large data sets representative of Ethiopian and Rwandan districts.

As shown in Table 12 below, Ethiopian regions during 1996–2011 experienced significant convergence in mean (column (1)) that is however not robust to the inclusion of initial poverty (column 2) and other control variables, especially the proportion of households that live in urban areas in a given region --- which is particularly important as growth tends to be urban-biased (column 3). On the other hand, we observe at least in the initial period (1996–2005) that Ethiopian regions enjoyed a positive direct effect of initial poverty (column 4), which is consistent with what we find in the country-level panel analysis (as reported in Table 10). In Ethiopia, the positive link between initial poverty and subsequent growth in mean is likely related to the strong policy orientation in this period that shifted public resources towards "disadvantaged" regions.

Table 12: Regressing Mean Income Growth on Initial Poverty and Initial Income, Ethiopia (1996-2011)

	(1)	(2)	(3)	(4)
Initial mean	-0.0528*	-0.0221	-0.0161	-0.0463
	[-2.66]	[-0.73]	[-0.53]	[-1.69]
Initial poverty		0.224	0.227	*0.253***
		[1.26]	[1.28]	*[3.7]*
Proportion of urban residents			-0.137	
			[-1.06]	
Intercept	0.906	0.890	0.890	0.751
	[6.91]	[6.75]	[6.71]	[4.3]
N	106	106	106	67
R^2	0.046	0.063	0.075	0.292

Notes: Columns (1) to (3) apply to the full sample. Column (4) is for period 1996–2005. T-ratios are in parentheses. The regression equation is Equation (4) from Section II: $g_i(\mu_{it}) = \alpha + \beta ln\mu_{it-\tau} + \gamma lnH_{it-\tau} + \varepsilon_{it}$; and the method is fixed effects. T-ratios are in brackets and corrected for heteroskedasticity. ** significant at 1%; * significant at 5%.

As shown in Table 13 below, this positive direct poverty effect contributed to 40 percent of the Ethiopian poverty convergence rate of -0.20 (t-ratio is -1.81), which is quite significant. This is consistent with and larger than what we find in SSA at the country level (Table 11).

Finally, Table 13 shows that Rwanda regions also experienced significant poverty convergence significant at the 10% level. The convergence rate, however, is noted to be much larger than sum of the three effects (-0.12 versus -0.008). As noted in Section II, this likely suggests that poverty convergence within Rwandan regions during 2000-2010 is driven by factors not included in the model specifications, such as policies oriented toward the poorest regions; though testing this hypothesis goes beyond the scope of this paper.

Table 13: Decomposition of Poverty Convergence Rate in Ethiopia and Rwanda

	Ethiopia	**Rwanda**
(1) Mean convergence effect	-0.130	-0.008
(2) Direct effect of poverty	-0.080*	-0.001
(3) Indirect effect of poverty	0.015	0.001
Computed Poverty Convergence=(1)+(2)+(3)	-0.196	-0.008
Poverty Convergence Rate from Regression Analysis	-0.200*	-0.120*
	[-1.81]	[-1.80]

Notes: The table reports the three contributing effects to poverty convergence in Equation (6): $\frac{\partial g_i(H_{it})}{\partial lnH_{it-\tau}} = \eta\beta(1 - H_{it-\tau})\left(\frac{\partial lnH_{it-\tau}}{\partial ln\mu_{it-\tau}}\right)^{-1} + \eta\gamma(1 - H_{it-\tau}) + [-\eta g_i(\mu_{it})H_{it-\tau}]$. 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): $g_i(H_{it}) = \alpha_i^* + \beta_i^* \ln H_{it-\tau} + \epsilon_{it}^*$.

V. Conclusion

Though a very important inquiry, poverty convergence is much less studied than convergence in mean, which is somewhat ironic as a most important reason for which all human societies pursue economic growth, is that growth lifts men out of poverty. Further, much of the sparse empirical literature on poverty convergence currently relies on analysis of cross-sectional data, and found a lack of poverty convergence in the developing world in the sense that during a given period in time, developing countries starting out poorer did not enjoy larger (more negative) poverty reduction rate than those starting out richer, as the advantage of growth or mean convergence effect is greatly weakened by an indirect poverty effect and a strongly adverse direct poverty effect during at least 1977-2007.

In an effort to depict a more comprehensive picture of poverty convergence in the developing world, we apply a dynamic panel analysis involving estimation of a system GMM and a difference GMM with FOD transformation (FODGMM) proposed by Arellano, Bond, and others (1991; 1995; 1998) to four panel data sets covering, respectively, some 90 LDCs from two periods (i.e. 1977-2007 and 1981-2014), 42 Ethiopian during 1995-2010, and 33 Rwandan regions during 2000-2010.

We find that when information from the time-series dimension is considered, LDCs --- all as one group or those from SSA as a group --- did do enjoy faster subsequent poverty reduction within themselves as their initial poverty incidences decline over time; as initial poverty only partly and indirectly weakens the advantage of growth or mean convergence effect, while a direct poverty effect is either negligible or significantly positive (in SSA countries during 1977-2007). We obtain similar findings from analyzing the Ethiopian and Rwanda data, where a significantly positive direct effect --- which is likely explained by the strong anti-poverty policies the government is committed --- accounts for 40 percent of Ethiopian's poverty convergence during 1995-2005.

Appendix: Countries in the 1981-2014 Panel

	Country Name	First	Last	Welfare	Region
1	Albania	1996	2012	C	Europe and Central
2	Armenia	1999	2014	C	Europe and Central
3	Bangladesh	1983.5	2010	C	South Asia
4	Belarus	1998	2014	C	Europe and Central
5	Bolivia	1990.5	2014	I	Latin America and the
6	Bosnia and	2001	2011	C	Europe and Central
7	Botswana	1985.57	2009.25	C	Sub-Saharan Africa
8	Brazil	1981	2014	I	Latin America and the
9	Bulgaria	1989	2007	C	Europe and Central
1	Burkina Faso	1994.25	2014	C	Sub-Saharan Africa
1	Burundi	1992	2006	C	Sub-Saharan Africa
1	Cambodia	1994	2012	C	East Asia and Pacific
1	Cameroon	1996	2014	C	Sub-Saharan Africa
1	Central African	1992.43	2008	C	Sub-Saharan Africa
1	Chile	1987	2013	I	Latin America and the
1	China	1990	2013	C	East Asia and Pacific
1	Colombia	1992	2014	I	Latin America and the
1	Costa Rica	1981	2014	I	Latin America and the
1	Cote d'Ivoire	1985.08	2008	C	Sub-Saharan Africa
2	Croatia	1998	2010	C	Europe and Central
2	Czech Republic	1988	2012	I	Europe and Central
2	Djibouti	2002	2013	C	Middle East and North
2	Dominican	1986	2013	I	Latin America and the
2	Ecuador	1987	2014	I	Latin America and the
2	El Salvador	1989	2014	I	Latin America and the
2	Estonia	1995	2004	C	Europe and Central
2	Ethiopia	1995.25	2010.5	C	Sub-Saharan Africa
2	Gambia, The	1998	2003.29	C	Sub-Saharan Africa
2	Georgia	1996	2014	C	Europe and Central
3	Ghana	1987.5	2005.67	C	Sub-Saharan Africa
3	Guatemala	1986.5	2014	I	Latin America and the
3	Guinea	1991	2012	C	Sub-Saharan Africa
3	Guinea-Bissau	1991	2010	C	Sub-Saharan Africa
3	Guyana	1992.5	1998	I	Latin America and the
3	Honduras	1989	2014	I	Latin America and the
3	Hungary	1998	2007	C	Europe and Central
3	India	1983	2011.5	C	South Asia
3	Indonesia	1984	2014	C	East Asia and Pacific
3	Iran, Islamic	1986	2013	C	Middle East and North
4	Jamaica	1988	2004	C	Latin America and the

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	Country Name	First	Last	Welfare	Region
41	Kazakhstan	1996	2013	C	Europe and Central
42	Kenya	1992	2005.3	C	Sub-Saharan Africa
43	Kyrgyz Republic	1993	2014	C	Europe and Central
44	Lao People's	1992.2	2012.2	C	East Asia and
45	Latvia	1997	2009	C	Europe and Central
46	Lesotho	1986.54	2010	C	Sub-Saharan Africa
47	Lithuania	1996	2008	C	Europe and Central
48	Macedonia, former	1998	2008	C	Europe and Central
49	Madagascar	1993.3	2012	C	Sub-Saharan Africa
50	Malawi	1997.83	2010.2	C	Sub-Saharan Africa
51	Malaysia	1984	2009	I	East Asia and
52	Mali	1994	2009.8	C	Sub-Saharan Africa
53	Mauritania	1987	2014	C	Sub-Saharan Africa
54	Mexico	1984	2014	C	Latin America and
55	Moldova	1997	2014	C	Europe and Central
56	Mongolia	1995	2014	C	East Asia and
57	Morocco	1984.5	2006.9	C	Middle East and
58	Mozambique	1996.27	2008.6	C	Sub-Saharan Africa
59	Nepal	1995.5	2010.1	C	South Asia
60	Nicaragua	1993	2005	C	Latin America and
61	Niger	1992.85	2014	C	Sub-Saharan Africa
62	Nigeria	1985.25	2009.8	C	Sub-Saharan Africa
63	Pakistan	1987	2013.5	C	South Asia
64	Panama	1989	2014	I	Latin America and
65	Paraguay	1990	2014	I	Latin America and
66	Peru	1985.5	1994	C	Latin America and
67	Philippines	1985	2012	C	East Asia and
68	Poland	1993	2014	C	Europe and Central
69	Romania	1998	2013	C	Europe and Central
70	Russian Federation	1993	2012	C	Europe and Central
71	Rwanda	1984.5	2013.7	C	Sub-Saharan Africa
72	Senegal	1991.25	2011.2	C	Sub-Saharan Africa
73	Sierra Leone	1989.75	2011	C	Sub-Saharan Africa
74	Slovak Republic	2004	2009	C	Europe and Central
75	Slovenia	1998	2003	C	Europe and Central
76	South Africa	1993	2011	C	Sub-Saharan Africa
77	Sri Lanka	1985	2012.5	C	South Asia
78	Swaziland	1994.83	2009.2	C	Sub-Saharan Africa
79	Tajikistan	1999	2014	C	Europe and Central
80	Tanzania	1991.92	2011.7	C	Sub-Saharan Africa

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	Country Name	First	Last	Welfare	Region
81	Thailand	1981	2013	C	East Asia and Pacific
82	Trinidad and Tobago	1988	1992	I	Latin America and the
83	Tunisia	1985	2010.	C	Middle East and North
84	Turkey	1987	2013	C	Europe and Central
85	Uganda	1989	2012.	C	Sub-Saharan Africa
86	Ukraine	1995	2014	C	Europe and Central
87	Uruguay	1981	2014	I	Latin America and the
88	Uzbekistan	1998	2003	C	Europe and Central
89	Venezuela, Republica	1981	2006	I	Latin America and the
90	Vietnam	1992.	2014	C	East Asia and Pacific
91	Zambia	1991	2010	C	Sub-Saharan Africa
	The following are in the 1981-2014 Panel but not the 1977-2007 Panel				
92	Azerbaijan	1995	2008	C	Europe and Central
93	Belize	1993	1999	I	Latin America and the
94	Benin	2003	2011.	C	Sub-Saharan Africa
95	Bhutan	2003	2012	C	South Asia
96	Cabo Verde	2001.	2007.	C	Sub-Saharan Africa
97	Chad	2003	2011	C	Sub-Saharan Africa
98	Congo, Democratic	2004.	2012.	C	Sub-Saharan Africa
99	Congo, Republic of	2005	2011	C	Sub-Saharan Africa
10	Fiji	2002.	2008.	C	East Asia and Pacific
10	Haiti	2001	2012	I	Latin America and the
10	Kosovo	2003	2013	C	Europe and Central
10	Maldives	2002.	2009.	C	South Asia
10	Mauritius	2006.	2012	C	Sub-Saharan Africa
10	Micronesia, Federated	2005	2013	C	East Asia and Pacific
10	Montenegro	2005	2014	C	Europe and Central
10	Namibia	2003.	2009.	C	Sub-Saharan Africa
10	Papua New Guinea	1996	2009.	C	East Asia and Pacific
10	Sao Tome and Principe	2000.	2010	C	Sub-Saharan Africa
11	Serbia	2002	2013	C	Europe and Central
11	Timor-Leste	2001	2007	C	East Asia and Pacific
11	Togo	2006	2011	C	Sub-Saharan Africa
11	Tonga	2001	2009	C	East Asia and Pacific
11	West Bank and Gaza	2004	2009	C	Middle East and North

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Appendix: Countries in The 1977-2007 Panel

	Country	First	Last	Welfare	Region
1	Albania	1996.8	2005	C	Europe and Central Asia
2	Armenia	1998.5	2003	C	Europe and Central Asia
3	Bangladesh	1991.5	2005	C	South Asia
4	Belarus	2000	2005	C	Europe and Central Asia
5	Bolivia	1990.5	2005	I	Latin America and the
6	Bosnia and	2001	2004	C	Europe and Central Asia
7	Botswana	1985.5	1993.9	C	Sub-Saharan Africa
8	Brazil	1981	2005	I	Latin America and the
9	Bulgaria	1989	2003	C	Europe and Central Asia
10	Burkina Faso	1994	2003	C	Sub-Saharan Africa
11	Burundi	1992	2006	C	Sub-Saharan Africa
12	Cambodia	1994	2004	C	East Asia and Pacific
13	Cameroon	1996	2001	C	Sub-Saharan Africa
14	Central	1993	2003	C	Sub-Saharan Africa
15	Chile	1987	2003	I	Latin America and the
16	China	1981	2005	C	East Asia and Pacific
17	Colombia	1995	2003	I	Latin America and the
18	Costa Rica	1981	2005	I	Latin America and the
19	Cote d'Ivoire	1985	2002	C	Sub-Saharan Africa
20	Croatia	1998	2005	C	Europe and Central Asia
21	Czech	1988	1996	I	Europe and Central Asia
22	Djibouti	1996	2002	C	Middle East and North Africa
23	Dominican	1986	2005	I	Latin America and the
24	Ecuador	1987	2005	I	Latin America and the
25	El Salvador	1989	2003	I	Latin America and the
26	Estonia	1995	2004	C	Europe and Central Asia
27	Ethiopia	1981.5	2005	C	Sub-Saharan Africa
28	Gambia, The	1998	2003	C	Sub-Saharan Africa
29	Georgia	1996	2005	C	Europe and Central Asia
30	Ghana	1987.5	2005.5	C	Sub-Saharan Africa
31	Gautemala	1987	2006	I	Latin America and the
32	Guinea	1991	2003	C	Sub-Saharan Africa
33	Guinea-	1991	2002	C	Sub-Saharan Africa
34	Guyana	1992.5	1998	I	Latin America and the
35	Honduras	1990	2005	I	Latin America and the
36	Hungary	1998	2004	C	Europe and Central Asia
37	India	1977.5	2004.5	C	South Asia
38	Indonesia	1984	2005	C	East Asia and Pacific
39	Iran, Islamic	1986	2005	C	Middle East and North Africa
40	Jamaica	1988	2004	C	Latin America and the

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	Country	First	Last	Welfare	Region
41	Kazakhstan	1996	2003	C	Europe and Central Asia
42	Kenya	1992.4	2005.4	C	Sub-Saharan Africa
43	Kyrgyz	1988	2004	I	Europe and Central Asia
44	Lao PDR	1992.2	2002.2	C	East Asia and Pacific
45	Latvia	1998	2004	C	Europe and Central Asia
46	Lesotho	1986.5	2002.5	C	Sub-Saharan Africa
47	Lithuania	1996	2004	C	Europe and Central Asia
48	Macedonia,	1998	2003	C	Europe and Central Asia
49	Madagascar	1980	2005	C	Sub-Saharan Africa
50	Malawi	1997.5	2004.3	C	Sub-Saharan Africa
51	Malaysia	1984	2004	I	East Asia and Pacific
52	Mali	1994	2006	C	Sub-Saharan Africa
53	Mauritania	1987	2000	C	Sub-Saharan Africa
54	Mexico	1984	2006	C	Latin America and the
55	Moldova,	1997	2004	C	Europe and Central Asia
56	Mongolia	1995	2005	C	East Asia and Pacific
57	Morocco	1984.5	2007	C	Middle East and North Africa
58	Mozambique	1996.5	2002.5	C	Sub-Saharan Africa
59	Nepal	1995.5	2003.5	C	South Asia
60	Nicaragua	1993	2005	I	Latin America and the
61	Niger	1992	2005	C	Sub-Saharan Africa
62	Nigeria	1985.5	2003.7	C	Sub-Saharan Africa
63	Pakistan	1987	2004.5	C	South Asia
64	Panama	1979	2004	I	Latin America and the
65	Paraguay	1990	2005	I	Latin America and the
66	Peru	1990	2005	I	Latin America and the
67	Philippines	1985	2006	C	East Asia and Pacific
68	Poland	1996	2005	C	Europe and Central Asia
69	Romania	1998	2005	C	Europe and Central Asia
70	Russian	1993	2005	C	Europe and Central Asia
71	Rwanda	1984.5	2000	C	Sub-Saharan Africa
72	Senegal	1991	2005	C	Sub-Saharan Africa
73	Sierra Leone	1989.5	2003	C	Sub-Saharan Africa
74	Slovak	1988	1996	I	Europe and Central Asia
75	Slovenia	1998	2004	C	Europe and Central Asia
76	South Africa	1993	2000	C	Sub-Saharan Africa
77	Sri Lanka	1985	2002	C	South Asia
78	Swaziland	1994.5	2000.5	C	Sub-Saharan Africa
79	Tajikistan	1999	2004	C	Europe and Central Asia
80	Tanzania	1991.9	2000.4	C	Sub-Saharan Africa
81	Thailand	1981	2004	C	East Asia and Pacific

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	Country	First	Last	Welfare	Region
82	Trinidad and	1988	1992	I	Latin America and the
83	Tunisia	1985	2000	C	Middle East and North Africa
84	Turkey	1987	2005	C	Europe and Central Asia
85	Uganda	1989	2005	C	Sub-Saharan Africa
86	Ukraine	1996	2005	C	Europe and Central Asia
87	Uruguay	1992	2005	I	Latin America and the
88	Uzbekistan	1998	2003	C	Europe and Central Asia
89	Venezuela,	1981	2005	I	Latin America and the
90	Vietnam	1992.7	2006	C	East Asia and Pacific
91	Zambia	1991	2004.2	C	Sub-Saharan Africa
	The following are in the 1977-2007 Panel but not The 1981-2014 Panel				
92	Algeria	1988	1995	C	Middle East and North Africa
93	Argentina	1986	2005	I	Latin America and the
94	Egypt, Arab	1990.5	2004.5	C	Middle East and North Africa
95	Jordan	1986.5	2006	C	Middle East and North Africa
96	Turkmenistan	1988	1993	I	Europe and Central Asia
97	Yemen, Rep.	1992	2005	C	Middle East and North Africa